ABSTRACT

Title of dissertation:	TESTING ECONOMIC MODELS OF HOUSEHOLD RESOURCE ALLOCATION
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This dissertation examines the role of household resource allocation on individual human capital accumulation. The main contributions of the dissertation is providing evidence first that families play an active role on individual investment and second that cost and benefit within the household are not shared evenly among members.

First, using multiple births as an exogenous shift in family size, I investigate the impact of the number of children on child investment and child well-being. Using data from the 1980 US Census Five-Percent Public Use Micro Sample, 2SLS results demonstrate that parents facing a change in family size reallocate resources in a way consistent with Becker's Quantity and Quality model. A larger family generated by a twin on a later birth reduces the likelihood that older children attend private school, increases the likelihood that children share a bedroom, reduces the mother's labor force participation, and increases the likelihood that parents divorce. The impact of family size on measures of child wellbeing, such as educational attainment, the probability of not dropping out of school and teen pregnancy is, however, less clear. The results do indicate that for both measures of child investment and child well being, the 2SLS estimates are statistically distinguishable from

OLS estimates indicating an omitted variables bias in the single equation model.

Second, using data from the National Health Interview (NHIS) and Behavioral Risk Factor Surveillance System (BRFSS), I examine the effect of female employment and predictors of obesity for married men and women. I use the fact that there is a clear relationship between female labor force participation (FLFP) and age structure of children in the household in order to identify the impact of FLFP. When children are small mothers tend to stay at home; later when children start kinder garden or school mothers are able to come back to paid activities. I find that for married men with less than high school, female employment raises their Body Mass Index (BMI). However I do not find evidence that female employment increases women's BMI or the likelihood of obesity.

TESTING ECONOMIC MODELS
OF HOUSEHOLD RESOURCE ALLOCATION

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2005

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To my parents who always told me that education was the only thing that I could inherit. They gave the first spark.

To my beloved *Alexandra* who gave the love, motivation and patience to face every obstacle, and herself as an example of a brave human being.

ACKNOWLEDGMENTS

I am specially indebted to William Evans and Seth Sanders for their support and patience. I also want to thank Jonah Gelbach and Jeffery Smith for their help and encouragement. Last, but not least, I benefited from the comments of Roberto Alvarez, Daniel Aromi, Roger Betancourt, Julian Cristia, Juan Jose Diaz, Eugenio Giolito, Judy Hellerstein, Alexandra Jabin, Hoda Makar, Rodrigo Soares, Ye Zhang and seminar participants at the University of Maryland, Universidad Carlos III de Madrid, University of Bern and 17th Annual Congress of the European Society for Population Economics Society (13th to 15th of June 2003, New York City). It is impossible to remember all, and I apologize to those I've inadvertently left out.

Lastly, thank you all and thank God!

All the errors are of course mine.

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Chapter 1

Introduction

Since Becker's formalization of a *Household production model*, and more generally of an economic approach of *Human behavior,* there has been a growing theoretical and empirical literature in economics addressing the household's role in the allocation of goods and time within the household and in specific on human capital accumulation (Pollack, 2002).

Part of this growing interest in how families combine time and markets goods to produce more basic commodities not only comes from the natural intellectual curiosity to test the strong prediction in Becker's benchmark models but also for the unprecedented changes that families have faced during the last fifty years such as the increasing movement of woman out of home, delaying in the time of the first marriage and reduction of fertility among others (Hotz, Klerman and Willis, 1997). All these changes bring on a still open questions about how the families have reacted to these changes and who if there is someone in particular in the family, bearing the cost or benefits associated to this process. In fact, the recognition that allocation rules within the household may not always protect the most vulnerable members is of great significance for the selection and design of policies.

Chapter 2 addresses an old issue that comes from Becker's seminal quantity & quality model; Do families with more children invest less per child? There is wide-spread acceptance of a trade-off between number of children and "child quality" implied by Becker's model. However the degree of empirical support of this relationship depends on the variables that have been used as measures of quality and the data used. To date, the literature has been characterized in large part by three common elements. First, not all but most studies on the tradeoff between child quality and quantity have been conducted using data from developing countries. Second, there is a strong tendency to equate "child quality" with either measures of child wellbeing. However, when Becker speaks about quality he is specifically addressing child investment. The effects on child wellbeing will depend on other factors. Finally, and importantly most of the literature has a tendency to think about changes in the number of children as affecting only resources related to investment in children. However, most standard models of the family (either the Unitary model or the more recent bargaining models) suggest that changes in resources or resource requirements will affect all family members and other factors determine how much children are affected relative to other family members. One empirical example is that studies using time diaries show that when parents are faced with shortages of time they first spend less time cleaning, cooking and less time sleeping but protect time spent with children. (Bianchi, 2005).In this chapter by using US Census data for the year 1980 and multiple births as source of variation in family size finds evidence that supports Becker's model. An exogenous increase in family size reduces the probability of a child attending private school, increases the probability of sharing bedroom, lowers the labor participation of the child's mother and raises the probability of divorce. However for a second group of variables that I believe more closely related to child well-being, such as highest grade attended, grade retention, teen pregnancy or likelihood of dropping out school, I do not find evidence that family size has an impact.

In chapter 3 essentially I try to answer what happened with husband weight when wives return to the labor market. The literature addressing the rapid growth in the incidence in obesity in the US seems to center the attention on the supply of calories or on technologic factors accounting for the rise in obesity. In this chapter I explore another potential cause, which is the very large rise in female labor force participation over the last 40 years. A household production models predict that as female wages rise (closing the gap with male wages) wives will spend more time in the labor market and less time in household production. While families with higher incomes can afford better quality food (”less caloric”) and they have a higher demand for health, families with lower income will be able to afford only caloric intensive food such as fast-food. Using the *National Health Interview* (NHIS) I find that female employment has a positive impact on Body Mass Index (BMI) for married men with less than high school. However I do not find a impact for all samples of women or men with high school or more. This finding is consistent with men facing an increase in the cost of home cooking with a positive impact on body weight. Women face an offsetting rise in the level of physical activity and households with husbands with more income i.e more levels of education can afford prepared food with less calories. The magnitude of these findings is larger than found elsewhere in the literature. This is primarily because I take account of the endogeneity of female labor force participation. The analysis from the *Behavioral Risk Factor Surveillance System* (BRFSS) survey reveals that married men with less than high school or married men with college degree or more face an increase in their BMI and the likelihood of being obese if they live in states with a positive shock in female labor demand. The results also show that for married men with higher levels of education female demand shocks produce an increase in the levels of physical activity. This last element plus the positive impact of female demand shocks on BMI and obesity rate suggests that the channel through which female labor force participation raises a man’s weight must be through a higher consumption of calories which is consistent with a lower consumption of fruit and vegetables that we find associated to female demand shocks for this group.

Finally Chapter 5 provide the conclusions.

Chapter 2

Impact of Family Size on Investment in Child Quality: Multiple Births as a Natural Experiment

2.1 Overview

During the last forty, years a multidisciplinary research effort has shown the essential role that family background (parents' education, parents' age, marital status, family income, parents' employment, fertility, type of neighborhood, etc.) in the educational attainment and future economics success of children (Haverman and Wolfe, 1995). In particular, the relationship between family size and children's outcomes is conventionally addressed in what is known as the "quantity-quality" model (Becker, 1960; Becker and Lewis, 1973; Becker and Tomes, 1979, 1986).[1] The key insight of this model is that the number of children in the household (quantity) and child investment (quality) are determined by parents in a framework similar in many ways to the one in which households decide their demand for any other generic commodity. However, quantity and quality are linked in a way unlike other commodities: their shadow prices are cross–related such that an exogenous increase in the demand for either of these two factors produces an increase

[1] As Haveman and Wolfe (1995) point out, Becker's model of home investments in children can be considered as one of four main research lines when child outcomes are restricted to scholastic achievements. The other three lines that are mentioned are: a) Estimates of intergenerational income correlations through improved measures of father's earnings and adjustment for life–cycle bias; b) Research using siblings to control for common family influences on children's attainment; c) Research that attempts to address measurement error problems through estimating the reliability and validity of survey reports of family variables.

in the “cost” of the other factor.[2]

A direct implication of the model is a trade–off between child investment and number of children in the family. In the empirical literature, however, this negative influence of family size has been often studied at the level of child wellbeing. Nevertheless, independently of the outcomes that have been used the evidence has supported a negative influence of family size even on measures of child wellbeing. However there is still doubt among researchers whether this observed impact is causal, given the simultaneity of fertility and child outcomes.[3] Additionally, the link between child wellbeing and family size is less clear when families are able to reallocate resources among different types of child investment. Many studies that have addressed the endogeneity of family size, and find a negative impact of family size on child wellbeing, have been done for undeveloped or developing economies where we can assume that families have fewer degrees of freedom to reallocate resources.

In this paper, I study the impact of family size on two groups of variables. The first group consists of variables that measure investments in children. Although their impacts on child wellbeing is not empirically clear, these variables reflect the allocation of household resources by parents or other household members. The second group of variables are

[2]If we assume that there is no discrimination between children in the household, a family that chooses high levels of investment in child quality would face a higher “cost” if it decided to have an additional child since the desired quality for that child is high. Similarly, and keeping the assumption that there are no differences in quality among children within the household, a family that has a preference for a large family size would face a higher cost of increasing the quality of its children as the additional cost of raising quality applies to more children.

[3]Despite doubts about the causal relationships between these two variables, we see that many times it is assumed as one of the benefits of family planning that households will invest more in children’s human capital once a smaller family size is reached.

more traditional measures of child wellbeing that are thought to be alterable by a familiy's investments in their children, not necessarily they reflect household's investment. Following Rosenzweig and Wolpin (1980a, 1980b), I use multiple births as source of variation in family size. In particular I make use of an event of multiple births on the second or higher birth as an exogenous shock to family size. Using data from the 1980 US Census 5-percent Public Use Micro Samples data, I demonstrate that parents who have experienced an exogenous change in family size re-allocate resources consistent with Becker's *Quantity & Quality* model. An additional younger sibling reduces the likelihood that older siblings attend a private school, reduces their mother's labor force participation, increases the likelihood their parent's divorce and, makes it more likely that children share a bedroom. In contrast to the results linking family size to investments, I find little evidence that an exogenous change in family size alters measures of child wellbeing such as educational attaintment, the probability of not dropping out of school and teen pregnancy. Moreover, for the sub-sample of non-white children with young mothers, family size has a *positive* impact on highest completed grade. This suggest that while larger families induce parents to rearrange child inputs, parents do this in a way that may not affect child outcomes. I do however find evidence that single equation estimates of the quantity/quality trade-off in both the child investments and child well being models are subject to an omitted variable bias. In nearly all cases, the 2SLS estimates of the impact of family size on child investments and outcomes are statistically distinguishable from their OLS counterparts.

The paper is organized as follows. The second section presents a brief literature review. Section three explains the empirical methodology used to address the problem of identification. The fourth section describes how the variables and samples have been constructed and provides a descriptive analysis. Section five presents the results and section six, the conclusions.

2.2 Previous Empirical Evidence

The literature linking family size and child wellbeing can be cataloged into three groups of studies based on the measures of child quality. The first line of research has used scholastic achievements (Rosenzweig and Wolpin, 1980; Blake, 1981; Hauser and Sewell, 1986; Hanushek, 1992; Hill and O' Neill, 1994) or cognitive development (Belmont and Morolla, 1973; Wolfe, 1982) as measures of child quality. In general, these studies find that children from larger families have lower academic performance than children from smaller families.

A second line of research has used labor outcomes, such as wages or labor force participation as measures of quality (Duncan, 1968; Wachtel, 1975; Brittain, 1977; Olneck and Bills, 1979; Kessler, 1991). The main assumption behind these studies is that child quality is directly linked to future labor market success. Therefore, children from households with more siblings would be more likely to have lower wages and lower labor force participation. These studies find little evidence of an impact of family size on wages or labor force participation. For example, Kessler (1991) using the National Longitudinal Survey (NLSY) 1979-1987, finds that mothers from small families work less when they are young and more when they are mature compared to mothers that come from bigger families; however this is eventually explained by differences in the number of children that these two groups of mothers have.

Finally, a third group of studies relate family size to the intergenerational transmission of wealth (Tomes, 1981; Pestieau, 1984). Although the primary interest of these studies has been to analyze the equalizing role of inheritance and the substitution between human capital and inherited material wealth, these studies find that family size has a negative impact on per-capita bequests.

Despite the differences in the measures of child quality employed by these studies, there are three elements that generate doubts about whether most of the studies have identified a causal impact of family size on child "quality".

First, Becker's quantity and quality model is a model of investment where households decide the level of resources allocated per child (quality). The model assumes these investments lead to higher levels of child quality. The empirical evidence to date has primarily provided evidence about the impact of fertility on outcomes of investment rather than the investments themselves. Outcomes such as educational attainments or future labor market outcomes are produced with many inputs, home production being one. In fact, the introduction of home production and therefore the division of time between home and market activities introduces an additional ambiguity to the overall impact of family size; parents facing an exogenous change in fertility could substitute market investment for home investment activities such that they minimize the overall impact on child wellbeing. For example, a shift in family size increases the cost of maternal labor force participation inducing an increase in the average number of hours that mothers spend with their children, and therefore has a likely positive impact on child's development. On the other hand, the reduction in mother's labor force participation might reduce the total amount of resources in the household. In fact, the empirical evidence supports the claim that fertility has a negative impact on female labor participation (Rosenzweig and Wolpin, 1980; Angrist and Evans, 1996). However, the impact on child wellbeing is still ambiguous. Some empirical evidence shows the impact of the mother's work behavior as not statistically significant (Hayes and Kamerman, 1983; Hayns, 1982; Hanushek, 1992). However Hill and O'Neill (1994) find that an increase in the mother's hours at work has a significant negative effect on her child's achievements where this effect is only partially compensated for by a higher income. Also, Leibowitz (1974) demonstrates that the quantity and quality of a mother's time spent in preschool home education has a significant and positive impact on her child's IQ.

Second, although the quantity and quality trade–off has been the leading view regarding the relationship between family size and child's success, we can postulated a different type of relationship that does not necessarily imply a negative impact of the number of children in the household on their present and future achievements. For example, in a household there is a process of interaction among siblings, this socialization might imply that children learn from each other such that the "price" of quality could decrease with family size. In particular, we could think that although older siblings may perceive a reduction in their wellbeing as they have more siblings, they may obtain skills (for example responsibility, leadership, etc.) that could be highly profitable in the future.[4] Consistent with an alternative relationship, Zanjonc (1976) formalize that family size does not matter per se but rather the predominant interaction within family's members. These different channels through which quantity might act on child wellbeing make the over all impact of family size on child welfare even more ambiguous.

Third, while many studies show a negative correlation between family size and child achievement, there is some reservation whether this quantity-quality relationship is causal. The issue stems directly from the model that establishes a simultaneous determination of quantity and quality, explained in more detail in the following sections. In order to solve

[4] In fact, we can conjecture a richer model where there are external effects associated with number of children such that the overall impact on child quality is positive.

this problem Rosenzweig and Wolpin (1980a, 1980b) use the occurrence of multiple births (twins) in the household as an identification strategy. Thus, using the ratio of twin births over the total number of pregnancies as a proxy of children price in one study, and a dummy variable that accounts for the occurrence of multiple births as an instrument in the other study, they estimate the impact of family size on child achievement and mothers' labor participation, respectively. The results of these two studies reveal that an exogenous change in family size has: a) a negative impact on levels of schooling for all children in the family unit in a national sample of 2,939 farm households in India (Rosenzweig and Wolpin, 1980a) and ; b) a negative impact on labor participation for a sample of 12,605 U.S. women [5] (Rosenzweig and Wolpin, 1980b).

In order to address the endogenous nature of family size, I appeal to multiple births as a natural experiment. Although this source of identification has already been used (Rosenzweig and Wolpin, 1980a 1980b; Black *et al.*, 2005), this research enhances the literature in two ways. First, I use data from a developed country U.S. Census data for the year 1980. Therefore, unlike previous studies that use data from developing countries, I use households that are likely to have more degrees of freedom when facing changes in fertility, such that changes in family size are more likely to affect type of investment than child wellbeing. In fact, Black *et al.* (2005) using administrative data for Norway find that once birth order is taken in account and the variable twin births is used as instrument the effect of number of children on children's educational attaintment is negligible or non existent when birth order is taken in to account. Second and related to the previous point, in order to reduce the chance of Type II error, I make an explicit distinction in

[5] A national random sample of women containing detailed information about life-cycle pregnancy outcomes. For more details see Rosenzweig and Wolpin (1980b).

the impact of an increase in the number of children on variables that can be linked to child investment (quality) from other variables that might be considered as outputs of investment which probably are closer to wellbeing but do not necessarily reflect directly the allocation of resources by the parents. Up to date Conley (2004) using the 1990 Census data and sibling sex composition as source of variation in family size is one of the few studies that not only analyzes the impact of number of children on outcomes of investment but also investment. Conley's results reveal that number of children not only reduces the probability of attending private school (investment) but also increases the likelihood of being "*held back*" (output).

2.3 Empirical Methodology

The following bivariate regression model represents a simpler version of the causal relationship I want to estimate,

$$y_i = \alpha + \gamma n_i + \varepsilon_i \qquad i = 1, \ldots, T \tag{2.1}$$

where y_i represents a measure of child investment (inputs into the production of child quality) or a measure of child wellbeing, n_i represents family size, i indexes observation, and for simplicity in the exposition other covariates are left implicit.

The impact of family size on child quality is measured by γ. The intuition of Becker's Quality and Quantity model suggests that OLS estimates of this equation may be subject to an omitted variable bias since the $cov(n_i, \varepsilon_i)$ is not zero[6]. According to the Becker

[6]For the simplest case where child quality depends only on family size, OLS over–estimates the trade–off since $plim((N'N)\varepsilon/T) < 0$, with N the column vector of the family size. Families that have a higher amount of children are not only families that face a higher shadow price for child quality but are also families with a higher relative preference for family size over child quality. Simultaneously, families with

model, households with a higher number of children are those that face a higher shadow price for child quality and therefore choose lower level of quality per child. However, those families with more children are more likely to be the ones with higher preferences for number of children or lower cost associated to family size, independent of the preferred level of child investment. In the same way, families with few children face a lower shadow price for child quality and therefore are more likely to invest more in child quality. Those families that choose higher levels of child investment may be more likely to have a higher preference for child quality i.e a higher cost for family size. Therefore, statistical inference about the impact of family size on child quality using differences in the average level of quality between families with different family size will be biased because we do not account for these households having not only different prices but also having different preferences for family size and child quality.

Following Rosenzweig and Wolpin (1980a, 1980b), I use multiple births I use multiple birth as source of variation in family size. In specific I use the event of multiple births on the second or higher birth as an exogenous change in family size. Women who experience a multiple birth have some ability to adjust their subsequent fertility. For example, a mother that would like four children may simply quit having children if on her third birth she delivers twins. Given the limited size of most families in the US, however, multiple births will shift the number of children for most families. Therefore multiple births would not only provide a shift in the number of children in the family but also should be orthogonal to the child quality preferences.

fewer children are the ones with a lower price for child quality but are also the ones with a higher preference for child quality reinforcing the impact on child quality where this last impact is captured by ε. However, for a more general case where child quality depends not only on family size more assumptions are required to sign the bias.

There are two types of twins, the most common of the multiple pregnancy: identical (*monozygotic*) and fraternal (non–identical, *dizygotic*). Identical twins occur when a single embryo divides in two embryos. Identical twins have the same genetic makeup and its incidence is equal in all races, ages groups and countries (3.5 per 1000 births). Fraternal twins occur when two separate eggs are fertilized by separate sperms. The occurrence of fraternal twins, unlike identical twins, varies and there are several risk factors that may contribute. First, the incidence is higher among the Afro–American population. Second, non–identical twin women give birth to twins at rate of 1 set per 60 births, which is higher than the rate of 1 of every 90 births, at the national level. Fourth, women between 35 to 40 years of age with four or more children are three times more likely to have twins than a woman under 20 without children. Finally, multiple births are more common among women who utilize fertility medication. Given the period under analysis(where fertility drugs are not an issue), the most concerning of these factors, in our case, is the hereditary factors for which I cannot control (American Society for Reproductive Medicine, 2004). However, there is not priori information that women are acting differently based in this hereditary information or that hereditary factors are associated to a particular group of the population.

However, the way that I use of multiple births limits the sample I use in the analysis. I restrict attention to the oldest child in the household who is not a multiple birth child but has at least one younger sibling. These children are all from families that planned on having a second child, but may not have banked on having a third. More importantly, by focusing our attention on the oldest child, we examine children affected by multiple births through family size rather than through others factors directly related to being part of a multiple birth[7]. For example, among twins and higher order multiple birth children, i.e. triplets, quadruplets, etc., rates of low birth weight and infant mortality are 4 to 33 times higher compared to singleton births. Moreover, twins and other higher order multiple births are more likely to suffer life–long disabilities when they survive (National Vital Statistics Report, 1999). Therefore, the sample is restricted to oldest siblings in the household that are not from a multiple birth since being part of a multiple birth or being a younger sibling of twins or other higher order multiple birth is conditional on the occurrence of multiple births in the household (post–treatment). However it seems a waste of information and therefore power, keeping only the oldest sibling and not considering all sibling that were before the twin birth, I prioritize bias over precision. Families, that face an event of multiple births are those families with a greater chances to face this event in a following pregnancy. The restriction of the sample to oldest siblings is important because there is some evidence that the trade–off between quantity and quality may be lower for the oldest child, since the first born child, at least for sometime, would belong to a smaller family than the rest of the siblings, thereby generating an advantage for them (Kessler, 1991). For that reason the impact that is found in the following analysis may be considered as a lower bound of the average impact of multiple birth for the complete sample of children. Therefore the observational unit in equation (1.1) is the oldest child

[7]It is important to keep in mind that the event of multiple births not only increases the number of children in the household but also reduces the timing among siblings that belong to a multiple births to zero. Therefore an estimate of γ using multiple births as identification strategy will produce an estimate for the joint treatment. A priori the overall impact of a change in timing on child investment and child wellbeing is not clear. On the one hand the reduction in timing may be associated with an increase in physical, financial and psycho–social stress for parents that has a negative effect on child investment and child wellbeing. On the other hand there may exist some scale economies that reduce the average cost of child investment.

(sibling) in the household that does not belong to a multiple birth and has at least one additional sibling.

Let mb_i_s denote the binary instrument, multiple birth, that takes a value equal to one for families where the oldest child is followed by a multiple birth and zero if followed by a singleton sibling in the s birth. The Instrumental Variable (IV) estimate of γ in the equation is the Wald estimate

$$\hat{\gamma_{IV}} = \frac{\bar{y_1} - \bar{y_0}}{\bar{n_1} - \bar{n_0}}, \tag{2.2}$$

where $\bar{y_1}$ represents the mean of y_i for the observations with $mb_i\_s = 1$ and the other terms are similarly defined.

Whether or not the occurrence of multiple births is an appropriate instrument depends on the legitimacy of the following two assumptions. The first one is that the correlation between the instrument and the endogenous variable is different from zero. The second one, non-testable, is no correlation between the instrument and the error term in the regression. The first assumption implies that there should be enough correlation between multiple births and family size (formally, $cov(n_i, mb_i\_s) \neq 0$), so an average difference in family size $(\bar{n_1} - \bar{n_0})$ exists and can be measured properly. The second assumption implies that there should not be a correlation between multiple births and the error term (formally, $cov(\varepsilon_i, mb_i\_s) = 0$), so that any impact that is observed over the variable of interest $(\bar{y_1} - \bar{y_0})$, should be necessarily attributed to a change in family size. Therefore, if both assumptions hold, a causal relationship between family size and the outcome, y, can be identified.

Despite the fact that the second assumption is non-testable, the random nature of multiple births, the choice of the observational unit under analysis (oldest child in the household that does not belong to a multiple birth), the inclusion of other variables that are correlated with the incidence of multiple births such as age of the mother, race and parents' education,[8] as well as the analysis of the impact of twining in a specific birth, s, make it more likely that this assumption holds.

The impact of family size on child outcomes, as it is presented in equation (1), is constant across observations. This assumption may be unrealistic given the obvious heterogeneity in households' preferences. An extensive literature in program evaluation has mentioned the importance of addressing this heterogeneity in the impact of a specific "treatment". Heckman (1997) calls attention to the role of the heterogeneity and the sensitivity of IV to assumptions about how individuals internalize this heterogeneity in their decisions of being part of the treated group (i.e. the selection of family size). Imbens and Angrist (1994) have shown that IV estimates can be interpreted as "Local Average Treatment Effects" (LATE) in a setting with heterogeneity in the impacts and with individuals that act recognizing this heterogeneity. In this case, γ_{IV} identifies the impact of an increase in family size on child quality for those families that have had more children than they otherwise would have because they had multiple births.[9] Therefore, as Imbens

[8] Mothers with more education tend to postpone childbearing increasing the likelihood of multiple births.

[9] Although multiple births can be considered as a random event, it has been shown that the use of fertility drugs increases the likelihood of this event. Additionally, it can be argued that the use of fertility drugs could be associated with households with a higher preference for children and their quality. Under this last assumption, the LATE estimate associated with multiple births would be measuring the average impact for this specific group of households rather than the impact of family size for a more representative group of households. In fact there is a broad acknowledgement that the rate of multiple births has increased in the last two decades, which has been attributed jointly to a higher use of fertility drugs and a change in the timing of the first birth. A closer look at the evolution of the twin ratio (total twin births over total number of births, per 1000), reveals that the explosive increase in multiple births did not begin before 1985

and Angrist pointed out, LATE is dependent on the instrument that is being used.

2.4 Data, Variables and Descriptive Statistics

The primary data for this project is the 1980 Census Five-Percent Public Use Micro Sample (PUMS). The selection of this data source, and the particular year, is based on three facts. First, for this particular year, the census provides information about a respondent's age and quarter of birth that can be used to identify twin births. Second, since multiple births are rare, I need a large sample in order to have adequate statistical power. As I show below approximately 1.8% of all births are multiple births and less than 1% of all oldest children in our sample belong to households with a multiple birth. However, the two samples that provide the core of our results contain between seven hundred and three hundred thousand observations. Finally, census data provides a rich set of variables that allows me to construct different measures of child investment and child wellbeing.

The observational unit is the oldest sibling in a household that does not belong to a multiple birth and lives in a family with at least one additional sibling. Therefore I have one observation per family for the sub-sample of families with two or more children. For each of these children, I construct information about child investment and child wellbeing, the total number of siblings in the household, as well as other socioeconomic variables such as parents' education, race, state of residence, etc. that may be correlated with their investments in their children.

(Martin and Park, 1999). Therefore, since we are working with children that were younger than eighteen years old in 1980, i.e. born between 1962 and 1980, it seems reasonable to rule out that multiple births were mainly associated with households that had been using fertility drugs and therefore with a greater preference for children quality.

The number of children in a family is defined as the number of children younger than eighteen years old that have the same non step mother that for simplicity from here onward I call biological mother. This number of children can be lower than the real number of children in the family since I do not observe older siblings who are no longer living at home. I delete families where it is not possible to identify the biological mother in the household. This restriction avoids problem that blended families may have two children with the same age and quarter of birth that "look" like twins in the data but have different mothers.

The Becker model establishes that child quality is positively related to particular types of investments in children and exogenous shocks in family size will alter the level of per child investment and hence child quality. It is difficult to define and measure what is meant by child quality, and although it is a subjective concept, we can agree that child quality is multidimensional. Likewise, there are numerous types of investments or expenditures we could make on children that we hope might improve their chances of success in education, the job market, the marriage market, etc. The distinction between inputs and outcomes is essential for my analysis and as a result, I estimate models with two different sets of outcomes. The first group are variables that I associate with child investment (inputs for child quality), are variables that reflect allocation of resources to children. The second group, variables that I relate to child wellbeing (outputs of child quality), are variables that may use "child investment" as an input but are not necessarily able to capture changes in allocation of resources by household members. An example of variables in this second group, is the set of variables related to scholastic achievements. While scholastic achievements may be affected by child investment, i.e. time assigned by parents, school type, family structure, etc., they do not necessarily show a change in allocation by the family and also they might be affected by other factors such as child ability.

We can postulate lists of investments and outcomes, but without knowing the production process, we do not know whether the postulated outcomes are determined by the investments. In past research, almost all researchers have focused on testing the Becker model by examining the tradeoff between family size and outcomes. A more direct test would be to examine whether the inputs are determined by exogenous shocks to family size. Focusing on inputs is a more powerful test than using outcomes since inputs are one step closer to assessing the effects of family size in the causal chain, and reducing the chance of Type II errors.

For the group of variables that can be seen as child investment I define seven variables that although their relationship with child wellbeing is not always clear are under the control of the parents and therefore reflect their allocation of resources. The first variable "Attends Private School" is a dummy variable that takes a value equal to one if a child between 6 and 18 years of age attends a private institution or church related school, and zero otherwise. Numerous authors have demonstrated that educational outcomes are higher for students that attend private school. In fact, Evans and Schwab (1995) find that a typical student attending a Catholic high school has a greater chance of finishing high school and entering a four-year college. Although there is some question about whether this impact is causation or correlation, there is no question that parents who enroll their children in private schools are the ones with higher income. I also define a second variable, "Nursery", for children younger than six years old. It takes a value equal to one for children that are attending school and zero otherwise. Studies for developing countries reveal that children attending nursery school have better performances on reading and math tests, as well as a lower failure rate during their first year in elementary school (Pozner, 1982; Filp et al. 1984).

The following variable, “Migrate”, takes a value of one if a child’s mother has moved counties over the past five years and zero otherwise.

The fifth variable, “Share bedroom”, is a dummy variable equal to one if the number of children in the household is higher than the number of “available” bedrooms for children, where “available” bedrooms is the total number of bedrooms minus the number of bedrooms allocated to parents and other adults in the household.

Two variables that are potentially measures of investment are the mother’s labor force participation and hours of work.[10] As was mentioned above, the impact of mother’s labor force participation on child wellbeing is ambiguous. Working mothers may spend less time with their children but have more income that could be allocated to child investment. Independent of this ambiguity an important aspect of these two variables is the information provided about the substitution from market goods to home production.

The final measure of child investment is the dummy variable “Divorce” that takes a value one if the child’s mother is currently divorced, separated or is in their second or higher marriage, and zero otherwise.[11] Brown and Flinn (2002) demonstrate the simultaneous interaction between child quality and the decision to divorce in their model of the family dynamics. Parents receive utility from child quality; as a result, exogenous increases in child quality makes divorce more costly. Simultaneously, a reduction in the likelihood of getting divorced motivates a higher investment in child quality. Empirical evidence has

[10] While labor force participation has been defined for the complete sample, “hours at work” has been defined only for the sample of mothers that are employed.

[11] To ensure that I capture the impact of increasing family size on family structure I restrict the sample to oldest children that were born while their parents were married.

long shown that children of divorced parents have lower achievement than children from intact families (Haveman and Wolfe, 1995). Manski et al. (1992), using the National Longitudinal Study of Youth (NLSY), found that living in an intact family increases the chances of high school completion. Ginther and Pollak (2003) show that there are no differences in educational outcomes between stepchildren and their half-siblings who are the joint biological children of both parents. However, children that belong to "blended" families have lower outcomes than children that live in traditional "nuclear" families where all children have the same biological parents. These results support McLanahan and Sandefur (1994) finding of similar outcomes between stepchildren and children in families with a single parent.

Because of data limitations in the Census PUMS, there are only four variables that measure child wellbeing. The first is the "Highest Grade" which is the highest grade completed for those currently not enrolled in school or the current grade for those currently in school. This outcome has been defined for all children between six and eighteen years old. I exclude from this definition children younger than six years old in order to avoid noise that reflects the participation in nursery school. The second output variable is named "Behind" which is a dummy variable that equals one if the highest completed grade is lower than the mode by age in years, quarter of birth and state, and zero otherwise.[12] "Behind" identifies whether children are progressing in class with their cohort and is a measure of educational attainment. Children who repeat a class are often at risk of dropping out of high school. The quantity-quality model would predict a negative impact of additional children on the highest completed grade and a positive impact on the probability of being

[12]Age has been measured in quarters and the idea of using as reference the mode by age and state, is to capture the heterogeneity in the rules about when a child can start school. These rules differ among states and they are usually a function of the quarter of birth of the child.

behind. The third variable, "Attend School", is defined for the sub-group of children between sixteen and eighteen years old. This variable takes a value equal to one if an individual attends school and zero otherwise. This variable captures the probability of not being a drop out. The fourth variable "Have Children" is a dummy variable defined for girls between thirteen and eighteen years old. This variable takes a value equal to one if a girl has had a child and zero otherwise. This variable aims to capture the impact of the number of young siblings in the household on the probability of teenage childbearing. The latter has been related many times to low future labor market outcomes.

Following Bronars and Grogger (1994) and Angrist and Evans (1998), I identify multiple births by exploiting the fact that the 1980 census reports age in years as of April 1, 1980 (the first day of the second quarter) plus the quarter of birth. If two or more children in the household have the same age, quarter of birth and biological mother, I assume that these children are twins. To study potential heterogeneity in the impact of the number of children, I construct two sub-samples: oldest children with one or more siblings and oldest children with two or more siblings. For the first of these sub-samples the instrument is defined as mb_i_2, and takes a value equal to one if the second birth in the family is a multiple birth and zero otherwise. For the sub-sample of children who belong to families with three or more children, the instrument is defined as mb_i_3, and takes a value equal to one if the third pregnancy in the household is a multiple birth and zero otherwise.

Table 2.1 presents the proportion of multiple births for the complete sample of children younger than eighteen years old. Using the algorithm outlined above, I classify 1.8% of these children as multiple births of which 1.77% are twins. These percentages are quite close to numbers reported by the National Vital Statistical Service (NVSS) showing that 1.95% of births over the 1962 to 1968 period were twins and 1.86% of births for the period 1971 to 1979 were twins.

Multiple births not only increases the number of children in the household but also reduce the spacing among siblings that belong to a multiple birth to zero. Therefore an estimate of γ using multiple births as an identification strategy will produce an estimate for the joint treatment i.e. an increase in number of children and a change in children spacing. While multiple births change birth spacing for all families that face a multiple birth, only for some families this event produces a change in the completed family size. For some families, likely the ones with the number of children closer to the desired family size, the event of a multiple births will produce a change in family size and a reduction in the space among sibling that belong to a multiple birth to zero. For other families, probably the ones far from a desired family size, the event of multiple births produces only a change in the spacing among children. In previous sections, when the theoretical relation between quality and quantity was explained, it was done in the context of a static model where n_i is the total number of children that the family has decided to have when fertility is completed. However, empirically what is observed is the number of children that a family has at a particular moment rather than the completed number of children. In order to study this heterogeneity in the treatment, the samples are divided by the mother's age: all children, children with mothers that are 32 years old or younger, and children with mothers that are older than 32 years at the time of the census.[13] While

[13] In the ideal world we would like either to consider only women that have reached the desired family size or to know the desired family size. A potential way to do it is constraining the sample to children with mothers older than forty years old. However by constraining the sample in this way we are keeping household where is more likely that some of the children had already left home. According with US Census Bureau information, in 1980 there were approximately 3.6 millions births. From this birth less than 5%

multiple births would likely be an exogenous increase in the number of children and child spacing for older mothers, (who are closer to reaching the desired family size or already), for younger mothers multiple births might only change the timing of their third child.

Tables 2.2 to 2.4 present the descriptive statistics for the samples of all children; children with "younger" mothers and children with "older" mothers. For the sample of all children the average age of a child is approximately eleven years old. However, if I restrict the sample to children who are older than six years old (i.e. those in school age), the average age is thirteen years old. On average, children in the sample are in eighth grade which is consistent with the average age observed. Both parents have approximately high school as their highest completed grade and for the sample of all children (without a restriction in family size), I observe an average of 1.88 children in the household. African Americans and Hispanics are over–represented in the sample of families with three or more children. It is notable that the number of children is higher for families with older mothers, which at least partially reflects that households with older mothers have completed fertility.

When I split the sample by family size and mother's age, I reproduce the empirical regularity that the occurrence of multiple births increases as family size and mother's age increase: while approximately 1% of the oldest children in the complete sample belong to families with multiple births, when the sample is restricted to oldest children with older mothers and with three or more children in the household, I find that almost 4% of the children belong to families with multiple births.

For the variables linked to outputs of child quality I find that when the sample is restricted to families with three or more children, there is a small increase in the proportion

happen to women older than 35 years and less than 20% to women older than 30 years. In this way I take 32 years old as cut off to divide the sample among women that are fader or closer of complete fertility.

of teen pregnancy and in the proportion of children with a grade lower than the mode (14%), as well as a lower fraction of children between 16 and 18 years old that attend school, which is consistent with a negative impact of number of children.

A comparison of these numbers with national data for the year 1980 reveals some differences between the two set of numbers. The Alan Guttmacher Institute reports that nationwide for 1980, approximately 11% of teen women were mothers, which is higher than the 3% that I observe in our sample. Also it looks as if we get a high proportion of dropouts (approx. 20%). These differences can be explained in part by the construction of the sample. I have selected children for whom we are able to identify their mothers and who also have one or more siblings. Therefore, teen mothers that have left their parents, and for whom I cannot identify their mothers, or who do not have a sibling at home are missed in this study. For the proportion of drop-out our estimates are slightly higher. McMillen et al.(1994) show that approximately 15% of children between 16 and 24 years old have not finished high school or were not enrolled in school in 1980. The explanation may be related to the group age considered. In fact, if I restricted the sample to children between 16 and 18 years old, the proportion of dropouts should rise. Therefore 20% of dropout students for the population of children between 16 and 18 years old is a reasonable proportion given the previous evidence.

For the variables used as inputs of child quality I find that when the sample is restricted to larger family sizes there is a reduction in the proportion of students attending private or church related schools (14% to 12%)[14], lower maternal labor force participation (53% to 48%) that is consistent with the increase in the proportion of children in nursery

[14]These proportions are similar to the 13% nationwide enrollment in private institutions for the year 1980 in grades k-12 (*Digest of Education Statistics*).

school (41% to 49%), a higher fraction of children that *potentially* share a bedroom (19% to 38%) and a lower number of children whose mother has migrated during the last five years (23% to 21%). Nevertheless, it does not appear that constraining the sample to bigger family size affects the number of hours worked or the "*probability*" of divorce.

Table 2.5 presents differences in means for some of the demographic variables between children that do not live in families with multiple births and the ones that do. These differences reveal a known empirical regularity about the occurrence of multiple births (Angrist and Evans, 1996; Mullin and Wang, 2002): parents from households with multiple births are older, are more likely Afro–American and have a higher level of education -after controlling for race. This finding reflects the evidence that Afro–Americans start families earlier. That women with more years of schooling are more likely to have twins might reflect that they were postponing childbearing to older ages, and more educated women are much more likely to postpone childbearing.

2.5 Results

2.5.1 First Stage

Table 2.6 presents the first stage regression of the number of children on multiple births with and without covariates. The top half of the table provides the results for the full sample of children (two or more children), while the bottom half reports the results for families with three or more children. The first two columns present the estimates for the complete sample of children while columns (3) to (6) show the estimates for the sample of children with "younger" and "older" mothers. The point estimates for the impact of multiple births in the second pregnancy (MB_2) are approximately 0.80 for the three samples. The impacts of multiple births in the third pregnancy (MB_3) are slightly higher, but not statistically different than the impacts of multiple births in the second pregnancy. For both MB_2 and MB_3 the t-statistics are over 40. Children that belong to families with multiple births either in the second or third pregnancy have on average almost one sibling more than other children.

The finding that multiple births in the third pregnancy have a slightly larger impact on family size than in the second pregnancy is likely related to the fact that the sample of households with two or more children include *some* households whose desired family size is not being affected by multiple births. For these households multiple births in the second birth affect only the timing of the third or fourth child. However, when the sample is restricted to households with three or more children, the likelihood that multiple births are changing family size is higher. Consistent with this explanation, point estimates for the sub-sample of children with older mothers are lower than the estimates for the sub-sample of children with younger mothers. The reason for this result is that the sample of children with young mothers includes mothers for whom the impact of multiple births seems to affect family size, however in the long run (when the desired family size is reached) does not affect family size but only the timing of the third child.

Rosenzweig and Wolpin (1980b), and Bronars and Grogger (1994) find that the impact of multiple births disappears as the sample is constrained to older mothers. Unlike these previous studies that used twining in the first pregnancy, in our analysis the impact of multiple births is limited to the second and third pregnancy, where multiple births are more likely to affect family size.

2.5.2 Inputs and Outputs

Tables 2.7 and 2.8 present OLS and 2SLS estimates of the impact of the number of children on the seven variables that I characterize as inputs and on the four variables that I define as measures of wellbeing.

The OLS estimate for the number of children variable in the "Private School" equation shows that, contrary to the prediction of the quantity/quality model, the number of children has a positive impact on the probability of attending private school. However, an exogenous increase in the number of children generate by a multiple birth reduces the probability of attending a private school by approximately 1 percentage point for children that live in families with two or more children and 0.43 percentage points for the sample of households with three or more children. The Durbin–Wu–Hausman test reveals in both samples, that OLS and 2SLS estimates are statistically different from each other for both samples.[15] Therefore, treating as an exogenous variable would, in this instance, produced an inconsistent estimate and faulty inference. The positive coefficient on children OLS model may be due to the fact that most private school seats are in religious schools, and more religious families are both more likely to have larger families and enroll their children in these private schools.

For the sample of households with two or more children, the 2SLS estimate of the probability of attending nursery school shows that a shift in the number of children does not have a statistically significant effect. However, the Durbin–Wu–Hausman test shows that this impact is statistically different from the OLS estimate by a nearly 5 percentage

[15]In a framework with heterogeneity in the impact of family size the interpretation of the Durbin–Wu–Hausman test is not straight forward. OLS and 2SLS estimates would measure a potential *trade–off* between family size and child investment in different parts of the distribution (Heckman and Vytlacil, 2001).

point reduction in the probability of attending nursery school. The result for the sample of households with three or more children confirms that an exogenous shift in family size does not have a statistically significant impact, although this result is inconclusive since I cannot define whether or not this impact is statistically different from OLS estimate.

Both 2SLS and OLS estimates reveal that larger families increase the chance of the oldest child "sharing" a bedroom by a statistically significant amount. However, the Durbin–Wu–Hausman specification test rejects equality between the OLS and IV estimates for both samples. OLS estimates show that the impact on the probability of sharing bedroom moves from approximately 22 to 26 percentage points as I restrict the sample of families with more children. 2SLS estimates reveal the same pattern, however the impact of an exogenous increase in family size that comes from the event of multiple births, is considerable bigger for the sample of families with three or more children. For this last sample the impact is approximately 15 percentage points bigger than the 20 percentage points impact that I find for the sample of families with two or more children.

The results for maternal labor force participation are consistent with previous studies that have detected a statistically significant and negative impact of childbearing on female labor force participation. The results also indicate that OLS and 2SLS estimates are statistically different, again indicating an omitted variables bias in the single-equation models that treat family size as exogenous. OLS estimates for the sample of mothers who have two or more children reveal that an additional child reduced labor force participation by 8,6 percentage points, or by approximately 7,2 percentage points. When the endogenous nature of family size is considered, the impact of family size falls to 3,5 percentage points for mothers with two or more children and 4,2 points for mothers with three or more children. When the sample is restricted to mothers who are working, OLS estimates reveal that number of children reduces hours of work by approximately 4% for the sample of households with two or more children and by 3% for the sample of households with three or more children. Nevertheless, the 2SLS estimates show no statistically significant impact on hours worked. However, we are able to say that this estimate is statistically different from the OLS estimate only for the sample of households with two or more children.

A result that is particularly interesting is the impact of the number of children on the probability of their parents get divorced. The OLS estimates suggest that more children reduce the probability of getting divorced by approximately 2 percentage points for the sample of households with two or more children and by 1,6 percentage points for the sample with three or more children. However, these estimates are likely based by the fact that more stable families are the ones that choose to have more children or in other words, couples in order to have more children need more time together. When I use multiple births as a source of variation in family size I find that an additional child increases the probability of divorce by statistically precise 2,5 percentage points in the sample of households with two or more children. This finding, and given previous evidence that shows that children that grow up in "blended" families have lower achievements than children that live in traditional nuclear families, suggest that probably one of the channels through which family size is impacting child wellbeing may be through family structure. In particular, following Brown and Flinn (2002), an increase in family size makes it more likely of getting divorced because the lower investment in child quality reduces the cost of splitting up[16] but simultaneously because of the higher probability of divorce, parents will have a weaker incentive to invest in their children.

[16] The reduction in the cost comes from the reduction in utility that parents perceive at the moment of getting divorced since they spend less time with the children. Then they would perceive less consumption of child's quality that is an argument in the utility function.

The last four outcomes in Table 2.7 are the ones that I relate to child wellbeing. I observe that for the log of "Highest Completed Grade" and for the dummy variable "Behind", OLS estimates support the conventional wisdom that number of children has a negative impact on educational outcomes with a 0.34 to 0.49 percentage points reduction in the highest completed grade and an increase of 1.44 to 1.91 percentage points in the probability of having a grade lower than the mode by age and state. However, the 2SLS estimates do not show any statistically significant impact of number of children on either of these two outcomes in any of the samples. The Durbin–Wu–Hausman test shows that these impacts are statistically different from the OLS estimates for both outcomes in the sample of households with two or more children, and only for highest completed grade in the sub–sample of households with three or more children.

For the variable "Attend School", I find inconclusive results. The 2SLS estimates are not statistically significant for any sub–sample and not statistically different from the OLS estimates, where the latter show that family size reduces the probability of being enrolled by 0.94 and 1.24 percentage points for the samples of two or more children and three or more children, respectively.

Finally for the variable "Have Children", I observe that for both sub-samples, the 2SLS estimate for the impact of number of children is not statistically significant or statistically different from the OLS estimates.

If these last four variables were considered as measures of child quality it would look like the *Quantity–Quality* model is wrong or, if it is right, there would be other channels that produce a positive relationship between quantity and child wellbeing, and therefore a total observed impact that is not statistically different from zero for both samples. However, these variables are one step farther in the causal chain. In fact we can see these four variables as outputs of child investment. Thus, considering the investment in child quality as a multidimensional activity that provides many degrees of freedom, families may substitute among different types of investment such that the impact on the final output (wellbeing) is "*practically*" unchanged [17]. In fact, I find that as the family size grows, the oldest child in the household is less likely to attend private school, and more likely to share a bedroom and to belong to a "blended family". As well, I find that as the family grows there is a negative impact on the mother's labor force participation. While there is a kind of agreement about the impact of a reduction in the probability of attending private school, the impact of the rest of the variables on child wellbeing remains ambiguous. This ambiguity may explain the overall insignificant impact that I observe on the variables that I link to wellbeing.

2.5.3 Heterogeneity in Results by mother's age

I do not observe the desired family size but instead, the current number of children that a family has at the time of the census. While multiple births are likely to increase family size for women who experience a twin birth later in life, multiple births earlier in a woman's life might only affect the timing of their third (fourth) child for the sample of households with two (three) or more children.[18] However, I already showed that the

[17] Another possibility is to say that these variables are a bad proxy for child quality. For example, I could think that number of children might affect school performance, but to a degree that will not necessarily cause a child to fail a complete grade. However, even if our two educational outcomes were bad proxies for child quality, I would expect that the impact would not be statistically different from zero, but never positive as I find it for one of the sub–samples.

[18] Even if I constrain the sample to households for whom multiple births affect family size I will not be able to avoid the double treatment (increment in number of children and reducing the timing), but at least I ensure that the results are not driven only by changes in timing.

event of multiple births affects family size not only for *older mothers* but also for *younger mothers*. Nevertheless, the shift in family size may have a different impact in the short run, when the desired family size has not been reached, to the one that would have in the long run when it has been reached or is close to be reached. Therefore, in order to analyze the robustness of the previous results and to study potential differences in treatment associated with multiple births, I divide the sample by mother's age: 32 years old or younger and older than 32 years. Tables 2.9 and 2.10 presents the results for the sample of children with "*younger mothers*" (32 years old or younger) for whom the desired family size not necessarily has been reached, and tables 2.11 and 2.12, the results for the sample of children with "*older mothers*" for whom it is more likely that the desired family size has been reached.

The results in Tables 2.9 to 2.12 show that in qualitative terms our previous results are robust to division by mother's age. However, I observe that the impact on the variables *Divorce* and *Attend private school* is not statistically significant for the sample of *younger mothers*.[19] Nevertheless, the Durbin–Wu–Hausman specification test for this sample still reveals for these variables a statistical difference from the OLS estimates. In fact the OLS estimates show that number of children has a positive impact on the probability of attending private school and a negative influence on *Divorce*. I also find that the impact on maternal labor force participation and hours of work is higher for the sample of *younger*

[19]For the sample of households with three or more children and *younger mothers*, I find the counterintuitive result that a shift in family size produces an increase in almost 3% in the probability that the oldest sibling in the household attend private school. This results might be explained by the construction of the sample(households with relative younger mothers that already have tree or more children) since I might be considering families with higher preference for children and are probably over–representing families with stronger preferences for a particular type of school, such as catholic schools.

mothers. However, for the variable *hours at work* the Durbin–Wu–Hausman specification test does not show a difference from the OLS estimates.[20]

As expected, on the other hand, for the sample of households with "*older mothers*, I find a lower impact on the mother's labor force participation with 2SLS estimates that reveal a 1.7 and 3.3 percentage points reduction for the samples of two or more, and three or more children in the household, respectively. Nevertheless, the estimates are different from the OLS estimates only for the sample of households with two or more children. As well, I see that this sample of children, children with *older mothers*, is the one driving the results on the probability of attending private school and on the probability of getting divorced. The 2SLS estimates for the impact on the probability of attending a private school show that family size reduces this likelihood by 1.21 or 1.75 percentage points,

[20]This bigger impact on female labor force participation for the sample of younger mothers may also reflect the impact of child age. When the samples are divided by child age I observe a bigger impact for the sample of mothers with a younger oldest child, with a reduction in the probability of being part of the labor force of approximately 6 percentage points. However for mothers with an oldest child older than 12 years old I find that number of children has an insignificant impact on the mother's labor force participation. This result is consistent with the prediction of life cycle models of labor supply. There is a substitution of hours allocated to the labor market along the life cycle such that there is a reduction in the number of hours worked during childbearing that is compensated by an increase in hours worked in later periods. Also the division of the samples according to the difference in age between the oldest sibling and the second one(s) reveals that the impact of family size on mother's labor force participation is bigger for households that have a difference bigger than six years. One possible way to explain this result is to think that part of the time that mothers allocate in taking care of the children has a public good nature. Thus an increase in family size that makes it more costly to work and therefore reduces the labor participation will have a lower impact for women who have children closer in age. These mothers will stay less time out of the labor market because they can use the same time to take care of more than one child. As result, their human capital depreciates less and so it is less costly for them to return to the labor market.

depending on the sample. For the variable *Divorce*, a shift in family size produces a 3.56 and 0.96 percentage points increase in the likelihood of having faced a divorce for the samples with two or three more children, respectively.

While the differences found in the impact on the mother's labor force participation between these samples may be related to the reallocation of time in the labor market over the life–cycle, the differences in the impact on either the probability of attending private school or the variable *Divorce* may be related to two factors. First, an increase in family size as a result of multiple birth may impact these two outcomes in the long run but not in the short run. Second, younger mothers are more likely to be the ones for whom multiple births only produce a change in the timing of the birth but not an impact in the complete family size. Then the evidence may be associated with the fact that the impact on these two outcomes is through number of children but not through a change in birth spacing.

2.5.4 Heterogeneity in Results by sex and race

In this section I extend the heterogeneity analysis and examine whether the impact of having more siblings varies across race and sex of the oldest child. In order to make the presentation trackable, I concentrate on the five outcomes from the previous section with the most definite results in the 2SLS models: *attend private school*, *mother's labor force participation*, *divorce*, *behind* and *highest grade completed*. Tables 2.13 to 2.16 presents the results for the complete sample of households with two (three) or more children, and Tables 2.17 to 2.24 present the results for the samples of children with *younger* and *older* mothers, respectively.

For the complete sample, the results indicate that the impact of a larger family on private school enrollment is larger for boys than for girls. Dividing the sample by mother's age, I find that if there are differences by race or sex, these differences are concentrated in the sample of *older mothers*.[21] In fact, for this last sample, I find that the negative impact of more children on the outcome *attend private school* is driven by boys and by white children. I also find differences in the impact of children on the labor supply of the mother based on the sex of the oldest child. Those households where the oldest child is a boy are the ones with a bigger impact on the mother's labor force participation.

Although for the sample of children with *younger mothers* I do not find a clear difference when I divide the sample by race or sex, a result that is worth mentioning is the impact on *highest grade completed*. For this variable in the sample of non-white children, 2SLS estimate reveals that an increase in family size increases the highest completed grade by approximately 0.37 percentage points. The Durbin–Wu–Hausman specification test allows us to say that this previous estimate is statistically different from the OLS one. Finally, also in the sample of *younger mothers*, I find for the sample of white girls that an increase in family size has a positive impact on the probability of attending a private school for oldest children living in households with three or more children. The Durbin–Wu–Hausman specification test, however, does not allow us to say that these impacts are different from the corresponding OLS estimates.

2.6 Conclusion

This paper, using US census data shows that families allocate resources in a way consistent with Becker's *Quantity & Quality* model. An exogenous increase in family size generated by a twin (or other multiple birth) on a later birth makes that parents

[21]The fact that I cannot find signs of heterogeneity in the sample of children with *younger mothers* may also be related to the lower power that I have in this smaller sample.

rearrange child investment (quality) in the household. In particular, the 2SLS estimates demonstrate that an increase in number of the children reduces the likelihood that older children attend private school, increases the likelihood that children share a bedroom, reduces the mother's labor force participation, and increases the likelihood that parents divorce. Although the relationship of these variables with child wellbeing is not always clear they are under the control of the parents and therefore reflecting their allocation of resources.

When we go one step further in the causal chain, however, the results do not support a negative impact of number of children in the family on the group of variables that I think are closer to child wellbeing such as school grade, teen pregnancy or the probability of dropping out.

Therefore, the evidence that I find is completely consistent with models of household production where families facing an exogenous change in family size reallocate different types of child investment in order to minimize the impact on child wellbeing. In fact previous evidence that has found a negative impact of family size on child achievements, mainly in developing countries, can be explained by a lower capacity of some households in reallocating resources. Thus it is reasonable to think that a trade–off between number of children and different types of investments is a reality that all household face but a trade–off between family size and child wellbeing is restricted to those households that have fewer degrees of freedom to reallocate resources.

Under this evidence, family planning programs that focus the attention only in reducing family size would not necessarily produce an improvement in the child achievements (wellbeing) if other factors that limit the ability of the household members to reallocate resources are not solved. In fact, the finding of the paper reveals that we should ensure the ability of households to allocate resources more than give a *blind* financial aid. However the following step that is defining the potential factors that limit the ability of families to minimize a potential negative impact on child wellbeing is the tougher one.

Finally, in this paper I show evidence of omitted variable bias in OLS estimates. While 2SLS estimates do not reveal any impact on the variables that I relate to child wellbeing, OLS estimates support a trade–off between number of children and child wellbeing. In addition, for the group of variables that I link to child investment, OLS estimates either over–estimate the impact of family size or provide a counter–intuitive result. For example, the OLS estimates show that a shift in family size increases the probability of attending a private school and reduces the probability of getting divorced.

Type of birth in the population	Frequency	%
Singletons	2,678,550	98.20
Twins	48,266	1.77
Triples	705	0.03
Quadruples	12	0.00
Quintuples	10	0.00
Total	2,727,543	100.00

Table 2.1: Multiple Births Frequency.

	All	Two or more siblings	Three or more siblings
Age	10.78	11.65	13.21
	(5.69)	(4.86)	(4.06)
Mother's Age	36.08	35.47	36.22
	(9.03)	(7.24)	(6.34)
Father's Age	38.82	38.09	39.00
	(9.82)	(8.09)	(7.30)
Years of Education of the mother	12.21	12.19	11.80
	(2.52)	(2.52)	(2.59)
Years of Education of the father	12.73	12.82	12.46
	(3.22)	(3.25)	(3.38)
Number of Siblings	1.88	2.57	3.47
	(1.02)	(0.88)	(0.83)
White	0.80	0.81	0.76
Black	0.10	0.09	0.11
Asian	0.02	0.02	0.02
Hispanic	0.08	0.08	0.11
Multiple births at second pregnancy	0.005	0.009	0.024
Multiple births at third pregnancy	0.002	0.004	0.010
Multiple births	0.008	0.015	0.038
Mother in Home	0.89	1.00	1.00
Father in Home	0.82	0.86	0.86
Attend Private School?	0.14	0.14	0.12
In nursery school?	0.27	0.41	0.49
Migrate?	0.23	0.23	0.21
Share Bedroom?	0.14	0.19	0.38
Mother's works?	0.56	0.53	0.48
Mother's Hours at work?	31.51	30.88	30.28
	(15.19)	(15.37)	(15.86)
Parents divorced?	0.25	0.23	0.23
Behind Cohort?	0.12	0.12	0.16
Highest Completed Grade	8.01	7.89	8.15
	(2.10)	(2.09)	(2.11)
Enrolled in School?	0.80	0.83	0.81
Teen Mother?	0.07	0.03	0.04

Standard errors in parentheses. The standard error for proportions is not presented.

Table 2.2: Descriptive Statistics. Data consists of oldest children in the household. Complete Sample.

	Two or more siblings	Three or more siblings
Age	7.07	8.73
	(3.30)	(3.02)
Mother's Age	28.21	28.91
	(3.12)	(2.76)
Father's Age	31.05	32.00
	(4.63)	(4.59)
Years of Education of the mother	12.06	11.53
	(2.23)	(2.32)
Years of Education of the father	12.72	12.23
	(2.85)	(2.99)
Number of Siblings	2.40	3.32
	(0.70)	(0.66)
White	0.81	0.75
Black	0.075	0.10
Asian	0.01	0.01
Hispanic	0.09	0.13
Multiple births at second pregnancy	0.008	0.028
Multiple births at third pregnancy	0.003	0.009
Multiple births	0.012	0.040
Mother in Home	1.00	1.00
Father in Home	0.88	0.87
Attend Private School?	0.17	0.12
In nursery school?	0.39	0.48
Migrate?	0.30	0.29
Share Bedroom?	0.17	0.41
Mother's works?	0.45	0.38
Mother's Hours at work?	29.46	28.58
	(16.01)	(16.78)
Parents divorced?	0.22	0.24
Behind Cohort?	0.01	0.03
Highest Completed Grade	6.10	6.16
	(0.46)	(0.57)
Enrolled in School?	0.88	0.86
Teen Mother?	0.02	0.03

Standard errors in parentheses. The standard error for proportions is not presented.

Table 2.3: Descriptive Statistics. Data consists of oldest children in the household. Young Mothers.

	Old Mothers	
	Two or more siblings	Three or more siblings
Age	14.28	14.99
	(3.46)	(2.87)
Mother's Age	39.65	39.13
	(5.41)	(4.85)
Father's Age	42.27	41.84
	(6.69)	(6.19)
Years of Education of the mother	12.26	11.91
	(2.67)	(2.68)
Years of Education of the father	12.88	12.55
	(3.47)	(3.53)
Number of Siblings	2.66	3.53
	(0.96)	(0.89)
White	0.81	0.76
Black	0.09	0.11
Asian	0.02	0.02
Hispanic	0.07	0.10
Multiple births at second pregnancy	0.010	0.023
Multiple births at third pregnancy	0.004	0.010
Multiple births	0.016	0.038
Mother in Home	1.00	1.00
Father in Home	0.85	0.86
Attend Private School?	0.12	0.12
In nursery school?	0.61	0.66
Migrate?	0.18	0.18
Share Bedroom?	0.19	0.37
Mother's works?	0.57	0.52
Mother's Hours at work?	31.53	30.77
	(15.02)	(15.55)
Parents divorced?	0.24	0.23
Behind Cohort?	0.18	0.22
Highest Completed Grade	8.56	8.82
	(2.07)	(2.01)
Enrolled in School?	0.83	0.81
Teen Mother?	0.03	0.04

Standard errors in parentheses. The standard error for proportions is not presented.

Table 2.4: Descriptive Statistics. Data consists of oldest children in the household. Older Mothers.

	Two or more siblings	Three or more siblings
Age	-0.162	-0.176
	(0.058)**	(0.076)*
Mother's Age	-0.757	-0.435
	(0.086)**	(0.119)**
Father's Age	-0.637	-0.445
	(0.105)**	(0.148)**
Years of Education of the mother	-0.022	0.175
	(0.030)	(0.048)**
Years of Education of the father	0.012	0.220
	(0.042)	(0.069)**
Number of Siblings	-0.838	-0.893
	(0.010)**	(0.016)**
White	0.015	0.054
	(0.005)**	(0.008)**
Black	-0.027	-0.045
	(0.003)**	(0.006)**
Asian	0.006	0.004
	(0.002)**	(0.003)
Hispanic	0.006	-0.015
	(0.003)	(0.006)**

Standard errors in round parentheses * significant at 5%; ** significant at 1%

Table 2.5: Means differences between children that do not have twin siblings and whom do it.

			Younger Mothers		Older Mothers	
	(1)	(2)	(3)	(4)	(5)	(6)
	Uncond.	Cond. (a)	Uncond.	Cond. (a)	Uncond.	Cond. (a)
MB_2	0.838	0.840	0.875	0.876	0.806	0.823
	(0.010)**	(0.009)**	(0.015)**	(0.012)**	(0.014)**	(0.012)**
N. Observ.	757,769	757,769	277,084	277,084	480,685	480,685
R2		0.15		0.18		0.12
MB_3	0.875	0.854	0.899	0.888	0.861	0.841
	(0.016)**	(0.013)**	(0.024)**	(0.021)**	(0.020)**	(0.017)**
N. Observ.	285,175	285,175	80,842	80,842	204,333	204,333
R2		0.11		0.13		0.09

Standard errors in parentheses * significant at 5%; ** significant at 1%.

(a) Covariates in the model are dummies by age (measured in quarters), state, education of the parents, race, mothers age and sex.

Table 2.6: Impact of Multiple Births on Number of Children at Home.

Outcomes	Sample and Ages	OLS	2SLS	
Attend Private School?	6-18	0.0139	-0.0102	{25.60}
		(0.0005) **	(0.0048) *	
In nursery school?	less than 6	-0.0457	-0.0034	{12.01}
		(0.0032) **	(0.0126)	
Migrate?	0-18	0.0067	-0.0065	{2.71}
		(0.0008) **	(0.0081)	
Share Bedroom?	0-18	0.2285	0.2011	{22.94}
		(0.0008) **	(0.0079) **	
Mother's works?	0-18	-0.0859	-0.0363	{54.09}
		(0.0007) **	(0.0068) **	
Mother's Hours at work?	0-18 (a)	-0.0466	-0.0180	{6.67}
		(0.0012) **	(0.0111)	
Parents divorced?	0-18	-0.0207	0.0269	{63.40}
		(0.0006) **	(0.0060) **	
Behind Cohort?	6-18	0.0144	0.0018	{9.31}
		(0.0005) **	(0.0042)	
Highest Completed Grade	6-18	-0.0034	0.0001	{12.03}
		(0.0001) **	(0.0010)	
Enrolled in School?	16-18	-0.0094	-0.0153	{0.40}
		(0.0008) **	(0.0094)	
Teen Mother?	13-18	0.0037	0.0096	{0.81}
		(0.0006) **	(0.0066)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.
(a) The sample is additionally constrained to working mothers.

Table 2.7: OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with two or more children.

Outcomes	Sample and Ages	OLS	2SLS	
Attend Private School?	6-18	0.0161	-0.0043	{8.45}
		(0.0008) **	(0.0070)	
In nursery school?	less than 6	-0.0356	0.0064	{1.51}
		(0.0115) **	(0.0360)	
Migrate?	0-18	0.0055	0.0075	{0.02}
		(0.0012) **	(0.0125)	
Share Bedroom?	0-18	0.2541	0.3508	{96.86}
		(0.0012) **	(0.0099) **	
Mother's works?	0-18	-0.0718	-0.0421	{8.15}
		(0.0011) **	(0.0105) **	
Mother's Hours at work?	0-18 (a)	-0.0305	-0.0123	{1.03}
		(0.0022) **	(0.0181)	
Parents divorced?	0-18	-0.0166	0.0121	{9.55}
		(0.0009) **	(0.0093)	
Behind Cohort?	6-18	0.0191	0.0112	{1.07}
		(0.0009) **	(0.0077)	
Highest Completed Grade	6-18	-0.0049	-0.0012	{4.76}
		(0.0002) **	(0.0017)	
Enrolled in School?	16-18	-0.0124	-0.0035	{0.47}
		(0.0012) **	(0.0131)	
Teen Mother?	13-18	0.0028	0.0097	{0.45}
		(0.0010) **	(0.0104)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.
(a) The sample is additionally constrained to working mothers.

Table 2.8: OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with three or more children.

Outcomes	Sample and Ages	OLS	2SLS	
Attend Private School?	6-18	0.0116	-0.0059	{4.06}
		(0.0010) **	(0.0087)	
In nursery school?	less than 6	-0.0440	-0.0015	{10.60}
		(0.0034) **	(0.0135)	
Migrate?	0-18	0.0116	-0.0233	{5.43}
		(0.0018) **	(0.0151)	
Share Bedroom?	0-18	0.2640	0.2148	{25.41}
		(0.0011) **	(0.0098) **	
Mother's works?	0-18	-0.1256	-0.0733	{23.01}
		(0.0014) **	(0.0110) **	
Mother's Hours at work?	0-18 (a)	-0.0647	-0.0476	{0.62}
		(0.0030) **	(0.0220) *	
Parents divorced?	0-18	-0.0284	0.0101	{16.58}
		(0.0012) **	(0.0095)	
Behind Cohort?	6-18	0.0050	-0.0033	{19.20}
		(0.0005) **	(0.0019)	
Highest Completed Grade	6-18	-0.0010	0.0011	{12.79}
		(0.0001) **	(0.0006)	
Enrolled in School?	16-18	-0.0095	-0.1955	{0.57}
		(0.0091)	(0.2466)	
Teen Mother?	13-18	-0.0001	-0.0062	{0.27}
		(0.0033)	(0.0122)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value
of 3.84. Others covariates in the model are dummies by age (measured in quarters),
state of residence, education of the parents, race, parents age and sex.
(a) The sample is additionally constrained to working mothers.

Table 2.9: OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with two or more children. Younger Mothers.

Outcomes	Sample and Ages	OLS	2SLS	
Attend Private School?	6-18	0.0176	0.0290	{0.65}
		(0.0017) **	(0.0143) *	
In nursery school?	less than 6	-0.0320	0.0063	{1.10}
		(0.0120) **	(0.0383)	
Migrate?	0-18	0.0105	0.0384	{0.41}
		(0.0034) **	(0.0261)	
Share Bedroom?	0-18	0.3026	0.4338	{57.44}
		(0.0028) **	(0.0175) **	
Mother's works?	0-18	-0.0897	-0.0662	{1.70}
		(0.0025) **	(0.0182) **	
Mother's Hours at work?	0-18 (a)	-0.0389	-0.0080	{0.64}
		(0.0065) **	(0.0392)	
Parents divorced?	0-18	-0.0185	0.0191	{4.62}
		(0.0024) **	(0.0176)	
Behind Cohort?	6-18	0.0094	0.0113	{0.09}
		(0.0013) **	(0.0066)	
Highest Completed Grade	6-18	-0.0019	-0.0008	{0.57}
		(0.0003) **	(0.0015)	
Enrolled in School?	16-18	-0.0016	0.0636	{0.26}
		(0.0140)	(0.1276)	
Teen Mother?	13-18	-0.0021	-0.0296	{1.83}
		(0.0046)	(0.0209)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.
(a) The sample is additionally constrained to working mothers.

Table 2.10: OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with three or more children. Younger Mothers.

Outcomes	Sample and Ages	OLS	2SLS	
Attend Private School?	6-18	0.0145	-0.0121	{22.03}
		(0.0005) **	(0.0057) *	
In nursery school?	less than 6	-0.0645	-0.0262	{1.30}
		(0.0109) **	(0.0353)	
Migrate?	0-18	0.0050	0.0026	{0.07}
		(0.0008) **	(0.0094)	
Share Bedroom?	0-18	0.2168	0.1962	{8.58}
		(0.0006) **	(0.0071) **	
Mother's works?	0-18	-0.0742	-0.0170	{45.25}
		(0.0008) **	(0.0085) *	
Mother's Hours at work?	0-18 (a)	-0.0427	-0.0072	{7.68}
		(0.0013) **	(0.0129)	
Parents divorced?	0-18	-0.0193	0.0356	{51.78}
		(0.0007) **	(0.0077) **	
Behind Cohort?	6-18	0.0162	0.0055	{3.05}
		(0.0006) **	(0.0062)	
Highest Completed Grade	6-18	-0.0040	-0.0004	{7.85}
		(0.0001) **	(0.0013)	
Enrolled in School?	16-18	-0.0093	-0.0152	{0.41}
		(0.0008) **	(0.0094)	
Teen Mother?	13-18	0.0038	0.0096	{0.77}
		(0.0006) **	(0.0067)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.
(a) The sample is additionally constrained to working mothers.

Table 2.11: OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with two or more children. Older Mothers.

Outcomes	Sample and Ages	OLS	2SLS	
Attend Private School?	6-18	0.0156	-0.0175	{17.05}
		(0.0009) **	(0.0081) *	
In nursery school?	less than 6	-0.0861	0.0388	{1.31}
		(0.0456) *	(0.1184)	
Migrate?	0-18	0.0041	-0.0048	{0.41}
		(0.0013) **	(0.0139)	
Share Bedroom?	0-18	0.2440	0.3184	{40.03}
		(0.0013) **	(0.0118) **	
Mother's works?	0-18	-0.0677	-0.0333	{7.41}
		(0.0012) **	(0.0127) **	
Mother's Hours at work?	0-18 (a)	-0.0289	-0.0123	{0.68}
		(0.0024) **	(0.0203)	
Parents divorced?	0-18	-0.0169	0.0096	{5.86}
		(0.0010) **	(0.0110)	
Behind Cohort?	6-18	0.0199	0.0101	{0.93}
		(0.0011) **	(0.0102)	
Highest Completed Grade	6-18	-0.0053	-0.0012	{3.38}
		(0.0003) **	(0.0022)	
Enrolled in School?	16-18	-0.0124	-0.0035	{0.46}
		(0.0012) **	(0.0131)	
Teen Mother?	13-18	0.0030	0.0101	{0.45}
		(0.0010) **	(0.0106)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.
(a) The sample is additionally constrained to working mothers.

Table 2.12: OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with three or more children. Older Mothers.

Outcomes		OLS	2SLS	
Attend Private School?				
	White	0.0216	-0.0109	{35.66}
		(0.0006) **	(0.0055) *	
	Non-White	-0.0049	-0.0059	{0.01}
		(0.0007) **	(0.0095)	
	Male	0.0144	-0.0148	{19.62}
		(0.0007) **	(0.0066) *	
	Female	0.0133	-0.0055	{7.49}
		(0.0007) **	(0.0069)	
Mother's works?				
	White	-0.0929	-0.0314	{65.92}
		(0.0008) **	(0.0076) **	
	Non-White	-0.0665	-0.0548	{0.65}
		(0.0012) **	(0.0146) **	
	Male	-0.0863	-0.0454	{19.06}
		(0.0009) **	(0.0094) **	
	Female	-0.0855	-0.0265	{36.93}
		(0.0010) **	(0.0098) **	
Parents divorced?				
	White	-0.0211	0.0230	{45.43}
		(0.0007) **	(0.0066) **	
	Non-White	-0.0159	0.0417	{16.47}
		(0.0011) **	(0.0142) **	
	Male	-0.0187	0.0253	{28.47}
		(0.0008) **	(0.0083) **	
	Female	-0.0228	0.0289	{35.36}
		(0.0008) **	(0.0087) **	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.
(a) The sample is additionally constrained to working mothers.

Table 2.13: Heterogeneity by sex and race. Inputs. OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with two or more children. All mothers.

Outcomes		OLS	2SLS	
Behind Cohort?				
	White	0.0103	0.0007	{4.64}
		(0.0006) **	(0.0045)	
	Non-White	0.0206	0.0088	{1.36}
		(0.0010) **	(0.0102)	
	Male	0.0143	0.0043	{2.70}
		(0.0007) **	(0.0061)	
	Female	0.0145	0.0004	{6.49}
		(0.0007) **	(0.0056)	
Highest Completed Grade				
	White	-0.0024	0.0008	{10.26}
		(0.0001) **	(0.0010)	
	Non-White	-0.0051	-0.0032	{0.53}
		(0.0003) **	(0.0026)	
	Male	-0.0033	-0.0003	{4.01}
		(0.0002) **	(0.0015)	
	Female	-0.0034	0.0002	{8.13}
		(0.0002) **	(0.0013)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.

Table 2.14: Heterogeneity by sex and race. Outputs. OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with two or more children. All mothers.

Outcomes		OLS	2SLS	
Attend Private School?				
	White	0.0247	-0.0033	{10.42}
		(0.0011) **	(0.0087)	
	Non-White	-0.0014	-0.0040	{0.06}
		(0.0009)	(0.0108)	
	Male	0.0165	-0.0212	{17.29}
		(0.0011)	(0.0091) *	
	Female	0.0156	0.0132	{0.05}
		(0.0011) **	(0.0108)	
Mother's works?				
	White	-0.0774	-0.0488	{5.44}
		(0.0014) **	(0.0123) **	
	Non-White	-0.0610	-0.0275	{2.96}
		(0.0018) **	(0.0195)	
	Male	-0.0737	-0.0507	{2.58}
		(0.0015) **	(0.0144) **	
	Female	-0.0697	-0.0335	{5.73}
		(0.0016) **	(0.0152) *	
Parents divorced?				
	White	-0.0161	0.0094	{5.83}
		(0.0011) **	(0.0106)	
	Non-White	-0.0126	0.0151	{2.23}
		(0.0017) **	(0.0186)	
	Male	-0.0147	0.0075	{2.95}
		(0.0013) **	(0.0130)	
	Female	-0.0186	0.0171	{7.14}
		(0.0014) **	(0.0134)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.
(a) The sample is additionally constrained to working mothers.

Table 2.15: Heterogeneity by sex and race. Inputs. OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with three or more children. All mothers.

Outcomes		OLS	2SLS	
Behind Cohort?				
	White	0.0148	0.0154	{0.00}
		(0.0011) **	(0.0087)	
	Non-White	0.0241	0.0024	{2.01}
		(0.0017) **	(0.0154)	
	Male	0.0179	0.0144	{0.10}
		(0.0013) **	(0.0113)	
	Female	0.0205	0.0065	{1.94}
		(0.0013) **	(0.0102)	
Highest Completed Grade				
	White	-0.0037	-0.0017	{1.31}
		(0.0002) **	(0.0018)	
	Non-White	-0.0064	0.0000	{2.71}
		(0.0004) **	(0.0039)	
	Male	-0.0046	0.0011	{5.43}
		(0.0003) **	(0.0025)	
	Female	-0.0052	-0.0033	{0.68}
		(0.0003) **	(0.0023)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.

Table 2.16: Heterogeneity by sex and race. Outputs. OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with three or more children. All mothers.

Outcomes		OLS	2SLS	
Attend Private School?				
	White	0.0190	-0.0080	{7.77}
		(0.0012) **	(0.0098)	
	Non-White	-0.0084	-0.0003	{0.19}
		(0.0014) **	(0.0187)	
	Male	0.0121	-0.0036	{1.70}
		(0.0013) **	(0.0121)	
	Female	0.0111	-0.0082	{2.39}
		(0.0014) **	(0.0125)	
Mother's works?				
	White	-0.1345	-0.0818	{19.11}
		(0.0016) **	(0.0122) **	
	Non-White	-0.1018	-0.0380	{6.32}
		(0.0026) **	(0.0255)	
	Male	-0.1252	-0.0758	{10.95}
		(0.0019) **	(0.0150) **	
	Female	-0.1261	-0.0707	{12.00}
		(0.0019) **	(0.0161) **	
Parents divorced?				
	White	-0.0295	0.0018	{9.46}
		(0.0014) **	(0.0103)	
	Non-White	-0.0226	0.0403	{7.22}
		(0.0024) **	(0.0235)	
	Male	-0.0263	0.0046	{5.75}
		(0.0017) **	(0.0130)	
	Female	-0.0306	0.0166	{11.51}
		(0.0018) **	(0.0140)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.
(a) The sample is additionally constrained to working mothers.

Table 2.17: Heterogeneity by sex and race. Inputs. OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with two or more children. Younger mothers.

Outcomes		OLS	2SLS	
Behind Cohort?				
	White	0.0035	-0.0016	{6.46}
		(0.0005) **	(0.0021)	
	Non-White	0.0064	-0.0092	{9.06}
		(0.0011) **	(0.0053)	
	Male	0.0050	-0.0026	{8.10}
		(0.0007) **	(0.0028)	
	Female	0.0050	-0.0033	{10.63}
		(0.0007) **	(0.0027)	
Highest Completed Grade				
	White	-0.0008	0.0003	{3.47}
		(0.0001) **	(0.0006)	
	Non-White	-0.0015	0.0037	{9.08}
		(0.0003) **	(0.0017) *	
	Male	-0.0010	0.0011	{5.32}
		(0.0002) **	(0.0009)	
	Female	-0.0011	0.0008	{7.02}
		(0.0002) **	(0.0007)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.

Table 2.18: Heterogeneity by sex and race. Outputs. OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with two or more children. Younger mothers.

Outcomes		OLS	2SLS	
Attend Private School?				
	White	0.0291	0.0534	{1.69}
		(0.0025) **	(0.0189) **	
	Non-White	-0.0041	-0.0238	{1.30}
		(0.0019) *	(0.0174)	
	Male	0.0168	0.0139	{0.02}
		(0.0024) **	(0.0189)	
	Female	0.0183	0.0429	{1.35}
		(0.0024) **	(0.0213) *	
Mother's works?				
	White	-0.0930	-0.0711	{1.05}
		(0.0032) **	(0.0216) **	
	Non-White	-0.0844	-0.0523	{0.95}
		(0.0042) **	(0.0332)	
	Male	-0.0883	-0.0774	{0.19}
		(0.0036) **	(0.0250) **	
	Female	-0.0908	-0.0562	{1.73}
		(0.0036) **	(0.0266) *	
Parents divorced?				
	White	-0.0185	0.0235	{4.16}
		(0.0030) **	(0.0208)	
	Non-White	-0.0131	0.0070	{0.39}
		(0.0040) **	(0.0326)	
	Male	-0.0179	0.0154	{1.90}
		(0.0034) **	(0.0244)	
	Female	-0.0194	0.0226	{2.79}
		(0.0035) **	(0.0254)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.
(a) The sample is additionally constrained to working mothers.

Table 2.19: Heterogeneity by sex and race. Inputs. OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with three or more children. Younger mothers.

Outcomes		OLS	2SLS	
Behind Cohort?				
	White	0.0062	0.0084	{0.09}
		(0.0015) **	(0.0077)	
	Non-White	0.0116	0.0203	{0.53}
		(0.0023) **	(0.0121)	
	Male	0.0092	0.0021	{0.65}
		(0.0018) **	(0.0089)	
	Female	0.0099	0.0202	{1.18}
		(0.0018) **	(0.0097) *	
Highest Completed Grade				
	White	-0.0012	-0.0004	{0.22}
		(0.0003) **	(0.0018)	
	Non-White	-0.0027	-0.0020	{0.06}
		(0.0006) **	(0.0028)	
	Male	-0.0020	0.0013	{2.16}
		(0.0004) **	(0.0023)	
	Female	-0.0019	-0.0034	{0.61}
		(0.0004) **	(0.0020)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.

Table 2.20: Heterogeneity by sex and race. Outputs. OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with three or more children. Younger mothers.

Outcomes		OLS	2SLS	
Attend Private School?				
	White	0.0224	-0.0126	{28.36}
		(0.0007) **	(0.0066)	
	Non-White	-0.0040	-0.0087	{0.19}
		(0.0008) **	(0.0108)	
	Male	0.0151	-0.0198	{19.73}
		(0.0008) **	(0.0079) *	
	Female	0.0140	-0.0046	{5.12}
		(0.0008) **	(0.0082)	
Mother's works?				
	White	-0.0812	-0.0045	{62.82}
		(0.0009) **	(0.0097)	
	Non-White	-0.0559	-0.0620	{0.12}
		(0.0014) **	(0.0177) **	
	Male	-0.0750	-0.0291	{14.85}
		(0.0011) **	(0.0120) *	
	Female	-0.0733	-0.0040	{32.45}
		(0.0011) **	(0.0122)	
Parents divorced?				
	White	-0.0190	0.0337	{39.31}
		(0.0007) **	(0.0084) **	
	Non-White	-0.0154	0.0434	{10.99}
		(0.0013) **	(0.0178) *	
	Male	-0.0173	0.0370	{26.37}
		(0.0009) **	(0.0106) **	
	Female	-0.0214	0.0342	{25.38}
		(0.0009) **	(0.0111) **	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.
(a) The sample is additionally constrained to working mothers.

Table 2.21: Heterogeneity by sex and race. Inputs. OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with two or more children. older mothers.

Outcomes		OLS	2SLS	
Behind Cohort?				
	White	0.0127	0.0013	{2.88}
		(0.0007) **	(0.0067)	
	Non-White	0.0234	0.0226	{0.00}
		(0.0013) **	(0.0148)	
	Male	0.0161	0.0081	{0.76}
		(0.0009) **	(0.0092)	
	Female	0.0163	0.0030	{2.65}
		(0.0009) **	(0.0083)	
Highest Completed Grade				
	White	-0.0030	0.0011	{9.25}
		(0.0002) **	(0.0013)	
	Non-White	-0.0060	-0.0060	{0.00}
		(0.0003) **	(0.0035)	
	Male	-0.0039	-0.0008	{2.61}
		(0.0002) **	(0.0020)	
	Female	-0.0040	-0.0001	{5.61}
		(0.0002) **	(0.0016)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.

Table 2.22: Heterogeneity by sex and race. Outputs. OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with two or more children. older mothers.

Outcomes		OLS	2SLS	
Attend Private School?				
	White	0.0237	-0.0244	{24.82}
		(0.0012) **	(0.0097) *	
	Non-White	-0.0008	0.0051	{0.19}
		(0.0011)	(0.0137)	
	Male	0.0163	-0.0350	{25.05}
		(0.0013) **	(0.0103) **	
	Female	0.0149	0.0010	{1.25}
		(0.0013) **	(0.0125)	
Mother's works?				
	White	-0.0743	-0.0407	{5.16}
		(0.0015) **	(0.0149) **	
	Non-White	-0.0553	-0.0152	{2.78}
		(0.0020) **	(0.0241)	
	Male	-0.0705	-0.0415	{2.78}
		(0.0017) **	(0.0175) *	
	Female	-0.0647	-0.0256	{4.54}
		(0.0018) **	(0.0184)	
Parents divorced?				
	White	-0.0158	0.0045	{2.74}
		(0.0012) **	(0.0123)	
	Non-White	-0.0134	0.0186	{2.01}
		(0.0019) **	(0.0227)	
	Male	-0.0146	0.0049	{1.64}
		(0.0014) **	(0.0153)	
	Female	-0.0193	0.0141	{4.48}
		(0.0015) **	(0.0159)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical. The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.
(a) The sample is additionally constrained to working mothers.

Table 2.23: Heterogeneity by sex and race. Inputs. OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with three or more children. Older mothers.

Outcomes		OLS	2SLS	
Behind Cohort?				
	White	0.0166	0.0166	{0.00}
		(0.0013) **	(0.0115)	
	Non-White	0.0255	-0.0081	{2.49}
		(0.0020) **	(0.0214)	
	Male	0.0187	0.0180	{0.00}
		(0.0015) **	(0.0152)	
	Female	0.0214	-0.0006	{2.62}
		(0.0015) **	(0.0136)	
Highest Completed Grade				
	White	-0.0042	-0.0022	{0.76}
		(0.0003) **	(0.0023)	
	Non-White	-0.0070	0.0013	{2.58}
		(0.0005) **	(0.0052)	
	Male	-0.0050	0.0007	{3.19}
		(0.0004) **	(0.0032)	
	Female	-0.0056	-0.0031	{0.72}
		(0.0004) **	(0.0030)	

Standard errors in parentheses * significant at 5%; ** significant at 1%.
Parameters Estimates (Standard Errors) and {Hausman Test Statistic}.
The Hausman test statistic is for the null hypothesis that OLS and 2SLS are identical.
The test is distributed as chi-square with one degree of freedom and 95% critical value of 3.84. Others covariates in the model are dummies by age (measured in quarters), state of residence, education of the parents, race, parents age and sex.

Table 2.24: Heterogeneity by sex and race. Outputs. OLS and 2SLS Estimates of Child Input and Output Equations. Sample of households with three or more children. Older mothers.

Chapter 3

Female Labor Participation and its role on Obesity

3.1 Overview

Obesity has reached epidemic levels (Mokdad et al., 1999), making it a vital public health issue.[1] Among adults between ages 20 and 74 the prevalence of obesity has risen from 13.4% to 30.9% between 1960 and 2000. Children have not been excluded from this trend. In 2000, more than 15% of children aged 6 to 11 were obese. This percentage has tripled since 1964. Despite the fact that the increase in obesity is a phenomenon spanning all ages, races and both genders, minority groups have had a particulary rapid rise in obesity rates during the last decade. Overall, the obesity rate has increased approximately 5 percentage points between the periods 1988-94 and 1999-2000; for Blacks and Mexican Americans the increase was approximately 10 percentage points. In addition, for the period 1999-2000 the obesity rate among Black adults is higher than among whites. This is driven by the obesity rate of Black women.

This increase in obesity is particularly puzzling if we consider the evidence that shows only a modest gain in calorie consumption[2] (Lakdawalla and Philipson, pp. 2,

[1]Part of this public awareness comes first from the potential link between obesity and several disorders such as type II diabetes, hypertension, hypercholesterolemia, stroke, heart disease, arthritis and some types of cancer (endometrial, breast, prostate and colon). Some estimates reveal the cost of caring for people with entirely *preventable* obesity-related illness tops 70 billion per year, about half of which is paid by the government. Second, there is a strong lobby pushing for a re–classification of obesity as a disease and not only as a risk factor. In fact this re–classification of obesity might have a negative effect making health insurance unaffordable for many people.

[2]On the other hand, Cutler et al. (2003) show that a modest increase in the consumption of calories

2002) and the fitness mania that we face every day.

Obesity is a problem that is related to the imbalance between dietary intake and energy expenditure. Unlike many other health conditions, in the majority of cases obesity can be affected by behavioral change.[3] Weight is a state variable whose change over time results from a difference between calories consumed and calories burned. Under this framework one of the main explanations given for the increase in the proportion of obesity is technological change (Philipson and Posner, 1999; Lakdawalla and Philipson, 2002, Cutler et al., 2003)[4]. They argue that there has been a reduction in the real cost of calories while energy requirements have fallen. The problem with arguments based completely on technological change is that it is unlikely to explain the rapid rise in obesity that we have observed in recent decades.[5] A technological change also cannot account for

is enough to explain the change in the steady-state weight. In particular as they reported, the 10 to 12 pound increase in the median weight observed in the last twenty years requires only a net caloric imbalance of about 100 to 150 calories per day, an amount that they described as the amount of calories contained in three Oreo cookies or one can of Pepsi.

[3]This idea that most cases of obesity can be affected by behavioral change is one of the arguments that is given against the classification of obesity as a disease. Individuals that defend the disease classification argue that there is increasing evidence that relates some of the traditional diseases (for example some types of cancer) to specific risk behaviors. However, when this paper refers to obesity as a disease, it is not intended to defend a particular position.

[4]Technological change has been the preferred explanation because it is consistent not only with the rise in the incidence of obesity but also with the more or less stable overall consumption of calories in the population.

[5]Technological change seems a valid explanation for the log–term evolution of obesity among the population. In agricultural or industrial societies, work is energy consumption intensive and welfare systems are ungenerous. Technological change has freed up time from producing food, enabling a reallocation of time to other activities such as producing services. Therefore in a developed society work entails a lower consumption of energy and not engaging in production activities does not necessarily imply starvation.

the higher increase that we observe among minorities and other low income groups.

Household production might provide an additional explanation for the rapid rise in obesity – an increase in female labor force participation raises the cost of time intensive activities and induces a substitution into activities that are less time intensive but more goods intensive. In this context a rise in female labor force participation would induce a substitution out of home cooked meals into fast food and other types of prepared meals. This chapter suggests the rise in the cost of women's time coupled with a low level of non–labor income (tight budget constraint) might be behind the higher incidence of obesity observed in low income groups and minorities. It is important to stress that the impact of female labor force participation on obesity and on body weight in general is not straightforward. In order for it to increase obesity, we would expect mother's labor force participation to reduce the relative cost of eating out, and her earnings would be insufficient to afford less calorie intensive meals out. Less calorie intensive meals at home have a high cost in time. One potential equilibrium is reached with low-cost (time and price), calorie-intensive meals out. However, if resources generated in the labor market are sufficient to compensate for the rise in the cost of time, a second potential equilibrium is reached, less calorie intensive meals out. Additionally, the rise in women's time out the home can impact the weight of other household members. For example, working mothers might spend less time with their children who might spend more time in front of the TV or video games, factors that have been linked to higher gains in Body Mass Index (BMI)(Berkey et al., 2000). Also working women are more likely to send their children to daycare or nursery schools, whose impact on nutritional behavior is not at all clear.

In this chapter, I study the impact of female labor participation on the body weight of women and their husbands. I also examine direct inputs into body weight – the level of physical activity and nutrient intake. An analysis of married men allows us to investigate the impact of female labor force participation on other members in the household, (e.g. children), avoiding a genetic explanation. Using the *National Health Interview Survey* (NHIS) I found that female employment has a positive impact on Body Mass Index (BMI) for married men with less than a high school education. However I did not find an impact for all samples of women or men with high school or more. This finding is consistent with men facing an increase in the cost of home cooking with a positive impact on body weight. Women face an offsetting rise in the level of physical activity and households whose husbands have higher income can afford less calorie–intensive prepared food. The magnitude of these findings is larger than found elsewhere in the literature. This is primarily because I take account of the endogeneity of female labor force participation. The analysis from the *Behavioral Risk Factor Surveillance System* (BRFSS) survey reveals that married men with less than a high school education, or married men with a college degree or more, face an increase in their BMI and the likelihood of being obese if they live in states with a positive shock in female labor demand. The results also show that for married men with higher levels of education female demand shocks produce an increase in the levels of physical activity. This last element, plus the positive impact of female demand shocks on BMI and obesity rate, suggests that the channel through which female labor force participation raises a man's weight must be through a higher consumption of calories which is consistent with a lower consumption of fruit and vegetables that we find associated with female demand shocks for this group.

The rest of chapter 3 is organized as follows. The second section presents the literature review. Section three describe a simple household production model to formalize our hypothesis. Section four explains the empirical methodology used to address the problem of identification. The fifth section describes how the variables and samples have been constructed and provides a descriptive analysis of the variables. Section six presents the results and section seven, the conclusions.

3.2 Literature Review

Some limited evidence exists of a positive effect of labor force participation on the rate of obesity. Chou, Grossman and Saffer (2002) use micro-level data from the 1984-1999 Behavioral Risk Factor Surveillance System in order to study factors behind the rise of obesity. Among other variables[6], they analyze the impact of hours worked per week and hourly wage rates on body weight.[7] They find that wages and hours of work have a positive impact on body mass index and on the probability of being obese. They estimate that the elasticity of BMI with respect to wages is 0.03 and the elasticity of BMI with respect to hours is 0.04. When the probability of being obese is considered, these elasticities are 0.32 and 0.19, respectively.

The role of female employment has been studied in relation to its impact on child weight problems. Takahashi et al. (1999) find a positive relationship in a sample of Japanese children. For the US., Johnson et al. (1992) find no significant effect of maternal employment on nutrient intake in a sample of U.S. children ages 2 to 5. In other study

[6]Other variables in their analysis are per capita number of fast food restaurants, per capita full–service restaurants, the price of a meal in each type of restaurant, the price of food consumed at home, the price of cigarettes and clean indoor air laws.

[7]This information is extracted from the Current Population Survey (CPS). The assignment is based on 64 cells that are defined in terms of gender, race, marital status, and years of formal schooling. Hours worked is defined as the usual hours worked per week per in one of 64 cells in a given state and year multiplied by the employment rate in that cell. In the same way, hourly wage is defined as the average hourly wage rate in each of the cells multiplied by the employment rate in each cell.

of American children, Anderson et al. (2002) find that an increase in 10 hours per week in maternal employment increases the likelihood that a child is overweight by 0.5 to 1.0 percentage points depending on the specification and identification strategy.

The evidence about the impact of female labor force participation on the incidence of childhood obesity seems especially important given the stronger work requirements that have been progressively introduced by welfare reform in the U.S. during the 1990's. The assumption behind these tougher work incentives is that individuals will be more motivated to find a job, and will become independent of welfare. In fact, much of the evidence reveals that more individuals are working under the new welfare schemes. However, many policymakers and observers are concerned about the potentially harmful consequences of the new welfare system. In particular the evidence collected from Connecticut's reformed welfare system shows that mothers mothers are increasingly working, but there has not been a significant increase in their income. Also many of these newly working mothers are engaged in irregular work hours and in more than one job, which might be directly linked to obesity. Mothers have less time to cook or to supervise children's activities because they are working. However, the income generated is not sufficient which, in turn, increases the likelihood of consumption of fast food.

Some research has specifically studied the relationship between welfare programs and childhood obesity. The results are mixed depending on the outcomes and welfare program considered. Hofferd and Curtin (2003) find no evidence that programs such as the Food Stamp Program and the National School Lunch Program contribute to obesity among poor children. Haider et al. (2003) compare the change in the breastfeeding rate in states that adopted stringent work policies versus states that had lenient policies. The results show a greater drop in the breastfeeding rate after a child is six months old for new mothers enrolled in the Special Supplemental Program for Women (3.1 percent), versus a drop of 2.1 percent for all mothers.

3.3 Why Does female labor participation matter?

In order to formalize my hypothesis about the impact of female labor participation on adult obesity I use a simplified version of a static household production model. I assume that people prefer to feel full and therefore the amount or volume of food, V, enters positively in the utility function. While people like to feel full, within the range of calories typically consumed in a developed country, net calories, C, enter negatively into the utility function. A key problem is that large volumes of food typically entail large calorie intake, although as I explain below, agents can take costly actions to reduce calorie intake per unit of volume. As usual leisure, l, and the consumption of other goods, X, enter positively into the utility function. In particular the utility function takes the following form:

$$U(X, V, C, l) = \alpha_0 log(X) + \alpha_1 log(V) + \alpha_2 C^2 + \alpha_3 log(l) \tag{3.1}$$

$$with \qquad \alpha_0, \alpha_1, \alpha_3 > 0, \qquad and \qquad \alpha_2 < 0. \tag{3.2}$$

Therefore utility does not rise in the consumption of calories but instead rises from the volume of food intake. What this tries to capture in simplified fashion is the biological fact that the brain perceives the fullness of the stomach rather than net calories and this triggers the impulse to stop eating (CITE). The assumption that net calories enter negatively in the utility function represents the fact that the analysis done in this chapter starts from a steady state in body weight. In the context of the Lakdawalla and Philipson dynamic model, individuals in this model live only one period and they start this period with an "*ideal*" weight. Thus any level of calories that is either over or under the level of calories, $\overline{C}$, needed to keep that ideal weight will produce a reduction in the level of utility.

The volume of food is produced with a *Cobb–Douglas* technology,

$$V = V_x^{\beta_1} t_1^{(1-\beta_1)} \qquad 0 < \beta_1 < 1, \tag{3.3}$$

with t_1 representing the time allocated to produce a particular volume of food and V_x standing for any other input required. While home prepared food would require a more time intensive combination of inputs, eating *prepared food* would be an option more intensive in V_x. We could see V_x as a vector of inputs with different qualities, where its impact on total calories as well as the source of theses calories accounting for these differences among inputs[8]. In order to keep the presentation simple I assume that V_x represents an unique input and I abstract from differences in calories among inputs.

Individuals also select the average level of calories per unit of volume of food that is represented as

[8]In fast–food restaurants a higher proportion of the calories come from fat. A fat calorie is heavier than a protein or carbohydrate calorie. Calories from fat are more fattening than calories from proteins or carbohydrates. Our bodies tend to store excess calories from fat as fat more readily than they do excess calories from carbohydrates or proteins. Not only does the body store fat calories more easily, it also burns them less readily. The body, plotting to protect itself from starvation, will use up carbohydrate stores for energy before dipping into the fat reserves. The body must use more energy (or calories) to metabolize carbohydrates and proteins than it uses to burn fats. Fatty foods tend to pack more calories into a smaller volume than do carbohydrate and protein foods.

$$c = \theta_0 + \frac{\theta_1}{(1 + \theta_2 * t_2)} \qquad \theta_0, \theta_1, \theta_2 > 0, \tag{3.4}$$

where t_2 represents the time allocated in reduction of average calories. Time can be used to reduce calories in several ways. Raw foods (salad, vegetables) are often lower in calories but may take more attention to make tasty than more highly processed foods. An alternative is to use time to do research. It takes time to understand how to reduce calories in cooking.

An individual who does not spend time reducing calories, $t_2 = 0$, has an average level of calories in home cooking of $(\theta_0 + \theta_1)$. In the other extreme if individuals spent the complete available time reducing calories, the average level of calories would be $(\theta_0 + \frac{\theta_1}{(1+\theta_2 T)})$. Then as families allocate more time they can reduce average calories but at a decreasing rate. Specifically, θ_0 represents the amount of calories that can not be reduced, θ_1 the amount suitable to be reduced and θ_2 a parameter affecting the marginal impact of t_2 $(-\frac{\theta_1 \theta_2}{(1+\theta_2 t_2)^2})$. In this fashion we can define the total time cooking, t_{ck} as the sum of the time engaged in producing the food, t_1, and the time spent reducing the average calories, t_2.

Net calories, defined as the difference between calorie intake and calories burned, is represented as

$$C = cV - \overline{C}. \tag{3.5}$$

$\overline{C}$ can be seen as the basal level of calories that an individual needs in order to maintain a specific weight. In fact this basal requirement of calories depends (among other factors such as weight and age), on the level of physical activity that the individual carries on. However I left as exogenous $\overline{C}$ as well as the level of physical activity. In fact, we can think of this analysis as the short run version of the Lakdawalla and Philipson model, where the calories spent are unchanged and exogenous to the individuals.

We observe from expression 3.5 that individuals can reduce net calories in two ways: a) by reducing the volume of food; and b) by reducing the average amount of calories per volume. While the cost of reducing calories by reducing the volume of food consumed is the direct reduction in utility from a lower food consumption, the cost associated with the second option comes from the reduction in leisure time. In this way we do not need for individuals to eat more in order to gain weight, some may even eat less. What's important, however, is that people who gain weight might not necessarily eat a greater volume of food, they eat more calories than they burn in a particular period.

Individuals face the usual constraints. The first one,

$$T - l - t_{ck} - t_{work} = 0, \tag{3.6}$$

represents the constraint of time. The total time available, T, is divided among leisure, time cooking, t_{ck}, and time working, t_{work}. The second constraint is the budget constraint,

$$w * t_{work} + I_{nl} - X - p_x * V_x \geq 0, \tag{3.7}$$

where w and p_x are the hourly wage rate and the price of the ingredients in home cooking. Finally, I_{nl} stands for non–labor income. In our context, where we are studying the impact associated with female labor force participation, I_{nl} can be seen as husband's earnings.

The problem for the household can be reduced to selecting the optimum levels of X, V_x, V_1,V_2, t_1, t_2 and t_{work} that maximize 3.3 subject to 3.4, 3.5, 3.6 and 3.7.

From the First Order Conditions (FOC) we get the following expressions:

$$\frac{V_x\beta_1}{(1+\beta_1)V_{t_1}} = \frac{p_x}{w}, \tag{3.8}$$

$$\frac{\alpha_1 V_{t1}}{V} + 2\alpha_2 V_{t1} C(\theta_0 + \frac{\theta_1}{(1+\theta_2 * t_2)}) = -2(\frac{\theta_1\theta_2\alpha_2}{(1+\theta_2 * t_2)^2})VC. \tag{3.9}$$

Expression 3.8 represents the known rate of substitution among food production inputs that in the optimum equal the ratio of their shadow prices. From this expression we see that as wages increase, resulting in the greater cost of time, individuals shift from a more time intensive way of preparing food, *home cooking*, to more *market* input intensive technology.

Expression 3.9 represents the optimal division of time between food production (t_1) and calorie reduction (t_2). Optimally, an individual creates a situation where the marginal benefit associated with food production (left hand side of the expression) equals the marginal benefit of allocating time in calorie reduction (right hand side of the expression). We can see that the marginal benefit in food production falls for three reasons. First, individuals have a decreasing utility in food consumption. Second, there is decreasing returns in time allocated in food production. Finally, as individuals produce and consume more food they face a loss of utility associated with an increase in net calories, where this reduction in utility is increasing in the levels of net calories. On the other hand we can appreciate that the benefit associated with calorie reduction is increasing not only with the volume of food but also with net calories. However for a fixed volume and level of net calories the reduction in calories is decreasing with time.

Besides the simple form of the model I don't obtain an explicit solution. In order to have a perspective about the implications of the model, I solve it numerically for different wage and non-labor income levels. The solutions for some of the variables of interest are presented in figure 3.1 through figure 3.6.

Figure 3.1 presents the number of hours allocated in the labor market. As hourly wage increases, individuals spend more time in the labor market but it can be seen that the wage elasticity is higher for lower income levels. Similarly, for a given wage rate we see a reduction in the time working as we move up in the income groups and individuals are able to consume more leisure.

Figure 3.2 shows the total time allocated to cooking, while figures 3.3 and 3.4 shows its decomposition between food production and calorie reduction, respectively. As non-labor income rises, keeping wages constant, individuals allocate more time to cooking. They can only *afford* more ingredients, and also more time, because they allocate less hours to the labor market. In fact, as we see in figure 3.5, when non-labor income increases, individuals increase monotonically their consumption of food, but at a decreasing rate. This result is driven in part by a simplification in the model by not considering the existence of a *bliss* point such that food consumption over that level would produce a reduction in utility. This higher consumption of food, as non-labor income rises, increases the marginal utility associated with the allocation of time to calorie reduction as we can see in figure 3.4 and we already discussed with expression 3.9. When wage rate increases, individuals spend less time cooking, which is mainly driven by time in food production. The same regularity is observed for the time allocated in calorie reduction with the exception of the groups with lower levels of non-labor income where we observe a mild increase in the time allocated to calorie reduction as wages increase.

Another interesting result is how food consumption is impacted differently by an increase in wages across different income levels. While for lower income levels an increase in wages leads to an increase in food consumption, for higher income groups, I find that this rise in wages produces a reduction in food consumption. As non-labor income increases, individuals consume a higher proportion of food which brings down its marginal utility. Then, given this lower marginal utility for higher income groups, an equal rise in wages and an increase in the cost of time will drag out more hours of cooking with its consequent reduction in food consumption.

Finally, figure 3.5 presents the result for the total consumption of calories. As non-labor income increases individuals monotonically increase their consumption of calories which is mainly driven by the fact that I have not considered a bliss point in food consumption. Though we observe an increase in calories among all non-labor income groups as wages increase, we observe a steeper change for groups with lower levels of income. This flatter calories–wages profile for higher income groups results for two reasons. First, as we saw in figure 3.5, higher income groups reduce food consumption when they face an increase in wages. Second, higher income groups are the ones that are able to allocate more time to calorie reduction.

Therefore the impact of an increase in female labor participation ($\Delta_{t_{work}} > 0$)[9] on the equilibrium body weight will be the result of two competing forces. On the one hand, an increase in the the time allocated to paid activities will increase the cost of home food production (and physical activities that I have not modeled). As a result the household not only spends less time in physical activities but also increases the proportion of food that comes from the market. Although the rise in income associated with higher wages allows

[9]It is important to stress that t_{work} is endogenous in the model and in order to understand the overall impact of an increase in the time allocated to paid activities, we need to understand the sources that are behind the change. In particular in our model an increase in female labor participation produced by an increase in wages might have a completely different impact on body weight than an increase in the time allocated to female labor force participation that is produced by a reduction in non-labor income.

the household to increase all different sources of food (and food ingredients), for higher levels of income the proportion of calories might be reduced not only by switching to less caloric food alternatives but also by spending more time in calorie reduction. However, which of these two forces dominate is not clear. The lower the non-labor income, the higher the complementarity between time and *ingredients* (V_x) in the home food production, and the higher the cost of less caloric prepared food, the more likely it is that the overall impact of female labor participation on body weight is positive.

An aspect that has not been considered in the model, but is nonetheless important, is the composition of time in other activities at home. In particular, the rise in the cost of a woman's time has a direct impact on child investment. Some studies using time diaries reveal that children from households where mothers spend more hours in paid activities, spend more time watching TV or playing video games, which are two factors that have been linked to a higher incidence of child obesity.

3.4 The identification problem.

The specific question that I 'd like to address in this chapter is whether or not female labor force participation has an *impact* on body weight. One parameter of interest is

$$E(y_{i1}|t_h > 0) - E(y_{i0}|t_h > 0), \tag{3.10}$$

where y_1 represents a potential function of body weight if an individual is assigned a positive number of hours in the labor market (treated) and y_0 if not (non-treated). Empirically, great attention has been given to two measures of weight, the "obesity rate" and Body Mass Index (BMI). The BMI is defined as the weight in kilograms divided by the square of height in meters. A BMI between 20 and 22 is considered ideal for adults regardless of gender, between 23 and 25 is normal, a BMI over 25 and lower than 30 is considered overweight and adults that have a BMI over 30 are defined as obese. Although, BMI and obesity rate have been linked to risk factors, nothing ensures that these two variables would be sensitive enough to capture the impact of a rise in the opportunity cost of women's time in the short run. Departures from an ideal weight result from an imbalance between calorie intake and calorie use. Ideally we would like to measure the impact of female labor force participation on calories consumed and calories burned. However, many times due to data limitations, we only observe the outcome of body weight.

The parameter in expression 3.10 is known in the literature as the Average Treatment Effect on the Treated (ATET), and represents the average impact of the treatment, a positive number of hours in the labor market, for the population that is treated, i.e those that in effect engaged in paid activities.

In the context of the model presented in the previous section where y represents the total consumption of calories, and assuming that all individuals eat the same volume of food, V, and they can only choose between working a fixed amount of hours or not taking part at all in the labor market, we get the following expression for the ATET:

$$E(y_{i1}|t_h > 0) - E(y_{i0}|t_h > 0) = E(\frac{V\theta_1(t_2^{NW}(w, I_{nl}) - t_2^W(w, I_{nl}))}{(1 + \theta_2 t_2^{NW}(w, I_{nl}))(1 + \theta_2 t_2^W(w, I_{nl}))}), \tag{3.11}$$

where $t_2^W(w, I_{nl})$ and $t_2^{NW}(w, I_{nl})$ represent the optimal allocation of time in reduction of calories when the individual decided to work or not, respectively.

From expression 3.11 we see that the sign of the ATET is not clear and that it will depend on the average time allocated in calorie reduction for those that take part in the labor market. If those that take part in paid activities spend on average less time in calorie reduction, i.e., a substitution effect dominated to an income effect, the ATET would be positive. However the simplicity of this result stresses the importance that the ATET depends on who the compliers are.

We face a missing data problem trying to get an estimate of expression 3.11. For those that are taking part in the labor market we do not observe their counterfactual state, i.e the outcome that they would have if they had not engaged in paid activities. In fact, the observed outcome can be represented by the following bivariate regression model:

$$y_{ijt} = \alpha_0 + \alpha_1 * flfp_{jt} + \varepsilon_{ijt}, \tag{3.12}$$

where y_{ijt} represents a specific outcome for individual i, in household j in period t, $flfp_{it}$ denotes a dummy variable that stands for female labor force participation in household j in period t ($t_h > 0$). For simplicity in the exposition the other covariates are left implicit.

The non-random nature of $flfp_{it}$ and the missing data problem make the OLS estimate of α_1 a biased estimate of the true ATET. In fact in terms of our model individuals will take part in paid activities ($flfp_{it}$=1) if $U(X, V, C, l)^W > U(X, V, C, l)^{NW}$. Individuals will take part in the labor market if their costs in term of utility when working with respect to non–working are lower than their benefits. Among the costs are a reduction in leisure and a potential increase in total calories, and among the benefits is an increase in the consumption.

The sign of this bias is not clear and it depends on the source of the heterogeneity among treated and non–treated. For example, if we assume that those individuals that engaged in paid activities are the ones with lower cost in term of calorie reduction, or the ones with higher income effect such that they allocate more time in calorie reduction, OLS estimates of α_1 in equation 3.12 would underestimate the true ATET. More formally and in general terms the problem that we face is the fact that labor force participation is correlated with many other individual characteristics (observed and unobserved) that not only influence the decision to engage in paid activities but also might simultaneously be correlated with behaviors that affect body weight ($cov(flfp_{jt}, \varepsilon_{ijt}) \neq 0$). We would also underestimate the effect of female labor force participation on weight if more energetic people also have a high propensity to work. Similarly, individuals with a relative advantage in the market, the ones more "*able*", are the individuals that engaged first in paid activities and are therefore more likely to generate enough earnings to allow them to afford not only fast food but other less calorie–intensive alternatives. Also, the participation in the job market might require some degree of investment in personal care that can be more costly for those people with weight problems, who facing that cost, would opt to stay at home. In fact some evidence exists about discrimination against individuals with weight problems (Averett and Korenman, 1996). Women facing a lower potential wage may choose to stay at home. As a result of these unobserved factors, in this hypothetical case traditional Ordinary Least Squares (OLS) would underestimate the impact of the rise in the opportunity cost of a woman's time at home. On the other hand, if individuals who work are more likely to be exposed to environmental factors such as stress that end up producing weight gains, OLS will overestimate the impact of the rise in the opportunity cost of a woman's time at home.

In order to address this selection problem I use two non–experimental approaches. The first of these approaches uses the National Health Interview Survey (NHIS) and the fact that there is a clear relationship between female labor force participation and the age structure of children in the household. In particular, I use the institutional fact that there is minimum age eligibility in public kindergarten. Parents' ability to enroll a child in public kindergarten for the academic year depends on whether or not that child has turned five at the start of the academic year (with some variability on the age–at–entry rules among states). Gelbach (2002), using quarter of birth as instruments for public school enrollment, finds that among married women whose youngest child is five years old, free public school increases labor supply between 6–15 percent. As a result of this age-entry rule, the decision of being part of the labor force has elements, *discontinuities*, that make it similar to a Regression–Discontinuity (RD) design, first introduced by Thistlethwaite and Campbell (1960).

The idea of RD design is to incorporate additional information about the selection process. We know that the decision to take part in the labor force depends at least in part, on the value of a continuous and observed variable (children's age) relative to threshold score (school eligibility) in such a way that the probability of being part of the labor force is a discontinuous function of this variable at that threshold score. Individuals within a very small interval around the cutoff point will be very "similar," with some receiving the treatment and others not. Then comparing parents having a child just over the cutoff age with parents having with a child just below the age cutoff for attending public school, provides a good estimate of the impact of female labor participation on weight related outcomes. Assuming that each person has one child, and defining z as the child's age measured in months in September, the RD design estimated takes the following form:

$$\frac{\lim_{z\downarrow 60} E(y|z) - \lim_{z\uparrow 60} E(y|z)}{\lim_{z\downarrow 60} E(flfp|z) - \lim_{z\uparrow 60} E(flfp|z)}. \tag{3.13}$$

In order to get identification from expression 3.13 we need the following assumptions to hold:

(i) **Assumption 1.** The conditional mean function $E(\varepsilon|z)$ is continuous at the threshold value $z = 60$.

(ii) **Assumption 2.** The ATE function $E(\alpha_{i1}|z)$ is continuous at the threshold value $z = 60$.

(ii) **Assumption 3.** The ATE function $flfp_{ijt}$ is independent of α_{i1} conditional on z near to the cutoff.

While only assumption (i) is needed to hold for the case of a constant treatment effect in a *sharp* RD design, in our case of a *fuzzy* RD design with heterogeneous or varying treatments we need additional assumptions (ii) and (iii) to hold in order to identify the ATE (Van der Klaauw, 2002). This RD design is similar to an IV approach where in the RD design the discontinuity acts as an instrument. Under this parallel with IV, assumption (i) can be seen similar to the assumption of no correlation between the error term and the instrument such that the discontinuity is only acting trough a change in female labor force participation. The reasoning behind assumption (ii) is that differences in outcomes around the neighborhood of the discontinuity come from the treatment and not from heterogeneity in treatment since individuals with values of z close to the discontinuity are similar. Finally, assumption (iii) is a local form of the conditional independent assumption and the reasoning here is that individuals are not being selected or self–selected in the labor market on the basis of expected gains. In fact, as I have shown with a very simple model, it is expected that individuals are self selected on the basis of gains. Hahn, Todd and Van der Klaauw (2002) show that under less restrictive local monotonicity assumptions, similar to that proposed by Imbens and Angrist (1994), the ratio in expression 3.13 identifies a LATE at the discontinuity for the subgroup of individuals for whom the treatment changes discontinuously at the cutoff age.

In order to estimate expression 3.13, I estimate the following expression,

$$y_{ijt} = \alpha_0 + \alpha_1 * E(flfp_{jt}|z_{jt}) + g(z_{jt}) + w_{ijt}, \tag{3.14}$$

with $w_{ijt} = y_{ijt} - E(y_{ijt})$, $g(z_{jt})$ a specification of $E(\varepsilon_{ijt}|z_{jt})$ and

$$E(flfp_{jt}|z) = f(z_{jt}) + \gamma 1\{z_{jt} > 60\}, \tag{3.15}$$

where $f(z_{jt})$ is a continuous function of z_{jt} at $z_{jt} = 60$ and $1\{\}$ an indicator function.

Female labor participation not only increases the cost of home production (home cooking), it also has an impact on the level of activity, i.e., calories burned. While the impact of home production may affect all members in the household equally[10], the impact on calories burned is not homogeneous across individuals. Women substitute market production for household production with an ambiguous impact on the total number of calories burned. Children may allocate less time to physical activity and more time to watching TV or playing video games with an overall reduction in total calories burned. Finally, husbands may not change at all their level of calories burned. In order to address these differences in the types of "treatment" we split the sample into two relevant groups that may be affected by female labor force participation: married men and married women. While married men are mainly exposed to the shift in the cost of home cooking, married and single women are also exposed to a change in the level of activity. Therefore, under this framework we would expect the impact of female labor force participation to be larger for the sample of married men. It is important to mention that by focusing on the sample of married men we are <u>not</u> addressing the problem that women select non–randomly into the

[10]Under the assumption of scale economies in home cooking, household members should share "*one pot*" such that any shift in the cost of home production should impact all members in the household in a similar fashion.

labor market. There are many factors at the level of the household that may be correlated with female labor participation and husband body weight. For example, individuals might match (among other factors) on eating behavior and/or preferences for physical activity in the marriage market. Then, more active women (more likely to engage in paid activities) will be married to more active men (less likely to have weight problems) producing a downward bias in the estimate.

Figure 3.7 shows graphically the source of identification that I am trying to exploit. In general as the age of the youngest child in the family increases, the proportion of women working increases monotonically. However, after the age of 60 months we observe a jump in this proportion. In fact this jump or discontinuity looks more evident when we adjust a cubic polynomio in the youngest child's age and allowing a different intercept for those that have a youngest child older than 60 months. While a discontinuity at the age of 60 months is found when I repeat the exercise but define the discontinuity at 48 and 72 months of age, no signs of discontinuity are found.

Figures 3.8 and 3.9 show in the same fashion the profile of BMI and obesity rate against age of the youngest child. For both of these outcomes, there is an increase in the dispersion and the average as the youngest child gets older, although a jump or discontinuity is less clear around the age of 60 months.

In a second empirical approach I use the *Behavioral Risk Factor Surveillance System* (BRFSS) to develop a reduced form analysis given limited household information. In particular, I study the impact of exogenous changes to the demand for labor. Following the approach developed by Bartik (1991) and employed by Blanchard and Katz (1992), Bound and Holzer (2000), and Autor and Duggan (2003), I exploit cross-state differences in industrial composition and national-level changes in female and male employment to predict individual state employment growth. Specifically, I calculate the predicted employment change $\hat{\theta_{jt}}^s$ for state j and sample s between years t_0 and t as,

$$\hat{\theta_{jt}}^s = \sum_k \beta_{jkt_0}^s \theta_{kt}^s \qquad s = male, female, \tag{3.16}$$

where θ_{kt}^s is the percentage change in industry k employment share nationally for sample s and $\beta_{jkt_0}^s$ is the share of employment of individuals in sample s, state j in industry k in the initial year.

This methodology predicts what each state's change in employment would be if industry level employment changes occurred uniformly across states and state-level industrial composition was fixed by sex in the short term. States that had a relatively large share of female workers in industries declining nationally will, for example have predicted female employment decline.

3.5 Data, Variables and Descriptive Statistics.

3.5.1 Data and Variables

My analysis utilizes two data sets. The first data source, the *National Health Interview Survey* (NHIS) is a household survey fielded annually since 1957 by the U.S. Bureau of the Census for the National Center for Health Statistics (NCHS). The NHIS samples the civilian, non-institutionalized population in the United States. The NHIS is a cross-sectional household survey; sampling and interviews are conducted continuously throughout the year. The sampling plan follows a multistage area probability design that permits the representative sampling of households. Each year the NHIS randomly samples approximately 48,000 households with 108,000 members from 201 primary sampling units nationally. While the NHIS has been conducted continuously since 1957, the content of the survey has been updated about every 10-15 years. The main objective of the NHIS is to monitor the health of the United States population through the collection and analysis of data on a broad range of health topics. A major strength of this survey is the ability to display health characteristics by many demographic and socioeconomic characteristics. The NHIS contains data on height and weight for individuals older than 17 years old. This analysis uses every survey year from 1982 through 2000.

The NHIS contains both information on female labor participation and children's age structure. This makes this dataset useful in implementing the RD design. The downward side of this survey is that in most years there is information only on region of residence. Region is probably too large as geographic area to analyze using demand shocks described above.

The second data source is the *Behavioral Risk Factor Surveillance System* (BRFSS). The BRFSS is an ongoing, state-based telephone surveillance system supported by the Centers for Disease Control and Prevention (CDC). The purpose of the BRFSS is to collect uniform, state-based data on preventive health practices and risk behaviors that are linked to chronic diseases, injuries, and preventable infectious diseases in the U.S. population. Data is collected through monthly telephone interviews conducted among a sample of each state's adult population.[11]

There are two difficulties with the BRFSS. First because BRFSS is not a household survey we do not observe the spouse's labor force status. Second, before 1994, the BRFSS

[11] Telephone interviews have some limitations: Non–coverage of persons in households without telephones, interviews that are shorter than in-person interviews and collected data that cannot be verified by physical measurement or visual means. Based on the 1990 census, 95% of households in the United States have telephones. There is variation by state, as telephone coverage ranged from 87% in Mississippi to 98% in Massachusetts.

does not include information about children in the household. This is required to use the RD design estimation. Given these limitations, I limit the analysis of the BRFSS data to study the impact of female demand shocks on the weight–related outcomes of married men and women.

The advantage of BRFSS is that it includes information on levels of physical activity and nutrition in addition to weight and height. This allows us to examine directly the effects of female labor employment shocks on nutritional intake and physical activity which is important for two reasons. First, as discussed above the nutritional profile and level of activity might be correlated among family members. BRFSS gives us a unique opportunity to control to some degree for those factors directly. Second, weight is a stock measure which is the accumulation of decisions on physical activity and nutritional intake. In the short–run female labor force participation may be more related to these factors than to weight directly, although it may be correlated with weight in the long–run.

I use three dummy variables for level of physical activity. The first one takes a value of one if the individual participated in any physical activities or exercise, and zero otherwise. The second dummy variable takes a value of one if the individual participated in any physical activities or exercise other than walking, and zero otherwise. Finally the third dummy variable takes a value of one if an individual reports exercising on a regular basis and zero otherwise.[12] In addition to these three measures of activity I have information about the usual number of miles an individual jogs, runs, walks or swims, the number of times that an individual performed a particular activity in the previous month,

[12]To define if an individual exercises regularly I use the information about the number of times per week or per month she or he took part in an activity. If the person answered any number of times per week I define that individual as doing regular exercise and if she/he defines the regularity in terms of times per month, I define that person as doing exercise on an irregular basis.

and the number of minutes spent in that activity. The information about nutrition is reported as number of servings of a particular type of food. I use the number of servings per day as the unit of analysis. The types of food that I analyze are: Fruit, Vegetables, Green Salad, Potatoes (not French fries), Carrots. I study these five types of food because they are available for the eleven years under analysis, 1990-2000[13].

The data used to construct the estimates of changes in female employment by states is the March CPS for the period 1990–2000 where the weights for male or female employment by industry and states comes from the March CPS for the year 1989.

Because the information collected in the NHIS and BRFSS correspond to individuals aged 18 and older, the impact of female labor force participation on child obesity or other outcome for children is not addressed in this chapter.

3.5.2 Descriptive Statistics

The information about weight and height allows us to construct the Body Mass Index (BMI). NHIS and BRFSS information about weights and heights is self–reported. There is evidence that people are under–reporting weight; heavier people are the most likely to under–report. To address this problem I use information from the Third National Health and Nutrition Examination Survey (NHANES III) that contains self–reported and actual weight. Then by estimating the relationship between self–reported weight or height and the measured weight or height (and other covariates) I correct self–reported measures in the data sets used in this chapter.

Figure 3.10 shows growth in the obesity rate with an increase of almost 15 percentage points during the period 1978–2000. There has also been a monotonic increase in the

[13]It could be interesting to use servings of french fries, because they may quite correlated with fast–food consumption. However the information on french fries is available only for some years prior 1994.

average BMI. Although both surveys show the same pattern, NHIS reveals a higher average BMI and a higher obesity rate in all overlapping years. These differences can be explained in part by a higher proportion of minorities in the NHIS than in the BRFSS. Minorities have on average a higher BMI (as shown in tables 3.1 and 3.2).

Figures 3.11 and 3.12 give us a closer look at the shift in the distribution of BMI by comparing the extremes of the periods under analysis. At first glance, the distributions seem similar. This similarity contrasts with the fact that for the year 2000 we find approximately double the incidence of obesity observed in 1990 (BRFSS) and 15 percentage points higher than in 1978. The contrast is resolved by realizing that although there is a smooth shift in the complete distribution, a bigger mass has approached and passed the cut off of obesity, defined as BMI over 30.

Figures 3.13 to 3.14 show an interesting aspect of the rise in BMI during the last 20 years. First, for the complete period covered, the sample of married men with working spouses have a higher average BMI than the sample of married men with spouses who are not working. However, as we already indicated, this regularity may be only a selection phenomenon. On the other hand, married working women in all years have a lower average BMI than married women who are not working, a pattern which can also be related to sample selection. However, the rise in the average BMI has been greater for working women, with a reduction in the percentage difference from approximately 4% in 1982 to 1% in the year 2000 when we use the NHIS and from approximately 2% in 1990 to almost no difference in 2000 when the BRFSS is used. A potential explanation for this trend is that the rise in female labor participation has been associated with women having lower levels of education who not only face a higher opportunity in home production but also are not getting enough resources in the labor market compared to the first women that started the incursion in paid activities, who probably were the most able.

Tables 3.1, 3.2 and 3.3 present the descriptive statistics for the various variables and samples I use in the analysis. In addition to the information related to BMI that we observe in both surveys, the BRFSS shows that a lower proportion of working women (married or single) report exercising relative to non–working woman. Also, for the sample of working women, we observe that when they do exercise, they do less often (fewer times per month) or less intensely (miles or minutes) compared to women who are not working. Finally, the information about nutrition reveals that working women eat less of those types of food that we could define as "*healthy*".

3.6 Results

3.6.1 RD-Design analysis

Table 3.4 presents the impact of youngest child's school eligibility on female employment. Other variables I use in the model are a cubic polynomial in the age in months of the youngest child, respondent's age and age square, dummies by education, region of residence and race. The results show that those families with a youngest child eligible to attend school present a higher rate of female employment, approximately 6 percentage points higher. Theory tells us, keeping all the rest constant, that those mothers who rejoin the labor market have either higher potential wages or lower non-labor incomes. While a woman's education may be positively correlated with wages, her husband's education is negatively correlated with non–labor incomes. Dividing the samples between individuals with less than high school and those with high school or more, I find the opposite result. For those men with high school or more, I observe a higher point estimate on female employment than those with less than high school. I also find a higher point estimate for the sample of married women with less than high school. An interpretation of these results is the sorting process that we observe in the marriage market. Despite a positive impact on female employment for the sample of married men with less than high school, the value is not statistically significant which might be related to the considerably smaller sample size of men with less than high school.

Table 3.5 presents the impact of school eligibility on the logarithm of BMI and on obesity. Married women's average BMI and obesity fall with female employment. Interestingly, the impact of female employment is to raise the BMI and obesity rate of husbands, although the results are not statistically significant. Dividing the samples by level of education (less than high school and high school or more), we observe a stronger positive impact on both outcomes for the sample of individuals with less than a high school education. In fact for married women with a high school education or more we observe that school eligibility reduces the likelihood of being obese by almost 2 percentage points. These results are consistent with the fact that when mothers return to the labor market only those with higher non-labor incomes or higher salaries (higher income effect) are able to afford the cost of an increase in home production. By dividing the sample, we are able to capture this heterogeneity associated with education levels, but at the cost of losing power in our estimates.

In order to account for this heterogeneity while trying to minimize the cost of lower power associated with smaller sample sizes, I allow the impact of female employment to change by level of education while other coefficients are restricted to be the same across education groups. In order to do that, I define a dummy variable, *"Less than HS"*, that takes a value of one for those individuals with less than high school and zero otherwise and

I interact this with female employment [14]. For this specification, we have two endogenous variables (female employment and its interaction with the variable *"Less than HS"*). I instrument these two variables with school eligibility and its interaction with this new dummy variable. In order to compare the magnitude of this estimate, I also estimate a model without interaction for both sub–samples.

The result for the second stage and OLS estimates are presented in tables 3.6 and 3.7 for BMI, and tables 3.8 and 3.9 for obesity. Tables 3.6 and 3.8 show the results for the complete sample, and tables 3.7 and 3.9 for the sub–samples.

Results for BMI in table 3.6 reveal that female employment has a considerable positive impact on BMI for those individuals with lower levels of education. For married men with less than a high school education, I find that female employment increases BMI by approximately 13 percentage points (the 11.73 marginal effect associated with individuals with less than high school plus 1.17 percentage points of common effect). In the same fashion, for married women with less than high school, we find that female employment increases BMI by approximately 12 percentage points. However, only for the sample of married men am I able to reject the null hypothesis that the sum of these coefficients (i.e., the impact of female employment for those individuals with less than high school) equals zero. It is interesting to note that the impact for the sub–sample of married men with less than high school in table 3.7 is almost the same as the one we find

[14]Formally I tested the equality between the restricted (only the coefficient of female employment is different between the two samples) and unrestricted model (all coefficients are different between both samples). For married men I am not able to reject the null hypothesis that both models are statistically equal with p–values of 0.17 and 0.19 for BMI and Obesity, respectively. However for the sample of married women I rejected the equality between these models with p–values of 0.0016 and 0.01 for BMI and obesity, respectively.

for the model with interaction in the complete sample, 12.65 percentage points versus 12.9 percentage points, respectively.

In order to get the magnitude of this impact, consider an individual with a weight of 70 kilograms (approx. 155 pounds) whose height is 1.7 meters (approx. 5 feet 7 inches), i.e., a BMI equal to $\frac{72}{1.72^2} = 22.34$. For this individual an increase of 13% in his BMI implies a new BMI of 27.7 which is an increase of approximately 9 kilograms (approx. 20 pounds).

The results for obesity in table 3.8 do not show a statistically significant impact, neither for the sample of married men nor for the sample of married women. Despite this, the interaction term suggests a positive and significant marginal impact for women with less than high school.

This result of a positive and significant impact of female employment on BMI but no impact on obesity for married men suggests that the impact is concentrated mainly on the bottom part of the BMI distribution. These elements are important when we try to move to a more policy–oriented discussion. While an increase of 20 pounds has a negative connotation for someone closer to the threshold of being overweight or obese, for someone underweight an increase of 20 pounds might be even be positive.

As Van der Klaauw (2002) argues, identification of the treatment in a RD-design depends on having the correct specification of functions $f(z_{jt})$ and $g(z_{jt})$in expressions 3.14 and 3.15. Tables 3.9 and 3.10 present a sensitivity analysis for the sample of married men. As discussed earlier, the direct impact of female employment is very noisy and non–significant for any of the specifications. On the other hand, the marginal effect on individuals with less than high school is quite robust to the different specifications with the exception of the linear specification of $g(z_{jt})$ where lower values for this marginal impact is found. Table 3.11 presents the p-values for the null hypothesis that the impact of female employment is zero for individuals with less than high school. In fact if we about the linear specification for any of these two functions, in half of the cases we reject the null hypothesis at 5 percentage level, and in 3 of 4 cases at a 10 percentage level of confidence.

3.6.2 Demands Shocks: BRFSS.

Tables 3.13 and 3.14 show the estimates for the impact of female and male demand shocks. Table 3.14 presents the estimates when I do not allow the impact of female demand shocks to vary with education levels (Less than High School, **LHS**; High School, **HS**; Some College, **SC**; and College or more, **C**). Table 3.15 presents the estimates when I do allow the demand shocks to vary.

The results in 3.13 reveal for both samples, men and women, a positive impact associated with a shock in female demand on either BMI or obesity but a negative impact associated with male demand shocks. However, only for the sub–sample of women are these results statistically different from zero. One potential explanation for these differences in sign between male and female demand shocks might be the fact that men have a more inelastic supply. Then a particular shift in demand would imply at least in the short–run a steeper increase in wages, and a higher income effect, allowing some wives to leave the labor force. On the other hand, an increase in female demand, probably from a more elastic supply, implies more women are in paid activities with the consequent reduction in the time allocated in food production, but the same amount for men in household production. Another potential explanation is that female time has traditionally been important to food preparation both inside and outside the home. If this is true then food preparation outside the home also had the incentive to substitute out of labor and into other factors (food; capital) in the production function of meals such as fast–food restaurants or prepared food. At the same time, suppose families, are willing to pay a positive price for the *taste* of a meal but a negative price for the meal's calories or lack of assortment. Profit maximizing firms may substitute into tasty and cheaper food but out of low calorie and diverse food.

When I split the impact of female demand change, we can see again the degree of heterogeneity by level of education. For the sub–sample of married men, I find that those with less than a high school degree or those with a college degree or more have an increase in BMI and obesity when female employment rises (for BMI only at 10% confidence level). The cost of home production has two components: cost of market goods and the cost of time. Every household faces an increase in the cost of time when female wages increase. Households with lower levels of education (lower levels of non–labor income) can only afford more McDonald's type of food. As households get higher wages they can afford better quality food. However, as wages get even higher and there is less time needed eating "healthy", individuals may even be willing to increase the consumption of more calorie–intensive food if it is less time–intensive. To demonstrate this I construct two dummy variables. The first variable *Rec. F&V*, stands for recommended daily amount of fruit and vegetable servings, takes the value one for those individuals that eat 4.5 or more servings a day and zero otherwise.[15] The second variable *NR F&V,* takes a value of one for those individuals that eat less than 1.5 servings a day and zero otherwise. Consumptions under this level are associated with a higher incidence of chronic diseases (Hung HC, Joshipura KJ, Jiang R., et al., 2004). The results show that women and men

[15]2005 Dietary Guidelines for Americans. Center for Nutrition Policy and Promotion, US Department of Agriculture.

with higher levels of education are more likely to eat less than this minimal amount of fruit and vegetables. Only for married men with a high school degree do I find that female demand shocks reduce the likelihood of eating more than 4.5 recommended number of servings.

Finally, I also find for married men with higher levels of education that a demand shock in female employment is associated with higher levels of activity. This observation plus the positive impact on obesity and BMI for this group suggests that the potential imbalance comes from a higher consumption of calories which is consistent with the lower consumption of fruit and vegetables.

3.7 Conclusion

Using the *National Health Interview Survey* (NHIS) I find that female employment has a positive impact on Body Mass Index (BMI) for married men with less than a high school level of education. However I do not find an impact for all samples of women or men completing high school or more. This finding is consistent with men facing an increase in the cost of home cooking with a positive impact on body weight. Women may face an offsetting rise in the level of physical activity, and households with husbands with higher income (i.e., higher levels of education) can afford prepared foods that are less calorie intensive. The magnitude of these findings is larger than found elsewhere in the literature. This is primarily because I take account of the endogeneity of female labor force participation. The analysis from the *Behavioral Risk Factor Surveillance System* (BRFSS) survey reveals that married men with less than a high school education, or married men with a college degree or more, face an increase in their BMI and the likelihood of being obese, if they live in states with a positive demand shock for female labor. The results also show that for married men with higher levels of education, positive female demand shocks produce an increase in the levels of physical activity. This last element, plus the positive impact of female demand shocks on BMI and obesity rate, suggests that the channel through which female labor force participation raises a man's weight must be through higher consumption of calories. This is consistent with the lower consumption of fruits and vegetables that we find associated with positive female demand shocks for this group.

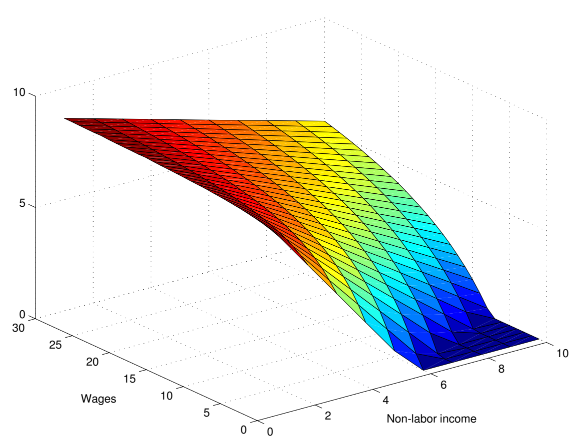

Figure 3.1: Hours spent working

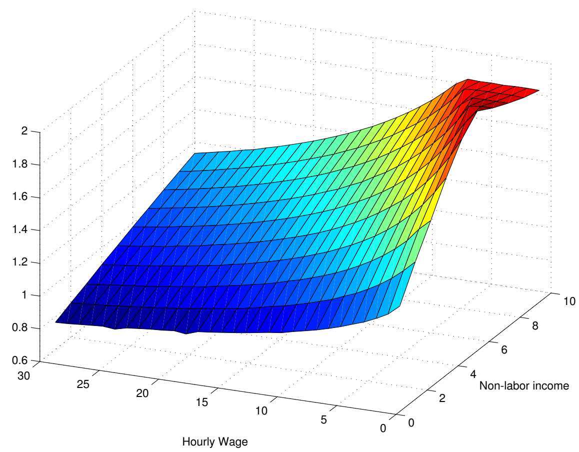

Figure 3.2: Total Time Cooking: Food production plus calorie reduction

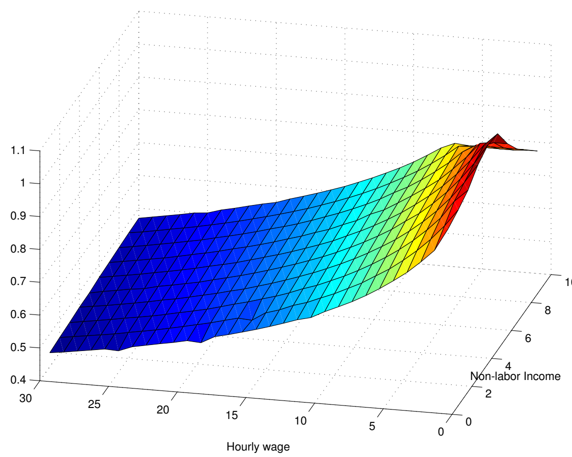

Figure 3.3: Time volume production

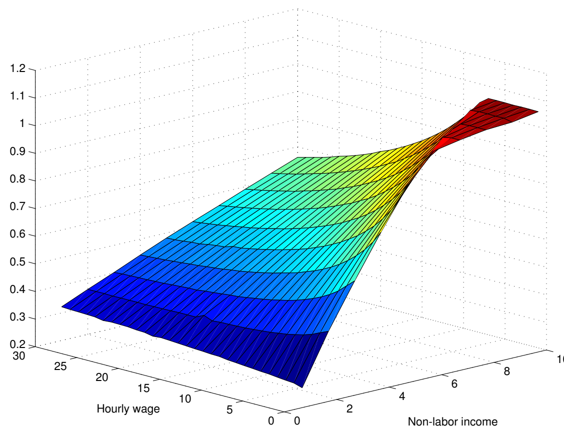

Figure 3.4: Time calorie reduction

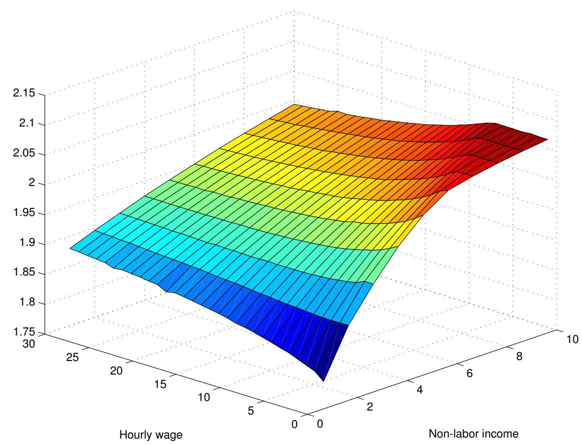

Figure 3.5: Food Consumption

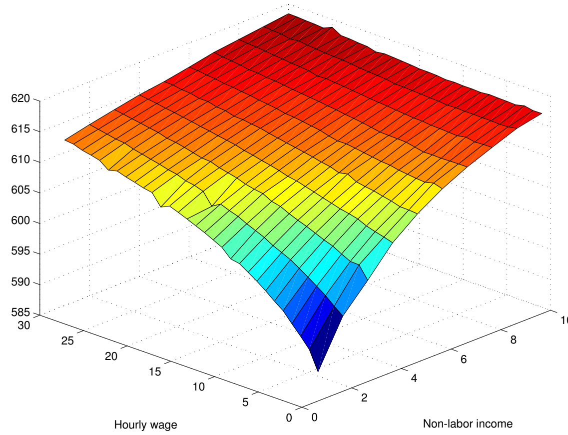

Figure 3.6: Total Consumption of Calories

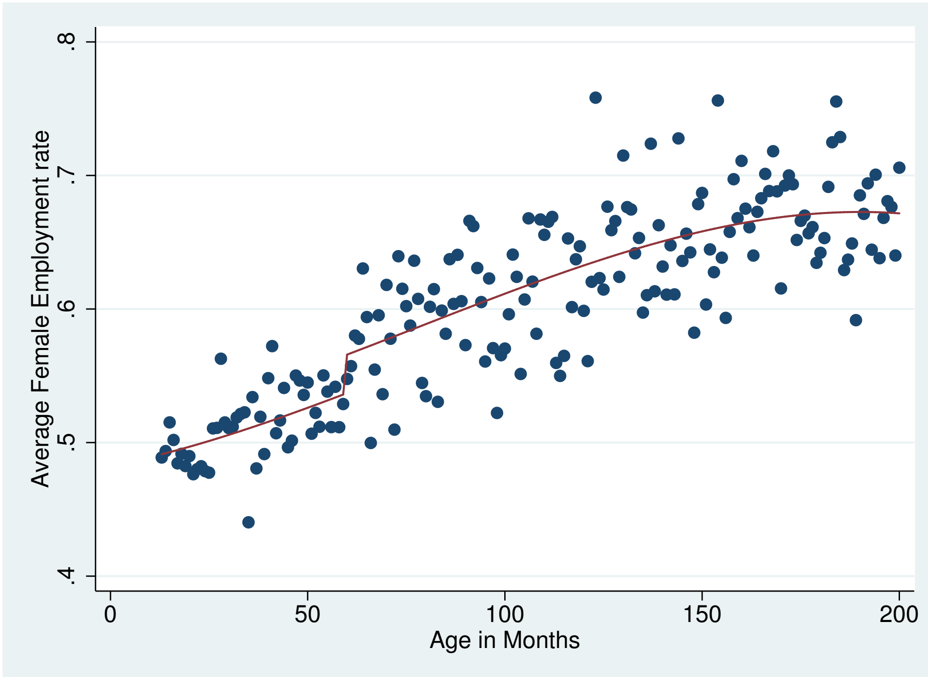

Figure 3.7: Average Female Employment by age in September measured in months of the youngest child

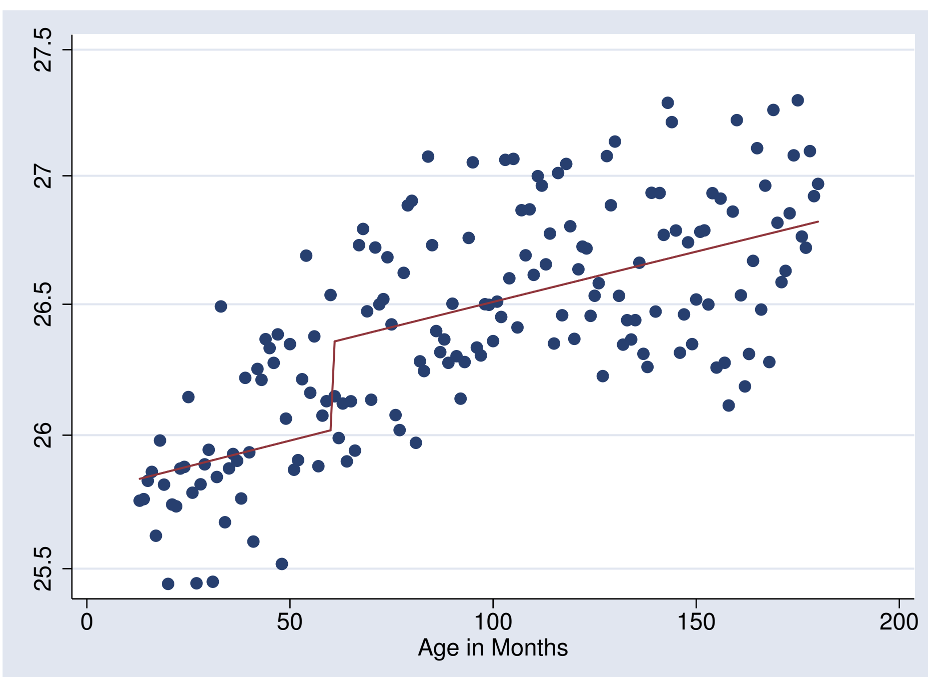

Figure 3.8: Average BMI by age in September measured in months of the youngest child

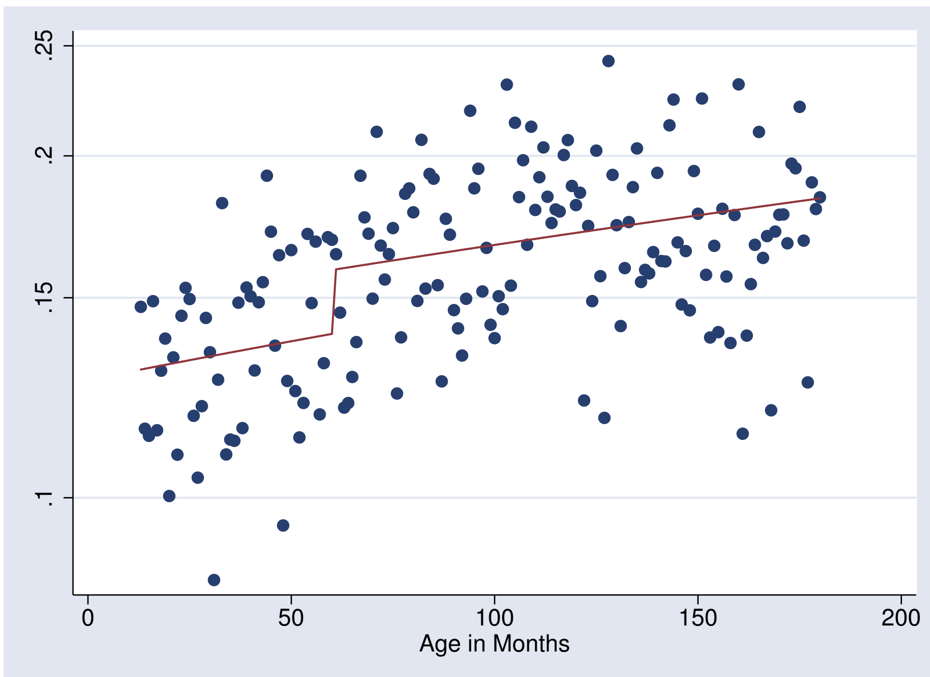

Figure 3.9: Obesity rate by age in September measured in months of the youngest child

.05

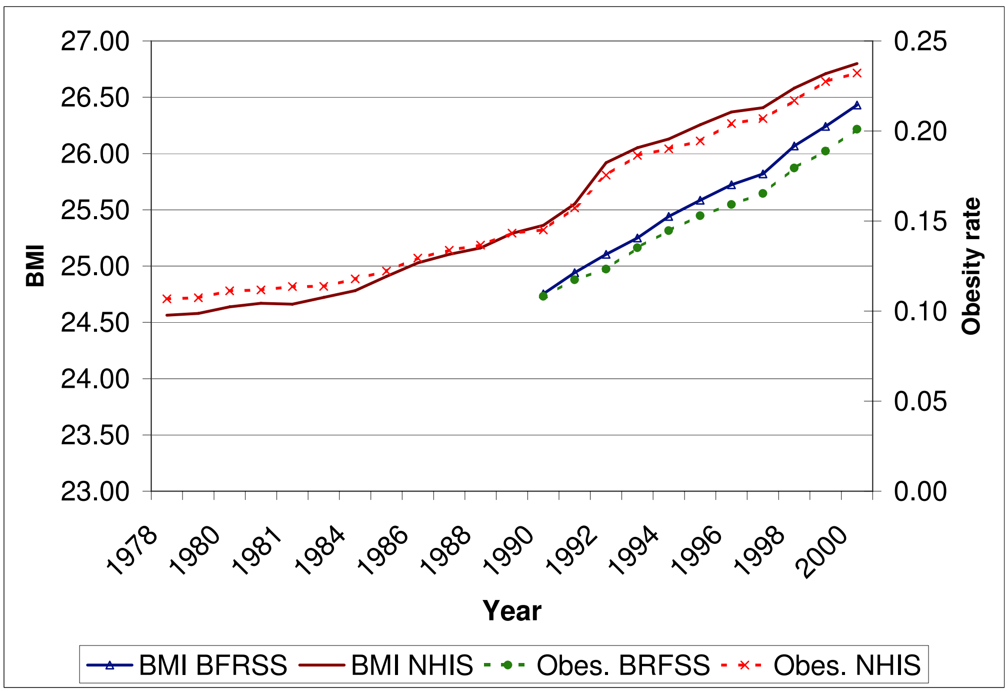

Figure 3.10: Evolving BMI and Obesity rates

	Married Men		Married Women	
	Non-working	Working	Non-working	Working
Age	52.653	42.780	49.778	39.958
	(17.790)	(12.784)	(17.631)	(12.008)
Number of children	0.897	1.028	0.923	1.034
	(1.286)	(1.185)	(1.296)	(1.186)
Less than High School	0.320	0.187	0.307	0.146
	(0.466)	(0.390)	(0.461)	(0.353)
High School	0.324	0.362	0.412	0.431
	(0.468)	(0.481)	(0.492)	(0.495)
More than High School	0.357	0.451	0.281	0.424
	(0.479)	(0.498)	(0.450)	(0.494)
White	0.651	0.600	0.652	0.599
	(0.477)	(0.490)	(0.476)	(0.490)
Black	0.049	0.069	0.048	0.068
	(0.217)	(0.254)	(0.214)	(0.252)
Asian	0.012	0.014	0.014	0.017
	(0.110)	(0.119)	(0.115)	(0.128)
Hispanic	0.278	0.307	0.276	0.308
	(0.448)	(0.461)	(0.447)	(0.462)
BMI	25.842	26.153	24.822	24.200
	(3.920)	(3.962)	(5.101)	(4.827)
Obesity	0.143	0.154	0.171	0.143
	(0.350)	(0.361)	(0.376)	(0.351)

Standard Deviations in parentheses.

Table 3.1: Descriptive Statistics, NHIS. Means for selected variables, 1982–2000

	Married Men	Married Women	
		Non-working	Working
Age	47.34	40.63	52.64
	(15.39)	(10.94)	(17.69)
Number of children	0.94	1.06	0.83
	(1.23)	(1.19)	(1.29)
Less than High School	0.12	0.06	0.17
	(0.33)	(0.24)	(0.38)
High School	0.31	0.33	0.39
	(0.46)	(0.47)	(0.49)
More than High School	0.56	0.61	0.44
	(0.50)	(0.49)	(0.50)
White	0.85	0.85	0.87
	(0.35)	(0.36)	(0.34)
Black	0.05	0.06	0.04
	(0.22)	(0.24)	(0.19)
Asian	0.02	0.02	0.02
	(0.13)	(0.13)	(0.12)
Hispanic	0.06	0.06	0.06
	(0.24)	(0.23)	(0.24)
BMI	26.70	24.98	25.25
	(4.14)	(5.06)	(5.06)
Obesity	0.17	0.14	0.15
	(0.38)	(0.35)	(0.36)

Standard Deviations in parentheses.

Table 3.2: Descriptive Statistics, BRFSS. Means for selected variables, 1994–2000

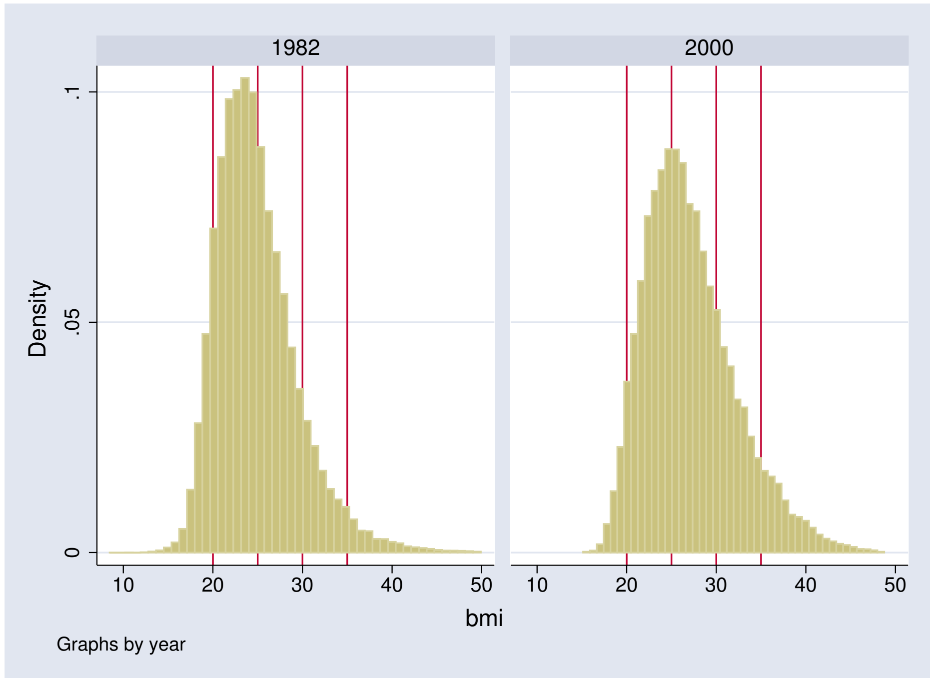

Figure 3.11: Body Mass Index, NHIS: 1982 vs. 2000

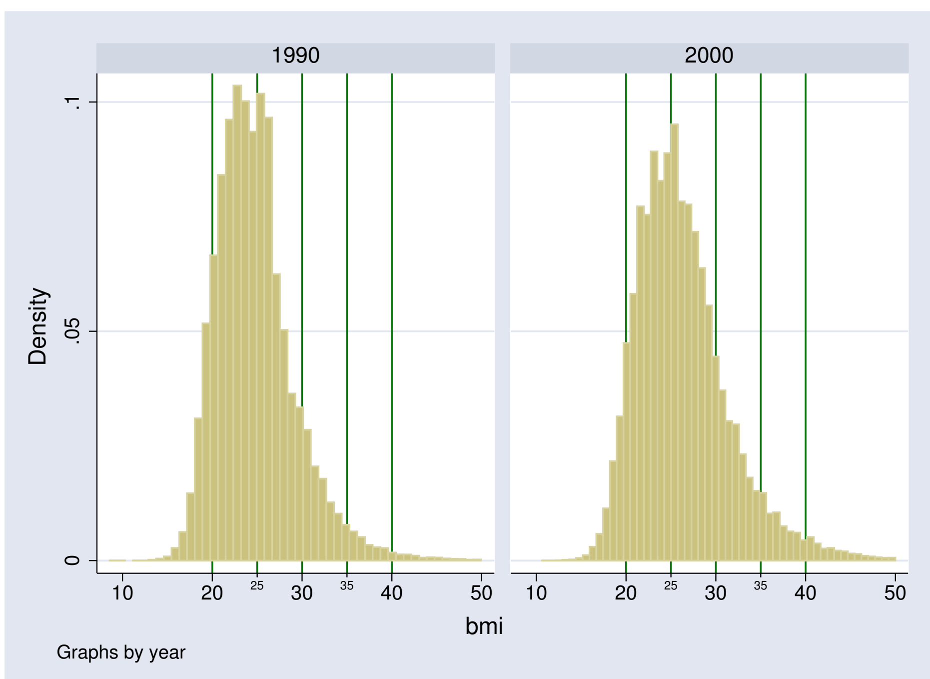

Figure 3.12: Body Mass Index, BRFSS: 1990 vs. 2000

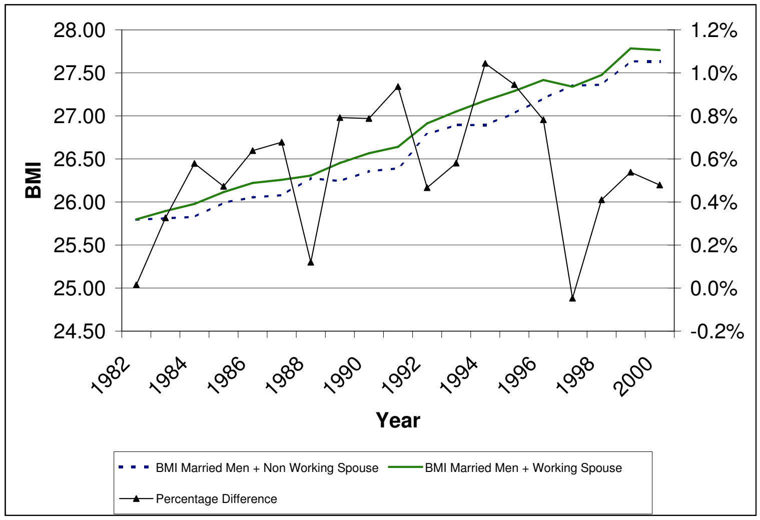

Figure 3.13: Body Mass Index, NHIS: 1982 vs. 2000. Married Men

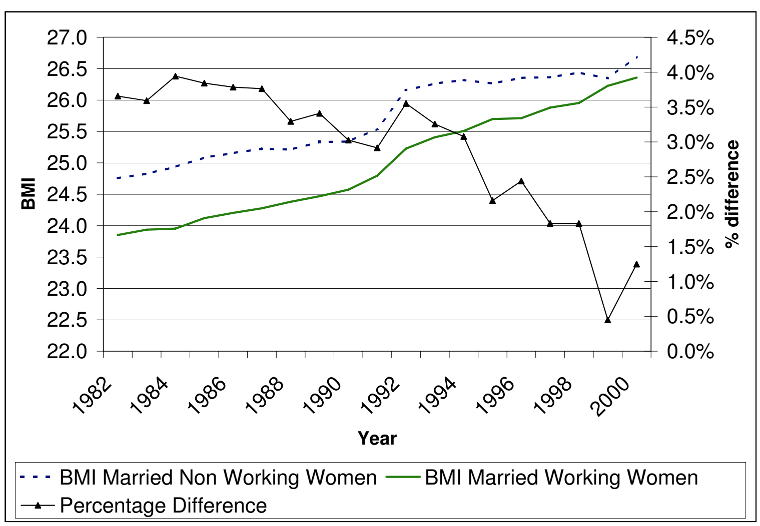

Figure 3.14: Body Mass Index, NHIS: 1982 vs. 2000. Married Women.

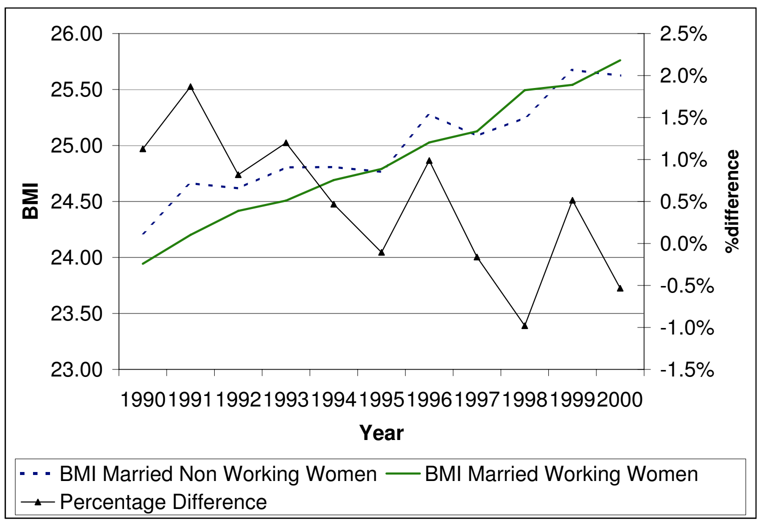

Figure 3.15: Body Mass Index, BRFSS: 1990 vs. 2000. Married Women.

	Married Men	Married Women	
	All	Non-working	Working
Any activity or exercise	0.72	0.74	0.70
	(0.45)	(0.44)	(0.46)
Any activity or exercise, but walking	0.45	0.31	0.28
	(0.50)	(0.46)	(0.45)
Regular activity or exercise	0.56	0.61	0.59
	(0.50)	(0.49)	(0.49)
Fruit	0.71	0.86	0.97
	(0.72)	(0.81)	(0.84)
Vegetables	0.48	0.53	0.56
	(0.47)	(0.48)	(0.51)
Green Salad	1.19	1.35	1.38
	(0.86)	(0.94)	(0.92)
Potatoes	0.25	0.30	0.32
	(0.36)	(0.41)	(0.44)
Carrots	0.37	0.35	0.40
	(0.38)	(0.36)	(0.40)
Miles	1.98	1.75	1.55
	(1.97)	(1.50)	(1.76)
Times per Month	12.64	12.77	14.36
	(8.89)	(8.01)	(8.85)
Minutes	126.66	91.14	88.37
	(96.35)	(72.28)	(72.77)

Standard Deviations in parentheses.

Table 3.3: Descriptive Statistics (Continuation), BRFSS. 1994–2000

	Complete Sample	Less than HS	HS or More
Men			
	Complete Sample	Less than HS	HS or More
$\hat{\gamma}$	0.0644	0.0455	0.0692
	[0.0123]***	[0.0304]	[0.0134]***
Women			
		Less than HS	HS or More
$\hat{\gamma}$		0.0867	0.0595
		[0.0303]***	[0.0131]***
Obs.	115483	20711	94772

Robust standard errors in brackets.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Others covariates in the model are age, age square, region of residence, dummies by education, dummies by race, number of children and cubic polynomio in the age of the youngest child the previous September.

Table 3.4: First Stage. Impact of age eligibility on female employment. NHIS.

	Complete Sample	Less than HS	HS or More
Men			
	Complete Sample	Less than HS	HS or More
Log (BMI)	0.0013	0.017	-0.0024
	[0.0036]	[0.0096]*	[0.0038]
Obesity	0.0084	0.0364	0.001
	[0.0086]	[0.0223]	[0.0092]
Obs.	113828	20711	93592
Women			
	Complete Sample	Less than HS	HS or More
Log (BMI)	-0.005	0.0038	-0.0072
	[0.0046]	[0.0128]	[0.0049]
Obesity	-0.0153	0.0012	-0.0194
	[0.0081]*	[0.0243]	[0.0084]**
Obs.	118107	19669	98438

Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.
Others covariates in the model are age, age square, region of residence, dummies by education, dummies by race, number of children and cubic polynomio in the age of the youngest child the previous September.

Table 3.5: Reduced Form. Impact of age eligibility on Selected Outcomes. NHIS.

Men	OLS	IV	OLS	IV
F. Employment	0.0072	0.0326	0.0064	0.0117
	[0.0015]***	[0.0388]	[0.0016]***	[0.0365]
F.Employment X Less than HS			0.0032	0.1173
			[0.0043]	[0.0493]**
p-value. H0: F. Emp.+F.Emp. X LHS=0			0.0153	0.0455
Women				
F. Employment	-0.0183	-0.0248	-0.0103	-0.0738
	[0.0019]***	[0.0513]	[0.0020]***	[0.0473]
F.Employment X Less than HS			-0.0087	0.1964
			[0.0056]	[0.0718]***
p-value. H0: F. Emp.+F.Emp. X LHS=0			0.0003	0.1775

Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.
Others covariates in the model are age, age square, region of residence, dummies by education, dummies by race, number of children and cubic polynomio in the age of the youngest child the previous September.

Table 3.6: Impact of Female Employment on Log(BMI). Complete Sample NHIS.

	Less than HS		HS or More	
Men	**OLS**	**IV**	**OLS**	**IV**
F. Employment	0.0084	0.1265	0.0066	-0.0241
	[0.0040]**	[0.0871]	[0.0016]***	[0.0410]
Women				
F. Employment	-0.0198	0.2017	-0.0099	-0.0912
	[0.0052]***	[0.1282]	[0.0020]***	[0.0578]

Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.
Others covariates in the model are age, age square, region of residence, dummies by education, dummies by race, number of children and cubic polynomio in the age of the youngest child the previous September.

Table 3.7: Impact of Female Employment on Log(BMI). Sub–samples NHIS.

Men	**OLS**	**IV**	**OLS**	**IV**
F. Employment	0.0116	0.1574	0.0125	0.1355
	[0.0036]***	[0.0946]*	[0.0039]***	[0.0886]
F.Employment X Less than HS			-0.0021	0.1253
			[0.0102]	[0.1144]
p-value. H0: F. Emp.+F.Emp. X LHS=0			0.2715	0.0905
Women				
F. Employment	-0.0314	-0.0362	-0.018	-0.1292
	[0.0035]***	[0.0927]	[0.0036]***	[0.0851]
F.Employment X Less than HS			-0.0228	0.3657
			[0.0108]**	[0.1373]***
p-value. H0: F. Emp.+F.Emp. X LHS=0			0.0001	0.1651

Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.
Others covariates in the model are age, age square, region of residence, dummies by education, dummies by race, number of children and cubic polynomio in the age of the youngest child the previous September.

Table 3.8: Impact of Female Employment on Obesity. Complete Sample NHIS.

	Less than HS		**HS or More**	
Men	**OLS**	**IV**	**OLS**	**IV**
F. Employment	0.007	0.3284	0.0132	0.035
	[0.0095]	[0.2218]	[0.0039]***	[0.0965]
Women				
F. Employment	-0.0443	0.213	-0.0166	-0.1154
	[0.0102]***	[0.2377]	[0.0036]***	[0.0997]

Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.
Others covariates in the model are age, age square, region of residence, dummies by education, dummies by race, number of children and cubic polynomio in the age of the youngest child the previous September.

Table 3.9: Impact of Female Employment on Obesity). Sub–samples NHIS.

			$g(z_{jt})$		
$f(z_{jt})$	Linear	Quadratic	Cubic	4th	5th
Linear	-0.014	0.0122	0.0132	0.0071	-0.0066
	[0.0235]	[0.0371]	[0.0371]	[0.0425]	[0.0451]
Quadratic	-0.0248	0.0182	0.019	0.0162	0.0052
	[0.0211]	[0.0368]	[0.0369]	[0.0421]	[0.0445]
Cubic	-0.0249	0.0174	0.0117	0.0053	-0.0064
	[0.0211]	[0.0368]	[0.0365]	[0.0414]	[0.0438]
4th	-0.0223	0.0222	0.0157	0.0066	-0.0057
	[0.0209]	[0.0360]	[0.0356]	[0.0414]	[0.0438]
5th	-0.021	0.026	0.0199	0.0115	-0.0069
	[0.0208]	[0.0360]	[0.0356]	[0.0413]	[0.0433]

* significant at 10%; ** significant at 5%; *** significant at 1%.
Others covariates in the model are age, age square, region of residence, dummies by education, dummies by race, number of children and cubic polynomio in the age of the youngest child the previous September.

Table 3.10: Sensitivity analysis. F.Employment Coefficient. Log(BMI). Complete Sample of Married Men NHIS, 1982–2000.

	$g(z_{jt})$				
$f(z_{jt})$	Linear	Quadratic	Cubic	4th	5th
Linear	0.0997	0.1098	0.1099	0.1068	0.0989
	[0.0480]**	[0.0497]**	[0.0498]**	[0.0504]**	[0.0499]**
Quadratic	0.0991	0.1193	0.1191	0.1178	0.1115
	[0.0478]**	[0.0497]**	[0.0497]**	[0.0503]**	[0.0497]**
Cubic	0.097	0.1168	0.1173	0.1142	0.1081
	[0.0476]**	[0.0493]**	[0.0493]**	[0.0497]**	[0.0492]**
4th	0.1002	0.1194	0.1195	0.1129	0.1073
	[0.0476]**	[0.0495]**	[0.0494]**	[0.0497]**	[0.0493]**
5th	0.0989	0.1192	0.1192	0.1133	0.1064
	[0.0475]**	[0.0496]**	[0.0495]**	[0.0499]**	[0.0490]**

* significant at 10%; ** significant at 5%; *** significant at 1%.
Others covariates in the model are age, age square, region of residence, dummies by education, dummies by race, number of children and cubic polynomio in the age of the youngest child the previous September.

Table 3.11: Sensitivity analysis. F.Employment X LHS impact. Log(BMI). Complete Sample of Married Men NHIS, 1982–2000.

	$g(z_{jt})$				
$f(z_{jt})$	Linear	Quadratic	Cubic	4th	5th
Linear	0.1117	0.0634	0.0615	0.116	0.2168
Quadratic	0.1602	0.0341	0.0335	0.0594	0.1096
Cubic	0.1712	0.0377	0.0455	0.0892	0.1595
4th	0.1369	0.0262	0.0332	0.0891	0.16
5th	0.1369	0.023	0.029	0.0763	0.1636

Table 3.12: Sensitivity analysis. p-value. H0: F. Emp.+F.Emp. X LHS=0. Log(BMI). Complete Sample of Married Men NHIS, 1982–2000.

M. Men	Log(BMI)	Obesity	Any Act. or Exerc.	Any Act. but walk	Reg. Act.	Rec. F&V	NR F&V	Miles	Times per Month	Time
Fshock	0.0011	0.0043	0.0135	0.0076	0.0003	-0.0024	0.0079	0.0305	-0.1437	2.1459
	[0.0011]	[0.0026]	[0.0056]**	[0.0056]	[0.0082]	[0.0038]	[0.0066]	[0.0872]	[0.1339]	[2.3363]
Mshock	-0.0013	-0.0022	0.0094	0.0025	0.008	0.0003	-0.005	-0.1144	-0.1215	-0.5598
	[0.0012]	[0.0030]	[0.0095]	[0.0072]	[0.0174]	[0.0047]	[0.0053]	[0.1304]	[0.2311]	[2.3070]
Married Women										
Fshock	0.0028	0.0045	0.0063	-0.0124	0.0025	0.0023	0.0067	-0.012	0.0501	-0.6593
	[0.0014]**	[0.0025]*	[0.0046]	[0.0060]**	[0.0075]	[0.0034]	[0.0048]	[0.0555]	[0.1322]	[1.8281]
Mshock	-0.0037	-0.0064	0.0004	0.0045	0.0046	0.0049	-0.0029	-0.0367	0.0661	0.8214
	[0.0014]**	[0.0026]**	[0.0067]	[0.0067]	[0.0077]	[0.0059]	[0.0042]	[0.1084]	[0.2096]	[1.8379]

Robust standard errors in brackets.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Others covariates in the model are age, age square, state of residence, number of children and dummies by education, year and race.

Table 3.13: Impact of Demand shocks on selected outcomes. BRFSS, 1990–2000.

	Log(BMI)	Obesity	Any Act. or Exerc.	Any Act. but walk	Reg. Act.	Rec. F&V	NR F&V	Miles	Times per Month	Time
M. Men										
FshockXLHS	0.0062	0.0177	0.0143	-0.0072	-0.0005	-0.005	0.0043	0.1064	-0.5762	5.3398
	[0.0036]*	[0.0082]**	[0.0091]	[0.0163]	[0.0236]	[0.0057]	[0.0142]	[0.1595]	[0.5048]	[5.7226]
FshockXHS	0.0009	-0.0023	0.0076	0.0089	-0.0155	-0.0051	0.0018	0.0345	-0.355	6.8384
	[0.0016]	[0.0045]	[0.0080]	[0.0101]	[0.0123]	[0.0027]*	[0.0088]	[0.1157]	[0.2185]	[2.8190]**
FshockXSC	-0.0026	-0.0019	0.0238	0.0225	0.0232	0.0026	0.0051	0.0039	-0.0936	-1.8897
	[0.0018]	[0.0045]	[0.0119]*	[0.0118]*	[0.0132]*	[0.0050]	[0.0096]	[0.0990]	[0.2331]	[4.0260]
FshockXC	0.0025	0.011	0.0109	-0.0016	-0.0025	-0.003	0.0172	0.0324	0.0617	0.3602
	[0.0013]*	[0.0037]***	[0.0052]**	[0.0100]	[0.0113]	[0.0065]	[0.0070]**	[0.0788]	[0.1231]	[2.8488]
Mshock	-0.0013	-0.0021	0.0095	0.0025	0.008	0.0003	-0.0052	-0.1143	-0.1224	-0.5465
	[0.0012]	[0.0029]	[0.0095]	[0.0072]	[0.0174]	[0.0046]	[0.0053]	[0.1303]	[0.2302]	[2.2990]
Married Women										
FshockXLHS	-0.0019	-0.0021	-0.0027	-0.0389	-0.0019	0.0002	0.0174	0.0139	-0.0582	-2.4185
	[0.0059]	[0.0111]	[0.0239]	[0.0128]***	[0.0233]	[0.0049]	[0.0110]	[0.0737]	[0.4011]	[4.2292]
FshockXHS	0.0026	-0.0033	0.0099	-0.0181	0.0014	0.0013	-0.003	-0.0398	0.0957	-1.7901
	[0.0019]	[0.0044]	[0.0062]	[0.0083]**	[0.0113]	[0.0048]	[0.0085]	[0.0540]	[0.2630]	[2.4035]
FschockXSC	0.0029	0.0065	0.0089	0.0006	0.0055	0.0049	0.0107	-0.0143	-0.1124	2.363
	[0.0023]	[0.0033]*	[0.0078]	[0.0104]	[0.0112]	[0.0057]	[0.0051]**	[0.0616]	[0.1081]	[3.8620]
FshockXC	0.0045	0.0129	0.0035	-0.0098	0.0024	0.0018	0.0088	0.0136	0.1763	-1.9751
	[0.0019]**	[0.0030]***	[0.0064]	[0.0063]	[0.0097]	[0.0041]	[0.0041]**	[0.0693]	[0.1386]	[2.1309]
Mshock	-0.0038	-0.0065	0.0002	0.0045	0.0046	0.0048	-0.0028	-0.0365	0.066	0.8128
	[0.0015]**	[0.0027]**	[0.0067]	[0.0067]	[0.0077]	[0.0059]	[0.0041]	[0.1085]	[0.2095]	[1.8244]

Robust standard errors in brackets.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Others covariates in the model are age, age square, state of residence, number of children and dummies by education, year and race.

Table 3.14: Impact of Demand shocks on selected outcomes. BRFSS, 1990–2000.

Chapter 4

Conclusion

The role of family background in human capital accumulation is well recognized in the literature. However the magnitude and channels through which fertility and female labor employment alter human capital accumulation still is not clear.

Chapter 2 uses US Census data for the year 1980 and multiple births as a source of variation in family size, to support Becker's model. An exogenous increase in family size reduces the probability of a child attending private school, increases the probability of sharing a bedroom, lowers the labor participation of the child's mother and raises the probability of divorce. However, for a second group of variables that I believe are more closely related to child well-being, such as highest grade attended, grade retention, teen pregnancy or likelihood of dropping out school, I do not find evidence that family size has an impact. These results come to advance the literature in three ways. First, I use data for a developed country, the US Census data for the year 1980. While multiple births may not necessarily change family size in an underdeveloped country given typically larger family sizes, in a developed country like the US, most families that have a multiple birth in a second or higher pregnancy exceed their desired family size. Also, it may be that in a developed country families have more ways to reallocate resources. When a family in a developed country is pushed towards subsistence substitution out of food, it may not be feasible to protect child education. But in developed countries, families may have more margins on which to adjust to shocks to family size. This higher degree of freedom among different type of investment makes less clear the link between a change in family size and child wellbeing. In order to address this last point, I make a clear distinction between variables that can be linked to investment in children from those that are closer to the wellbeing of children. This is my second contribution. Finally the third added value of my paper is including a group of variables that affect the family more generally. The idea is that families that face an exogenous change in the number of children may change the time and money spent in other activities, perhaps leaving untouched the investment per child.

In order to study the role of number of children on child investment and child wellbeing in chapter 2, I use the same strategy that was used by Rosenzweig and Wolpin (1980), that is the use of multiple births as exogenous and unexpected shift in family size. Why do we need this exogenous and expected source of variation? First, Becker's model explains that families that face bigger family size are the ones that not only face a higher price of quality, an effect that I would like to estimate, but they are also the ones that have a relatively lower preference for child investment for any level of investment. Therefore even if we were able to "constrain" the number of children in families, we would not be assured that the level of investment per child would be the same in families with a desire for larger families relative to families with a desire for smaller family size. Second, and not necessarily implied by the models, is the fact that there might be other unobserved variables that are correlated simultaneously with family size and child quality, creating a spurious relationship between this two variables.

My results are consistent with Becker's model. Family size affects resources dedicated to child investment such as the probability of attending private school, the probability of sharing bedroom, female labor participation and probability of divorce. Nevertheless, I do not observe an impact on variables that I used as measures of child wellbeing such as teen pregnancy, grade retention, highest grade completed or attended and probability of dropping out.

These findings may explain to some degree the differences in the results of the impact of number of children in the family on measures of wellbeing among studies that not only use the same measure of quality but also some using the same identification strategy. Rosenzweig and Wolpin (1980) and Black, Devereux and Salvanes (2004) both use the same measure of quality and the same identification strategy. However, these researchers come to different conclusions on the trade–off between the number of children and educational attainments. While Rosenzweig and Wolpin find that family size has a negative impact on education, Black et al. find no impact of family size on education. The difference in the results may be related to the type of households that have been studied. Wolpin uses data from India where we could think that households have fewer degrees of freedom when the face a exogenous change in family size to allocated resources among different types of investments so the relationship between investment and wellbeing. On the other hand, Black and company use data from Norway where it is easier to imagine that households have higher degrees of freedom, so the relationship between a particular type of investment and wellbeing is less clear.

If the finding of this chapter are correct, family planning efforts in developed countries may not necessarily improve child wellbeing. The success of such policies will depend on the families' ability to reallocate resources. In developing economies with less developed markets and institutions, a reduction in family size would improve child wellbeing more than in a developed economy.

In Chapter 3, using the *National Health Interview* (NHIS), I find that female employment has a positive impact on Body Mass Index (BMI) for married men with less than high school. However I do not find an impact for all samples of women or men with high school or more. This finding is consistent with men facing an increase in the cost of home cooking with a positive impact on body weight. Women face an offsetting rise in the level of physical activity and households with husbands with higher income (i.e., higher education) can afford prepared food that is less calorie intensive. The magnitude of these findings is larger than found elsewhere in the literature. This is primarily because I take account of the endogeneity of female labor force participation. The analysis from the *Behavioral Risk Factor Surveillance System* (BRFSS) survey reveals that married men with less than high school, or married men with college degree or more, face an increase in their BMI and the likelihood of being obese if they live in states with a positive shock in female labor demand. The results also show that for married men with higher levels of education, female demand shocks produce an increase in the levels of physical activity. This last element plus the positive impact of female demand shocks on BMI and obesity rate suggests that the channel through which female labor force participation raises a man's weight must be through a higher consumption of calories which is consistent with a lower consumption of fruit and vegetables that we find associated with female demand shocks for this group.

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