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

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November 3, 2004

Abstract

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 & 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 well being, such as educational attainment, the probability of not dropping out of school and teen pregnancy is, however, less clear. The results do however 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.

*I would like to thank William Evans, Jonah Gelbach, Seth Sanders, Rodrigo Soares and Jeffrey Smith for their comments and advice. I also want to thank Roberto Alvarez, Juan Jose Diaz, Alexandra Jabin and Ye Zhang for helpful comments and discussions. Finally I want to thank the participants at the 17th Annual Congress of the European Society for Population Economics Society (13th to 15th of June 2003, New York City) and the participants in the Applied Microeconomics seminars at the University of Maryland for their comments and advice. The usual disclaimers apply.

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1 Introduction

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 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 ground, 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 if this observed impact embeds a causal relationship given the simultaneity of fertility and child outcomes.[3] Additionally, the link between child wellbeing and family size is less clear

[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.

[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 big 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.

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 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 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 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 tradeoff 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 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 wellbeing.

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. Outccomes 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, I 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] These alternative 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 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 identification strategy has already been used (Rosenzweig and Wolpin, 1980a 1980b; Black *et al.*, 2004), this research enhances the literature in two ways. First, I use data of 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

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

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

changes in family size were more likely to affect type of investment than child wellbeing. In fact, Black *et al.* (2004) 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. Second and related to the previous point, in order to reduce the chance of Type II error, I make an explicit distinction in 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 not necessarily reflect directly the allocation of resources by the parents.

3 Empirical Methodology

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

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

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 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

[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 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.

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 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.

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

[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 one hand the reduction in timing may be associated to 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.

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 (1) is the Wald estimate

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

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 casual 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

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

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

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

[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 (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.

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.

The number of children in a family is defined as the number of children younger than eighteen years old that have the same 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 establish 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 to child investment (Inputs or 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 because that using outcomes since inputs are one step closer to family size in the casual chain, 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 reflecting 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 not 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 equals 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 of 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 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, these 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 mea-

[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.

sure 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 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. The introduction of this variable intends 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

[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.

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

Table 2 presents 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 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 under 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%)[13], lower maternal labor force participation (53% to 48%) that is consistent with the increase in the proportion of children in nursery 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 3 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.

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

5 Results

5.1 First Stage

Table 4 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 to 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.

5.2 Inputs and Outputs

Table 5 presents OLS and 2SLS the 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.[14] 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 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

[14]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).

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[15] but simultaneously because of the higher probability of divorce, parents will have a weaker incentive to invest in their children.

The last four outcomes in Table 5 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

[15]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.

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 [16]. 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.

[16] 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.

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.[17] However, I already showed that the 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. Table 6 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 table 7, 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 Table 5, 6 and 7 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*.[18] 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 mothers*.

[17] 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.

[18] 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.

However, for the variable *hours at work* the Durbin–Wu–Hausman specification test does not show a difference from the OLS estimates.[19]

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, 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

[19] 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.

produce a change in the timing of the birth but not a impact in the complete family size. Then the evidence may be associated to the fact that the impact on these two outcomes is through the channel of number of children but not through the channel of a change in birth spacing.

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*. Table 8 presents the results for the complete sample of households with two (three) or more children, and Tables 9 and 10 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*.[20] 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,

[20]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.

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.

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 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 (well-being) 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.

References

[1] Angrist, J. and W. Evans, "Children and Their Parents' Labor Supply: Evidence from Exogenous Variation in Family Size," *The American Economic Review* 88(3), 1998, pp. 450–477.

[2] Becker, G., "An Economic Analysis of Fertility," *Demographic and Economic Change in Developed Countries*, Princeton: Princeton University Press, 1960, pp. 209–240.

[3] Becker, G., "A theory of Social Interaction," *Journal of Political Economy*, 1960, 82, pp. 1063–1093.

[4] Becker, G. and H. G. Lewis , "On the Interaction between the Quantity and Quality of Children," *Journal of Political Economy*, Mar.-Apr. 1973, 81(2), Part 2, pp. S279-S288.

[5] Becker, G. and H. G. Lewis , "Child Endowments and the quantity and quality of Children," *Journal of Political Economy*, 1976, 84(4), Part 2, pp. S143-S162.

[6] Becker, G. and N. Tomes, "An Equilibrium Theory of Distribution of Income and Intergenerational Mobility," *Journal of Political Economy*, 1979, 87(6), pp. 1153-1189.

[7] Becker, G. and N. Tomes, "Human Capital and the Rise and Fall of Families," *Journal of Labor Economics*, 1986, 4(no 3, pt 2), pp. S1–S39.

[8] Black, S., P. J. Devereux and K. G. Salvanes, "The More the Merrier? The Effect of Family Composition on Children's Education," *National Bureau of Economic Research* (NBER), Working paper 10720, 2004.

[9] Blake, J., "Family Size and Quality of Children," *Demography* 4, 1981, pp. 421–442.

[10] Blau, F.D. and A. Grossberg, "Maternal Labor Supply and Children's Cognitive Development," *The review of Economics and Statistics*, 1992, 74(3), pp. 474–481.

[11] Bronars, S. and J. Grogger "The Economic Consequeces of Unwed Motherhood: Using Twin Births as a Natural Experiment," *The American Economic Review*, Dec. 1994, 84(5), pp. 1141-1156.

[12] Brittain, J. A., "The inheritance of economics status," *The Brookings Institution*, Washington D.C., 1977.

[13] Browning, M., "Children and Household Economic Behavior," *Journal of Economic Literature*, 1992, 30(3), pp. 1434–1475.

[14] Duncan, O. D., "Ability and achievements," *Eugenics Quarterly*, 1968, 15, pp. 1–11.

[15] Evans W. and R. Schwab, "Finishing High School and Starting College: Do Catholic Schools Make a Difference?," *The Quarterly Journal of Economics*, 1995, 110(4), pp. 941–974.

[16] Filp, J., S. Donoso, C. Cardemil, E. Schiefelbein, E. Dieguez and J. Torres, "Efeito da educacao pre-escolar formal sobre o rendimento escolar de criancas no final do primeiro

ano basico: um estudo de acompanhamento no Chile," *Sao Paulo, Cadernos de Pesquisa*, mayo 1984, n.49, pp.15–25.

[17] Ginther, D. K. and R. A. Pollak, "Does Family Structure Affect Children's Educational Outcome?," *National Bureau of Economic Research*(NBER), Working paper 9628, 2003.

[18] Hanushek, E. A., "The Trade-off between Child Quantity and Quality," *Journal of Political Economy*, 1992, 100(1), pp. 84–117.

[19] Haverman, R. and Barbara Wolfe, "Determinants of Children's Attainment: Review of Methods and Findings," *Journal of Economic Literature*, 1995, 33(4), pp. 1829–1878.

[20] Hauser, R. M. and W. Sewell, "Family Effects in a Simple Model of Education, Occupation Status, and Earnings: Findings from Wisconsin and Kalamazoo Studies," *Journal of Labor Economics*, 1986, 4, pp. S83–S120.

[21] Hayes, C. H., and S. B. Kamerman (eds) 1983. "Children of Working Parents: Experiences and Outcomes." Washington, DC: National Academy Press.

[22] Heckman, J., "Instrumental Variables: A Study of Implicit Behavioral Assumptions Used in Making Program Evaluations," *Journal of Human Resources*, 1997, 32(3), pp. 441–452.

[23] Heckman, J. and E. Vytlacil, "Policy–Relevant Treatment Effects," *American Economic Review*, 2001, 91(2), pp. 107–111.

[24] Heyns, B., "The Influence of parents' work on children's school achievement." In S. B. Kamerman and C. H. Hayes (eds), Families that work: Children in a Changing World. Washington, DC: National Academy Press.

[25] M. Anne Hill; June O'Neill, "The Family and Intergenerational Relations," Spec. issue of *Journal of Human Resources*, 1997, 29(4), pp. 1064–1100.

[26] Hotz, V. J., J. Klerman, and R. Willis, "The Economics of Fertility in Developed Countries," *Handbook of Population and Family Economics*, 1997, M. Rosenzweig and O. Stark, eds., Elsevier Science, 276-348.

[27] Kessler, D., "Birth Order, Family Size, and Achievement: Family Structure and Wage Determination," *Journal of Labor Economics*, 1991, 9(4), pp. 413–426.

[28] Leibowitz, A., "Home Investment in Children," *Journal of Political Economy*, 1974, 82(2), Part 2, pp. S111–S131.

[29] Manski, Charles, Gary Sandefur, Sara McLanahan, and D. Powers, "Alternative Estimates of the Effect of Family Structure during Adolescence on High School Graduation," *Journal of the American Statistical Association*, 1992, 87(1), pp. 25–37.

[30] McLanahan, S. and G. Sandefur, "Growing Up with A Single–Parent," *Cambridge, MA: Harvard University Press*,1994.

[31] McMillen, Marilyn M.; Kaufman, Phillip; Whitener, Summer D. "Drop-out Rates in the United States: 1993. U.S.," *Department of Education, National Center for Education Statistics*,1994.

[32] Martin, Joyce A. and Melissa Park, "Trends in Twin and Triplet Births: 1980-1997," *Vital Health Statistics*. National Center for Health Statistics, 1999, 47(24).

[33] Mullin, C. H. and P. Wang, "The Timing of Childbearing among Heterogeneous Women in Dynamic General Equilibrium," *National Bureau of Economic Research*(NBER), Working paper 9231, 2002.

[34] Olneck, M. and D. Bills, "Family Configuration and Achievements: Effect of Birth Order and Family Size in a sample of Brothers," *Social Psychology Quarterly*, 1979, 42, pp. 135-148.

[35] Mary M. Kent and Mark Mather, "What Drives U.S. Population Growth?," *Population Bulletin*, Population Reference Bureau, Vol. 57, No.4, Dec 2002.

[36] Pestieau P., "The Effects of Varying Family Size on the Transmission and Distribution of Wealth," *Oxford Economic Papers*, 1984, 36, pp. 400–417.

[37] Pozner, P., "El impacto del pre-escolar en los ninios de sectores populares," *So Paulo, Cadernos de Pesquisa*, ago.1982, n.42, pp.63–78.

[38] Rosenzweig, M. and K. Wolpin, "Testing the Quantity-Quality Fertility Model: The Use of Twins as a Natural Experiment," *Econometrica*, 1980, 48(1), pp. 227–240.

[39] Rosenzweig, M. and K. Wolpin, "Life-Cycle Labor Supply and Fertility: Causal Inference from Household Models," *The Journal of Political Economy*, 1980, 88(2), pp. 328–348.

[40] Taubman, P., "Sources of inequality in earnings ," North-Holland, Amsterdam, 1975.

[41] Tomes , N., "The Family, Inheritance, and the Intergenerational Transmission of Inequality," *Journal of Political Economy*, 1981, 89(5), pp. 928–958.

[42] Wachtel , P., "The Effects of School Quality on achievement attainment levels and lifetime earnings," *Exploration in Economic Research*, 1975, 2, pp. 502–536.

[43] Wolfe, J. R. , "The Impact of Family Resources on Child IQ.," *Journal of Human Resources*, 1982, 17, pp. 213–235.

Table 1

Multiple Births Frequency

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
Descriptive Statistics: Oldest Children that do not belong to a Multiple Birth.

	All Mothers			Young Mothers		Old Mothers	
	All	Two or more	Three or more	Two or more	Three or more	Two or more	Three or more
Age	10.78	11.65	13.21	7.07	8.73	14.28	14.99
	(5.69)	(4.86)	(4.06)	(3.30)	(3.02)	(3.46)	(2.87)
Mother's Age	36.08	35.47	36.22	28.21	28.91	39.65	39.13
	(9.03)	(7.24)	(6.34)	(3.12)	(2.76)	(5.41)	(4.85)
Father's Age	38.82	38.09	39.00	31.05	32.00	42.27	41.84
	(9.82)	(8.09)	(7.30)	(4.63)	(4.59)	(6.69)	(6.19)
Years of Education of the mother	12.21	12.19	11.80	12.06	11.53	12.26	11.91
	(2.52)	(2.52)	(2.59)	(2.23)	(2.32)	(2.67)	(2.68)
Years of Education of the father	12.73	12.82	12.46	12.72	12.23	12.88	12.55
	(3.22)	(3.25)	(3.38)	(2.85)	(2.99)	(3.47)	(3.53)
Number of Siblings	1.88	2.57	3.47	2.40	3.32	2.66	3.53
	(1.02)	(0.88)	(0.83)	(0.70)	(0.66)	(0.96)	(0.89)
White	0.80	0.81	0.76	0.81	0.75	0.81	0.76
Black	0.10	0.09	0.11	0.08	0.10	0.09	0.11
Asian	0.02	0.02	0.02	0.01	0.01	0.02	0.02
Hispanic	0.08	0.08	0.11	0.09	0.13	0.07	0.10
Multiple births at second pregnancy	0.00522	0.00934	0.02422	0.00845	0.02813	0.00986	0.02266
Multiple births at third pregnancy	0.00213	0.00381	0.00988	0.00279	0.00930	0.00440	0.01011
Multiple births	0.00830	0.01484	0.03848	0.01197	0.03986	0.01650	0.03793
Mother in Home	0.89	1.00	1.00	1.00	1.00	1.00	1.00
Father in Home	0.82	0.86	0.86	0.88	0.87	0.85	0.86
Attend Private School?	0.14	0.14	0.12	0.17	0.12	0.12	0.12
In nursery school?	0.27	0.41	0.49	0.39	0.48	0.61	0.66
Migrate?	0.23	0.23	0.21	0.30	0.29	0.18	0.18
Share Bedroom?	0.14	0.19	0.38	0.17	0.41	0.19	0.37
Mother's works?	0.56	0.53	0.48	0.45	0.38	0.57	0.52
Mother's Hours at work?	31.51	30.88	30.28	29.46	28.58	31.53	30.77
	(15.19)	(15.37)	(15.86)	(16.01)	(16.78)	(15.02)	(15.55)
Parents divorced?	0.25	0.23	0.23	0.22	0.24	0.24	0.23
Behind Cohort?	0.12	0.12	0.16	0.01	0.03	0.18	0.22
Highest Completed Grade	8.01	7.89	8.15	6.10	6.16	8.56	8.82
	(2.10)	(2.09)	(2.11)	(0.46)	(0.57)	(2.07)	(2.01)
Enrolled in School?	0.80	0.83	0.81	0.88	0.86	0.83	0.81
Teen Mother?	0.07	0.03	0.04	0.02	0.03	0.03	0.04

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

Table 3

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

	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 4
Impact of Multiple Births on Number of Children at Home

			Younger Mothers (<=32)		Older Mothers (>32)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Unconditional	**Conditional (a)**	**Unconditional**	**Conditional (a)**	**Unconditional**	**Conditional (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)**
Number of Observations	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)**
Number of Observations	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, mother's age and sex.

Table 5
OLS and 2SLS Estimates of Child Input and Output Equations.
Parameters Estimates (Standard Errors) and {Durbin-Wu-Hausman Test Statistic}.

Outcomes	Sample and Ages	Two or more Children OLS	2SLS		Three or more Children OLS	2SLS	
Attend Private School?	6-18	0.0139	-0.0102	{25.60}	0.0161	-0.0043	{8.45}
		(0.0005)**	(0.0048)*		(0.0008)**	(0.0070)	
In nursery school?	<6	-0.0457	-0.0034	{12.01}	-0.0356	0.0064	{1.51}
		(0.0032)**	(0.0126)		(0.0115)**	(0.0360)	
Migrate?	0-18	0.0067	-0.0065	{2.71}	0.0055	0.0075	{0.02}
		(0.0008)**	(0.0081)		(0.0012)**	(0.0125)	
Share Bedroom?	0-18	0.2285	0.2011	{22.94}	0.2541	0.3508	{96.86}
		(0.0008)**	(0.0079)**		(0.0012)**	(0.0099)**	
Mother's works?	0-18	-0.0859	-0.0363	{54.09}	-0.0718	-0.0421	{8.15}
		(0.0007)**	(0.0068)**		(0.0011)**	(0.0105)**	
Mother's Hours at work?	0-18 (a)	-0.0466	-0.0180	{6.67}	-0.0305	-0.0123	{1.03}
		(0.0012)**	(0.0111)		(0.0022)**	(0.0181)	
Parents divorced?	0-18	-0.0207	0.0269	{63.40}	-0.0166	0.0121	{9.55}
		(0.0006)**	(0.0060)**		(0.0009)**	(0.0093)	
Behind Cohort?	6-18	0.0144	0.0018	{9.31}	0.0191	0.0112	{1.07}
		(0.0005)**	(0.0042)		(0.0009)**	(0.0077)	
Highest Completed Grade	6-18	-0.0034	0.0001	{12.03}	-0.0049	-0.0012	{4.76}
		(0.0001)**	(0.0010)		(0.0002)**	(0.0017)	
Enrolled in School?	16-18	-0.0094	-0.0153	{0.40}	-0.0124	-0.0035	{0.47}
		(0.0008)**	(0.0094)		(0.0012)**	(0.0131)	
Teen Mother?	13-18	0.0037	0.0096	{0.81}	0.0028	0.0097	{0.45}
		(0.0006)**	(0.0066)		(0.0010)**	(0.0104)	

* significant at 5%; ** significant at 1%.
The Durbin-Wu-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, education of the parents, race, parent's age and sex.
(a) The sample is additionally constrained to working mothers.

Table 6

OLS and 2SLS Estimates of Child Input and Output Equations. Mothers 32 years old or younger.

Parameters Estimates (Standard Errors) and {Durbin-Wu-Hausman Test Statistic}.

		Two or more Children					**Three or more Children**				
Outcomes	**Sample and Ages**	**OLS**		**2SLS**			**OLS**		**2SLS**		
Attend Private School?	6-18	0.0116		-0.0059		{4.06}	0.0176		0.0290		{0.65}
		(0.0010)	**	(0.0087)			(0.0017)	**	(0.0143)	*	
In nursery school?	<6	-0.0440		-0.0015		{10.60}	-0.0320		0.0063		{1.10}
		(0.0034)	**	(0.0135)			(0.0120)	**	(0.0383)		
Migrate?	0-18	0.0116		-0.0233		{5.43}	0.0105		0.0384		{0.41}
		(0.0018)	**	(0.0151)			(0.0034)	**	(0.0261)		
Share Bedroom?	0-18	0.2640		0.2148		{25.41}	0.3026		0.4338		{57.44}
		(0.0011)	**	(0.0098)	**		(0.0028)	**	(0.0175)	**	
Mother's works?	0-18	-0.1256		-0.0733		{23.01}	-0.0897		-0.0662		{1.70}
		(0.0014)	**	(0.0110)	**		(0.0025)	**	(0.0182)	**	
Mother's Hours at work?	0-18 (a)	-0.0647		-0.0476		{0.62}	-0.0389		-0.0080		{0.64}
		(0.0030)	**	(0.0220)	*		(0.0065)	**	(0.0392)		
Parents divorced?	0-18	-0.0284		0.0101		{16.58}	-0.0185		0.0191		{4.62}
		(0.0012)	**	(0.0095)			(0.0024)	**	(0.0176)		
Behind Cohort?	6-18	0.0050		-0.0033		{19.20}	0.0094		0.0113		{0.09}
		(0.0005)	**	(0.0019)			(0.0013)	**	(0.0066)		
Highest Completed Grade	6-18	-0.0010		0.0011		{12.79}	-0.0019		-0.0008		{0.57}
		(0.0001)	**	(0.0006)			(0.0003)	**	(0.0015)		
Enrolled in School?	16-18	-0.0095		-0.1955		{0.57}	-0.0016		0.0636		{0.26}
		(0.0091)		(0.2466)			(0.0140)		(0.1276)		
Teen Mother?	13-18	-0.0001		-0.0062		{0.27}	-0.0021		-0.0296		{1.83}
		(0.0033)		(0.0122)			(0.0046)		(0.0209)		

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

The Durbin-Wu-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, education of the parents, race, parent’s age and sex.

(a) The sample is additionally constrained to working mothers.

Table 7

OLS and 2SLS Estimates of Child Input and Output Equations. Mothers older than 32 years old.
Parameters Estimates (Standard Errors) and {Durbin-Wu-Hausman Test Statistic}.

		Two or more Children					Three or more Children				
Outcomes	**Sample and Ages**	**OLS**		**2SLS**			**OLS**		**2SLS**		
Attend Private School?	6-18	0.0145		-0.0121		{22.03}	0.0156		-0.0175		{17.05}
		(0.0005)	**	(0.0057)	*		(0.0009)	**	(0.0081)	*	
In nursery school?	<6	-0.0645		-0.0262		{1.30}	-0.0861		0.0388		{1.31}
		(0.0109)	**	(0.0353)			(0.0456)	*	(0.1184)		
Migrate?	0-18	0.0050		0.0026		{0.07}	0.0041		-0.0048		{0.41}
		(0.0008)	**	(0.0094)			(0.0013)	**	(0.0139)		
Share Bedroom?	0-18	0.2168		0.1962		{8.58}	0.2440		0.3184		{40.03}
		(0.0006)	**	(0.0071)	**		(0.0013)	**	(0.0118)	**	
Mother's works?	0-18	-0.0742		-0.0170		{45.25}	-0.0677		-0.0333		{7.41}
		(0.0008)	**	(0.0085)	*		(0.0012)	**	(0.0127)	**	
Mother's Hours at work?	0-18 (a)	-0.0427		-0.0072		{7.68}	-0.0289		-0.0123		{0.68}
		(0.0013)	**	(0.0129)			(0.0024)	**	(0.0203)		
Parents divorced?	0-18	-0.0193		0.0356		{51.78}	-0.0169		0.0096		{5.86}
		(0.0007)	**	(0.0077)	**		(0.0010)	**	(0.0110)		
Behind Cohort?	6-18	0.0162		0.0055		{3.05}	0.0199		0.0101		{0.93}
		(0.0006)	**	(0.0062)			(0.0011)	**	(0.0102)		
Highest Completed Grade	6-18	-0.0040		-0.0004		{7.85}	-0.0053		-0.0012		{3.38}
		(0.0001)	**	(0.0013)			(0.0003)	**	(0.0022)		
Enrolled in School?	16-18	-0.0093		-0.0152		{0.41}	-0.0124		-0.0035		{0.46}
		(0.0008)	**	(0.0094)			(0.0012)	**	(0.0131)		
Teen Mother?	13-18	0.0038		0.0096		{0.77}	0.0030		0.0101		{0.45}
		(0.0006)	**	(0.0067)			(0.0010)	**	(0.0106)		

* significant at 5%; ** significant at 1% .
The Durbin-Wu-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, education of the parents, race, parent’s age and sex.
(a) The sample is additionally constrained to working mothers.

Table 8
OLS and 2SLS Estimates of Child Input and Output Equations.
Parameters Estimates (Standard Errors) and {Durbin-Wu-Hausman Test Statistic}.

	Two or more Children					Three or more Children				
Outcomes	**OLS**		**2SLS**			**OLS**		**2SLS**		
Attend Private School?										
White	0.0216		-0.0109		{35.66}	0.0247		-0.0033		{10.42}
	(0.0006)	**	(0.0055)	*		(0.0011)	**	(0.0087)		
Non-White	-0.0049		-0.0059		{0.01}	-0.0014		-0.0040		{0.06}
	(0.0007)	**	(0.0095)			(0.0009)		(0.0108)		
Male	0.0144		-0.0148		{19.62}	0.0165		-0.0212		{17.29}
	(0.0007)	**	(0.0066)	*		(0.0011)		(0.0091)	*	
Female	0.0133		-0.0055		{7.49}	0.0156		0.0132		{0.05}
	(0.0007)	**	(0.0069)			(0.0011)	**	(0.0108)		
Mother's works?										
White	-0.0929		-0.0314		{65.92}	-0.0774		-0.0488		{5.44}
	(0.0008)	**	(0.0076)	**		(0.0014)	**	(0.0123)	**	
Non-White	-0.0665		-0.0548		{0.65}	-0.0610		-0.0275		{2.96}
	(0.0012)	**	(0.0146)	**		(0.0018)	**	(0.0195)		
Male	-0.0863		-0.0454		{19.06}	-0.0737		-0.0507		{2.58}
	(0.0009)	**	(0.0094)	**		(0.0015)	**	(0.0144)	**	
Female	-0.0855		-0.0265		{36.93}	-0.0697		-0.0335		{5.73}
	(0.0010)	**	(0.0098)	**		(0.0016)	**	(0.0152)	*	
Parents divorced?										
White	-0.0211		0.0230		{45.43}	-0.0161		0.0094		{5.83}
	(0.0007)	**	(0.0066)	**		(0.0011)	**	(0.0106)		
Non-White	-0.0159		0.0417		{16.47}	-0.0126		0.0151		{2.23}
	(0.0011)	**	(0.0142)	**		(0.0017)	**	(0.0186)		
Male	-0.0187		0.0253		{28.47}	-0.0147		0.0075		{2.95}
	(0.0008)	**	(0.0083)	**		(0.0013)	**	(0.0130)		
Female	-0.0228		0.0289		{35.36}	-0.0186		0.0171		{7.14}
	(0.0008)	**	(0.0087)	**		(0.0014)	**	(0.0134)		
Behind Cohort?										
White	0.0103		0.0007		{4.64}	0.0148		0.0154		{0.00}
	(0.0006)	**	(0.0045)			(0.0011)	**	(0.0087)		
Non-White	0.0206		0.0088		{1.36}	0.0241		0.0024		{2.01}
	(0.0010)	**	(0.0102)			(0.0017)	**	(0.0154)		
Male	0.0143		0.0043		{2.70}	0.0179		0.0144		{0.10}
	(0.0007)	**	(0.0061)			(0.0013)	**	(0.0113)		
Female	0.0145		0.0004		{6.49}	0.0205		0.0065		{1.94}
	(0.0007)	**	(0.0056)			(0.0013)	**	(0.0102)		
Highest Completed Grade										
White	-0.0024		0.0008		{10.26}	-0.0037		-0.0017		{1.31}
	(0.0001)	**	(0.0010)			(0.0002)	**	(0.0018)		
Non-White	-0.0051		-0.0032		{0.53}	-0.0064		0.0000		{2.71}
	(0.0003)	**	(0.0026)			(0.0004)	**	(0.0039)		
Male	-0.0033		-0.0003		{4.01}	-0.0046		0.0011		{5.43}
	(0.0002)	**	(0.0015)			(0.0003)	**	(0.0025)		
Female	-0.0034		0.0002		{8.13}	-0.0052		-0.0033		{0.68}
	(0.0002)	**	(0.0013)			(0.0003)	**	(0.0023)		

* significant at 5%; ** significant at 1%

The Durbin-Wu-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, education of the parents, race, parent's age and sex.

Table 9
OLS and 2SLS Estimates of Child Input and Output Equations. Mothers 32 years old or younger.
Parameters Estimates (Standard Errors) and {Durbin-Wu-Hausman Test Statistic}.

	Two or more Children					Three or more Children				
Outcomes	**OLS**		**2SLS**			**OLS**		**2SLS**		
Attend Private School?										
White	0.0190		-0.0080		{7.77}	0.0291		0.0534		{1.69}
	(0.0012)	**	(0.0098)			(0.0025)	**	(0.0189)	**	
Non-White	-0.0084		-0.0003		{0.19}	-0.0041		-0.0238		{1.30}
	(0.0014)	**	(0.0187)			(0.0019)	*	(0.0174)		
Male	0.0121		-0.0036		{1.70}	0.0168		0.0139		{0.02}
	(0.0013)	**	(0.0121)			(0.0024)	**	(0.0189)		
Female	0.0111		-0.0082		{2.39}	0.0183		0.0429		{1.35}
	(0.0014)	**	(0.0125)			(0.0024)	**	(0.0213)	*	
Mother's works?										
White	-0.1345		-0.0818		{19.11}	-0.0930		-0.0711		{1.05}
	(0.0016)	**	(0.0122)	**		(0.0032)	**	(0.0216)	**	
Non-White	-0.1018		-0.0380		{6.32}	-0.0844		-0.0523		{0.95}
	(0.0026)	**	(0.0255)			(0.0042)	**	(0.0332)		
Male	-0.1252		-0.0758		{10.95}	-0.0883		-0.0774		{0.19}
	(0.0019)	**	(0.0150)	**		(0.0036)	**	(0.0250)	**	
Female	-0.1261		-0.0707		{12.00}	-0.0908		-0.0562		{1.73}
	(0.0019)	**	(0.0161)	**		(0.0036)	**	(0.0266)	*	
Parents divorced?										
White	-0.0295		0.0018		{9.46}	-0.0185		0.0235		{4.16}
	(0.0014)	**	(0.0103)			(0.0030)	**	(0.0208)		
Non-White	-0.0226		0.0403		{7.22}	-0.0131		0.0070		{0.39}
	(0.0024)	**	(0.0235)			(0.0040)	**	(0.0326)		
Male	-0.0263		0.0046		{5.75}	-0.0179		0.0154		{1.90}
	(0.0017)	**	(0.0130)			(0.0034)	**	(0.0244)		
Female	-0.0306		0.0166		{11.51}	-0.0194		0.0226		{2.79}
	(0.0018)	**	(0.0140)			(0.0035)	**	(0.0254)		
Behind Cohort?										
White	0.0035		-0.0016		{6.46}	0.0062		0.0084		{0.09}
	(0.0005)	**	(0.0021)			(0.0015)	**	(0.0077)		
Non-White	0.0064		-0.0092		{9.06}	0.0116		0.0203		{0.53}
	(0.0011)	**	(0.0053)			(0.0023)	**	(0.0121)		
Male	0.0050		-0.0026		{8.10}	0.0092		0.0021		{0.65}
	(0.0007)	**	(0.0028)			(0.0018)	**	(0.0089)		
Female	0.0050		-0.0033		{10.63}	0.0099		0.0202		{1.18}
	(0.0007)	**	(0.0027)			(0.0018)	**	(0.0097)	*	
Highest Completed Grade										
White	-0.0008		0.0003		{3.47}	-0.0012		-0.0004		{0.22}
	(0.0001)	**	(0.0006)			(0.0003)	**	(0.0018)		
Non-White	-0.0015		0.0037		{9.08}	-0.0027		-0.0020		{0.06}
	(0.0003)	**	(0.0017)	*		(0.0006)	**	(0.0028)		
Male	-0.0010		0.0011		{5.32}	-0.0020		0.0013		{2.16}
	(0.0002)	**	(0.0009)			(0.0004)	**	(0.0023)		
Female	-0.0011		0.0008		{7.02}	-0.0019		-0.0034		{0.61}
	(0.0002)	**	(0.0007)			(0.0004)	**	(0.0020)		

* significant at 5%; ** significant at 1%

The Durbin-Wu-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, education of the parents, race, parent's age and sex.

Table 10

OLS and 2SLS Estimates of Child Input and Output Equations. Mothers older than 32 years old. Parameters Estimates (Standard Errors) and {Durbin-Wu-Hausman Test Statistic}.

	Two or more Children					Three or more Children				
Outcomes	**OLS**		**2SLS**			**OLS**		**2SLS**		
Attend Private School?										
White	0.0224		-0.0126		{28.36}	0.0237		-0.0244		{24.82}
	(0.0007)	**	(0.0066)			(0.0012)	**	(0.0097)	*	
Non-White	-0.0040		-0.0087		{0.19}	-0.0008		0.0051		{0.19}
	(0.0008)	**	(0.0108)			(0.0011)		(0.0137)		
Male	0.0151		-0.0198		{19.73}	0.0163		-0.0350		{25.05}
	(0.0008)	**	(0.0079)	*		(0.0013)	**	(0.0103)	**	
Female	0.0140		-0.0046		{5.12}	0.0149		0.0010		{1.25}
	(0.0008)	**	(0.0082)			(0.0013)	**	(0.0125)		
Mother's works?										
White	-0.0812		-0.0045		{62.82}	-0.0743		-0.0407		{5.16}
	(0.0009)	**	(0.0097)			(0.0015)	**	(0.0149)	**	
Non-White	-0.0559		-0.0620		{0.12}	-0.0553		-0.0152		{2.78}
	(0.0014)	**	(0.0177)	**		(0.0020)	**	(0.0241)		
Male	-0.0750		-0.0291		{14.85}	-0.0705		-0.0415		{2.78}
	(0.0011)	**	(0.0120)	*		(0.0017)	**	(0.0175)	*	
Female	-0.0733		-0.0040		{32.45}	-0.0647		-0.0256		{4.54}
	(0.0011)	**	(0.0122)			(0.0018)	**	(0.0184)		
Parents divorced?										
White	-0.0190		0.0337		{39.31}	-0.0158		0.0045		{2.74}
	(0.0007)	**	(0.0084)	**		(0.0012)	**	(0.0123)		
Non-White	-0.0154		0.0434		{10.99}	-0.0134		0.0186		{2.01}
	(0.0013)	**	(0.0178)	*		(0.0019)	**	(0.0227)		
Male	-0.0173		0.0370		{26.37}	-0.0146		0.0049		{1.64}
	(0.0009)	**	(0.0106)	**		(0.0014)	**	(0.0153)		
Female	-0.0214		0.0342		{25.38}	-0.0193		0.0141		{4.48}
	(0.0009)	**	(0.0111)	**		(0.0015)	**	(0.0159)		
Behind Cohort?										
White	0.0127		0.0013		{2.88}	0.0166		0.0166		{0.00}
	(0.0007)	**	(0.0067)			(0.0013)	**	(0.0115)		
Non-White	0.0234		0.0226		{0.00}	0.0255		-0.0081		{2.49}
	(0.0013)	**	(0.0148)			(0.0020)	**	(0.0214)		
Male	0.0161		0.0081		{0.76}	0.0187		0.0180		{0.00}
	(0.0009)	**	(0.0092)			(0.0015)	**	(0.0152)		
Female	0.0163		0.0030		{2.65}	0.0214		-0.0006		{2.62}
	(0.0009)	**	(0.0083)			(0.0015)	**	(0.0136)		
Highest Completed Grade										
White	-0.0030		0.0011		{9.25}	-0.0042		-0.0022		{0.76}
	(0.0002)	**	(0.0013)			(0.0003)	**	(0.0023)		
Non-White	-0.0060		-0.0060		{0.00}	-0.0070		0.0013		{2.58}
	(0.0003)	**	(0.0035)			(0.0005)	**	(0.0052)		
Male	-0.0039		-0.0008		{2.61}	-0.0050		0.0007		{3.19}
	(0.0002)	**	(0.0020)			(0.0004)	**	(0.0032)		
Female	-0.0040		-0.0001		{5.61}	-0.0056		-0.0031		{0.72}
	(0.0002)	**	(0.0016)			(0.0004)	**	(0.0030)		

* significant at 5%; ** significant at 1%

The Durbin-Wu-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, education of the parents, race, parent's age and sex.