

PARENTAL TIME, BEHAVIORS AND CHILDHOOD OBESITY

A Dissertation

by

ANNETTE KUTEESA

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2010

Major Subject: Recreation, Park, and Tourism Sciences

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Co-Chairs of Committee,	William A. McIntosh Rodolfo M. Nayga Jr.
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ABSTRACT

Parental Time, Behaviors and Childhood Obesity.

(December 2010)

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The rates of childhood obesity remain high in spite of the enormous efforts dedicated to tackling the disease. This dissertation investigates the effect of two of its causes, including parental time and children's obesity risk behaviors. Trends in these causes have changed over time and might explain changes in obesity. The two factors are analyzed separately given the differences in impact process and concentration of literature. The data for the investigation is drawn from the Parental Time, Role Strains, Coping, and Children's Diet and Nutrition project.

In examining parental time, the attention is directed towards the mother's actual time spent with the child which has been associated with reduction in child weight status. The major aim is to test and correct for the problem of endogeneity stemming from unobserved health factors that can distort any meaningful causal impact of maternal time on child weight status. Using the household production theory, parental time allocation decisions towards child health are modeled and analyzed using instrument variable (IV) methods. Results indicate that the effect of mother's time

allocation reduces child weight status. Her decision to allocate time to the child is affected by unseen factors. Father's work to family spillover was found to be a valid instrument for mother's time with the child. Results were robust across different estimators.

In analyzing the relationship between childhood obesity risk behaviors and weight status, this study focuses on three child practices including breakfast intake, fast food consumption and sleep patterns. The main aim was to score their joint impact, while at the same time accounting for contextual factors. This work adopted the ecological systems framework which accommodates multiple factors. Based on this theory, a simultaneous system of equations considering child weight status, risk behavior and contextual factors was set up and analyzed using 3SLS. Findings indicated that dietary behaviors remain a major factor in affecting weight status. In addition, feedback mechanism from child weight status will influence the diet pattern adopted by the child. Sleep sufficiency had no effect on child weight status.

DEDICATION

I dedicate this dissertation to God who saw me through the twists and turns of the
program

ACKNOWLEDGEMENTS

I wish to extend many thanks towards my advisory committee who made the completion of this work possible. Special thanks goes to my co-chairs; to Dr. McIntosh, thank you for taking me on as your student, providing the relevant data and working with me to ensure that this dissertation takes a meaningful course. To Dr. Nayga, you remained my advisor throughout the turnarounds of my doctoral program, encouraging and working with me and every other professors involved, even at far off distances to ensure that I received the necessary support to handle this research. I am very grateful to Dr. Wu for sharing his econometric knowledge and insights which have made me better at envisioning socio-economic issues in a clearer way. To Dr. Ellis, without you joining my committee at the time that you did, I would never completed this research in timely manner. I am most thankful to your attention to methods, which have broadened my view especially behavioral theories.

I also wish to offer my sincere gratitude to Ms. Maguerite Van Dyke, the graduate advisor whose assistance contributed enormously to my coming this far in program. Thank you for always being able to listen and for presenting solutions to our never-ending concerns. To my fellow RPTS graduate students, thank you for your thoughtfulness. I will always remember the fun times at graduate dinners and class trips. Lastly, but not least, I would like to thank my parents for encouraging me to push through the program and for their support during the difficult times.

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CHAPTER I

INTRODUCTION

Childhood obesity trends and consequences

Childhood obesity remains a major challenge in the United States in spite of the tremendous research efforts that have been dedicated to it. Evidence indicates that one in every three children aged 2-19 years are overweight or obese a ratio that has persisted since 1999 (Hedley et al., 2004; Ogden, Carroll, & Flegal, 2008; Ogden et al., 2006; 2010; Centers for Disease Control (CDC), 2009a). A closer look at the condition using data from the National Health and Nutrition Examination Surveys (NHANES) indicates that the condition has increased in all ages, both genders and all ethnic groups (CDC 2009a). As seen in Table 1.1, the prevalence of obesity for children aged 2-5 years has more than doubled and nearly tripled for those aged 6-19 years over the past 30 years. In the case of gender and ethnicity, the surveys indicate that the proportion of obese male adolescents aged 12-19 years for non-Hispanic blacks, white and Mexicans in 1988 was 10.2%, 11.6% and 14.1% respectively. By 2006, the percentages stood at 22.9%, 16.0% and 21.1% respectively. Within the same period, the percentage of obese non-Hispanic, white and Mexican girls of the same age group increased from 13.2%, 7.4% and 9.2% to 27.7% 14.5% and 19.9% respectively. While it has been demonstrated that there have not been significant changes in the general prevalence of condition over the past 10years (Ogden et al., 2010), the fact is that trends are still high to warrant change.

Table 1.1: Prevalence of Obesity among U.S. Children and Adolescents*

Survey Periods	Ages 2-5 years	Ages 6-11 years	Ages 12-19 years
NHANESII (1976-1980)	5%	6.5%	5%
NHANESIII (1988-1994)	7.2%	11.3%	10.5%
NHANES (1999-2002)	10.3%	15.8%	16.1%
NHANES (2003-2006)	12.4%	17.0%	17.6%
NHANES (2007-2008)	10.4%	19.6%	18.1%

Note: * refers to Sex- and -age –body mass index \geq 95 percentile based on Centers for Disease Control (CDC) growth charts. Source: CDC website and Ogden et al., (2010).

The implication of such elevated levels of childhood obesity is that more and more children and adolescents are at risk of health, social, and psychological problems. Research indicates that obesity in children is linked to the occurrence of several health conditions such as diabetes, sleep apnea, asthma, among others (Must & Strauss, 1999; Dietz, 1998; Fagot-Campagna et al., 2000). Socially, obese children have been found to be marginalized, with fewer friendships (Strauss & Pollack 2003). Psychologically, obese children have perceived lower self-worth (Braet, Mervielde, & Vandereycken 1997) which continues to adolescence (Strauss, 2000). Strauss (2000) found that as obese adolescents have higher rates of sadness, loneliness, and nervousness and are more prone to engaging in deviant behaviors such as smoking and drinking. Given that obese children are most likely to become obese adults (see Serdula et al., 1993), the future population is likely to have higher number of obese adults and more adult weight related problems such as heart disease (Freedman et al., 2001).

Increasing obesity trends also means increases in related economic costs most of which are born by public institutions (Finkelstein et al., 2003; Wang & Dietz, 2002; NIH, 2009; Wolf & Coditz, 1998). Using National Health Interview Survey (NHIS)

data, Wolf and Coditz (1998) found that the total cost attributable to obesity in 1995 was 99.2 billion dollars, of which 51.64 billion mounted direct medical cost. Another study by Finkelstein, Fiebelkorn and Wang (2003) found that the average increase in medical expenditures attributed to adult obesity were \$732 with Medicare expenses reaching as high as \$1486 and Medicaid being as high as \$864 per recipient. More specifically Wang and Dietz (2002) who examined hospital discharges found that childhood obesity annual hospital costs resulting from treatment of children aged 6-17 years increased more than threefold from 35 million dollars between 1979-1981 to 127 million dollars from 1997-1999. Other economic losses attributed to obesity are linked to lower earnings (Cawley 2004) and wealth especially among obese women (Zargosky, 2005). Clearly the escalation of such dire consequences must be prevented. But this requires a reversal of the prevailing children's obesity trends which has been difficult so far.

Purpose of this research

Research posits that tackling the childhood obesity will involve understanding its causes which are several and complex in nature encompassing biological, behavioral and environmental factors. This dissertation seeks to examine the effect of two categories of factors on this condition including parental time and children's obesity risk behaviors. The former is characterized as an environmental factor while the latter is particular to the individual. While these subjects are not new to research, it is recognized that in affecting childhood obesity, each of these factors does so via various processes which investigations have not yet exhausted. This dissertation pursues the matter in a different

way compared to past studies. Given that the two factors are dissimilar in their impact on childhood obesity, their links to condition are examined separately. In addition literature is also spread across several disciplines.

The first task is to examine the effect of parental time on changes in weight status. The focus is on the actual time the mother's spends with her child, which is considered a key investment in children's development. A few studies have investigated this relationship showing that mother's time spent with the child discourages gains in child weight (McIntosh et al., 2006; You, 2005). However, none have addressed the issue of unobserved factors, whose effects can produce misleading results. The fact is that these unobserved factors have the capability of affecting both the child weight status and mother's time input, making it difficult to identify the real impact of the latter on the former (Rozenweig & Shultz, 1983; Shultz, 1984). In such situations it important that the effect of unseen variables be removed by fixed differences or by the use of instrumental variables (IV) that are linked to parental time input, but not the child weight outcome. This study undertakes the second method with the intension of identifying the appropriate instrument variables that meets all relevant criteria. In pursuing this objective, the researcher limits herself to economic literature because it offers better estimation methods concerning parental inputs. In this regard the household production model is adopted as the theoretical basis for this investigation. This theory is able to link parental allocation decisions to child health outcomes in manner that can facilitate empirical investigation. The model argues that parental time inputs and children's health outcomes are jointly connected possibly through unobserved factors and assists in

recognizing potential IVs. Suitable IVs are those that will adhere to relevant tests as specified by Cragg and Donald (1993); Staiger and Stock (1997); Stock and Yogo (2002); Kleibergen and Paap (2006), Fuller (1977), Baum, Shaffer, and Stillman (2003, 2007) and Greene (2003). A detailed discussion of these tests will be presented later in Chapter II of this dissertation. For empirical analysis this work prefers IV techniques particularly 2SLS. However 2SLS assumes independent and identically distributed errors. The method is inappropriate when this assumption is violated and is inefficient when the IVs are weak. Thus for consistency, results from this technique will be compared to results from similar IV estimators including limited information maximum likelihood (LIML), Fuller (k) and generalized methods of moments (GMM).

The second task of this work concerns the effect of the child's obesity risk behaviors on changes in weight status. Obesity risk behaviors are responsible for the maintenance of proper body weight. The interest here is directed towards breakfast habits, fast food consumption and sleep patterns. The first two contribute to energy intake into the body; the third is liable to adjustment of body hormones, which determine body weight. Tendencies in these habits among children have changed over time and may be linked to rising childhood obesity trends (Rampersaud, 2009; Nielsen et al., 2002; National Sleep Foundation (NIH), 2009). Past research has considered these behaviors separately and mostly free from contextual factors. This study aims at determining their joint significance for weight status while accounting for their contextual factors. This multiplex of factors demands an approach that accommodates the various factors and spheres of influence. This work draws on the fields of social

psychology and medicine, where much of literature concerning behavioral patterns and health is concentrated and generally involves the ecological systems theory (EST) (Davison & Birch, 2001; Gorin & Crane, 2000). Based on this theory, children's obesity behavioral patterns are seen as being influenced by factors from various environments that include families and communities. These patterns, in turn, cause changes in weight status. Based on this theory, an empirical model in form of a system of equations, constituting different obesity behaviors and child weight status is considered. Estimating systems of equations requires a consideration of several empirical issues, including the identification of the system and simultaneity in relationships and correlated errors. Various estimators have been established to examine systems of equations. In light of last two problems, this work considers three stage least squares (3SLS).

This study takes advantage of the same data set utilized by McIntosh et al. (2006) and You (2005) based on the Parental time, Role strains, Coping and children's Diet and Nutrition project. This study involved 300 households in the Houston Metropolitan Statistical Area. Samples are limited to two parent families with one child. Though the data is cross-sectional and provides us with just a one snap shot in time, it is comprehensive and includes information on several economic and sociological aspects of household time allocations and behaviors, making it possible for the researcher to pursue the goals stated earlier.

The remainder of this dissertation is as follows. Chapter II deals with aspects of parental time and childhood obesity and underscores the first task of this study. Chapter III considers the effect of children's obesity risk behaviors and childhood obesity which

comprises of our second task. Each of these chapters is self contained with sections of introduction, literature, empirical methods, data, empirical results and concluding remarks. Conclusions of findings and limitations encountered during this research are presented in Chapter IV.

CHAPTER II

PARENTAL TIME AND CHILDHOOD OBESITY

Introduction

Recent changes in parental time allocations (Bianchi, 2000; Sayer, Bianchi, & Robinson, 2004; Aguiar, & Hurst, 2007; Mosisa & Hipple, 2006) and the rise in childhood obesity rates (CDC, 2009a) have stimulated the reinvestigation of relationships concerning the two aspects with hopes of understanding and curtailing the later. Parental time is considered a major determinant of children's health outcomes and therefore might explain the ongoing obesity trends. Such information is highly relevant, given the several well known health (Dietz, 1998; Fagot-Campagna et al., 2000), social and psychological problems (Strauss & Pollack, 2003; Strauss, 2000; Dietz, 1998) as well as increases in health economic costs (Wang & Dietz, 2002; Finkelstein, Fiebelkorn & Wang, 2003) that the condition causes.

One approach of disentangling this connection has focused on the link between actual time the parent spends with the child and the child's weight status (e.g. You, 2005; McIntosh et al., 2006). Generally findings have shown that mother's time spent with the child is important to children's weight outcomes. Mothers who allocate less time to their children are likely to promote to unhealthy weight development of their child. This is possibly due to reduced time opportunities for preparing and supervising quality meals of their children. The effect of father's time on children's weight outcomes remains ambiguous.

Investigating relationships involving parental inputs and children's health outcomes can be problematic. A characteristic difficulty is that estimations can suffer from potential endogeneity stemming from unobserved health factors¹. It is known that children differ in health status part of which is observed and the other unobserved by the researcher but might be known to the parent and the child. What is disturbing is that unobserved health endowment can directly affect health outcomes through the health production technology and indirectly through the effect of inputs (Rosenwieg & Schultz, 1983; Schultz, 1984) in manner that deters drawing any meaningful causal relationships. Thus, on one hand, a child's weight status is influenced of time spent with the mother, on the other hand the parent's decision to spend time with the child may be influenced by some unobserved historical health incidence or inherent health deficiency associated with the child's weight status. Because of the variations in unobserved factors among children, the mother's parental time input and child weight outcome are likely to be correlated. Any ordinary least squares (OLS) estimation of the health technology will be biased. Consequently investigations seeking to study such causal links must take the necessary steps to account for the phenomenon.

Although studies explaining the connection between parent's time spent directly with child and childhood obesity have provided some understanding into the subject, efforts to address the above issue are minimal. This study seeks to explore the matter by focusing on the association between mother's actual time spent with the child and child

¹ Endogeneity may also come from measurement errors and omitted variables

weight status using micro-level data from Parental Time, Role Strains, Coping, and Children's Diet and Nutrition project that targeted households in the Houston area, Texas. Unobserved health factors can be corrected using fixed effects methods and or instrumental variable (IV) methods. The former removes the problem based on differences in fixed characteristics of individuals within and between families and geographical locations (e.g. Anderson, Butcher & Levine, 2003; Chia, 2008). The later involves the adoption of unique variable(s) that would in this case be correlated with mother's actual time with the child but uncorrelated with unobserved health factors. This study adopts the later. Choice for instrumental variable methods (IV) over fixed effects is partly because the available data do not permit the conducting such analyses. Moreover, some fixed effects methods can be subject to measurement error bias and will only control for fixed unobserved health factors. IV methods on the other hand can manage both fixed and variable unobserved health factors. The technique will correct for endogeneity from all other sources (i.e., measurement errors, omitted variables). The strength of instrumental variable methods (IV) rests on the fact that it allows for estimating the coefficient of interest consistently free from asymptotic bias (Greene, 2003). The challenge lies in identifying a valid instrument (Murray, 2006). Such a variable should pass all relevant minimum criteria. Moreover its correlation with mother's time should not be weak; if this is so then the resultant IV estimates will be largely inconsistent and OLS will be a better estimator (Bound, Jaeger, & Baker, 1995).

Under ordinary theoretical conditions, prices, wages and exogenous incomes are regarded as appropriate instruments of health inputs. However, much of the data

demands cannot be met by this study. This work considers a two parent family. It draws from the parents' work-family role indicators, which represent parental resources and time demands.

This work finds that exogenous income is an insignificant IV. Instead, negative fathers' work to family spillover as a unique IV for mothers' actual time spent with the child. The variable meets all minimum criteria for a relevant and valid IV. Negative work spillover is a characteristic that is discussed widely within family relations and psychological literature as a potential cause of work to family conflict and an upset of the work-family balance (e.g. Greenhaus & Kopelman, 1981; Grzywacz & Marks, 2002; Voydanoff, 1988, 2004; Fagan & Press, 2008). Basically, negative fathers' work spillover occurs when fathers' poor experiences related to their jobs and time demands from the work place are transferred to the home domain. These experiences are manifested as feelings, attitudes, and behaviors that limit the father's physical and psychological availability to undertake home roles. Moreover, they add to the stress level and alter the manner in which the spouse performs the required home tasks. Several studies on the crossover influence between husband and wives indicate that fathers' stress and work pressure brought from work to home is linked to increases in the stress level of the mothers (Hammer, Allen, & Grisby, 1997; Bolger, DeLongis, Kessler, & Wethington, 1989; Westman & Etzion, 1995; Jones & Fletcher, 1993)², her role overload (Crouter, Bumpus, Maguire, & McHale, 1999) and their difficulties in balancing work and family responsibilities (Fagan & Press, 2008). In such circumstances, mothers

² These studies have also indicated a reverse link but in much smaller magnitude.

respond by being supportive and increase their involvement in home activities to compensate for reduced fathers' availability. This impact of the father on the mother is associated with gender role expectations whereby women regard family demands and involvement as more important than work related demands (Pleck, 1977; Voydanoff, 1988; Karambaya & Reilly, 1992). Thus, when faced with changes work-family conflict women will restructure activities and engage in extensive coping strategies to meet their family needs. It is probably this reorganization that compromises the quality and quantity of maternal time spent with children, thus affecting children's weight status. The most recent evidence seems to suggest that increased maternal stress through interaction with food-related factors may have an impact on children's weight status in food insecure families (Lohman et al., 2009).

If father's negative work spillover is a valid IV, then it should have no influence on children weight status. Recent explorations of this link have produced very conflicting results, demanding a more critical look at the subject. On the one hand, You (2005) found fathers' work to family spillover irrelevant in influencing the weight status of children in all samples³. Moreover, her study utilized two different estimators. On the other hand, McIntosh et al. (2006) found the same variable to be significant in only the 9-11 year olds⁴. The variable used in these analyses was built from a subscale developed from a range of items meant to capture the father's experiences related to work and family. This latter study employs some of the same variables and draws on six factors compared with the former. However, some of the factors utilized in the latter are not the

³ You(2005) examined the pooled sample, sub-samples of 9-11 year olds and 13-15 year olds.

⁴ McIntosh et al. (2006) examined sub-samples of 9-11 year olds and 13-15 year olds

same as those used in the former; consequently the variables constructed in the present study are somewhat different. The interest of this study is directed at a pooled sample of children aged 9-15 years⁵ that was either not studied (see McIntosh et al., 2006) or found to be non-responsive to the effect of fathers' work to family spillover (see You, 2005).

The remainder of this chapter is organized as follows. The next section presents a review of past studies addressing the effect of parental time allocation on child obesity with special attention paid to correcting for unobserved factors and the use of instrumental variables. The focus is on the two works that have targeted actual time spent with the child and works that have dealt with time away from the child. This is followed by a presentation of the theoretical framework. This section underscores the importance of household production theory in evaluating parental time investments and children's health improvement and sets the stage for the conceptual framework. Following this is the section on empirical methods, issues and tests in determining the proper IV adopted in this work. Data and summary statistics are described here, after which is then followed by a discussion of the empirical results. This chapter is ended by a presentation of concluding remarks and possible policies.

Literature

In general economic literature concerning the effect of parental time and obesity is small but growing. Other than studies on actual time spent with the child, research has also proceeded from the opposite side by examining relationships between parental time

⁵Investigations into sub-samples of child produced no suitable IV. Thus were left out.

away from the child and childhood obesity, specifically “parental employment”. The combination of both offers more weight to understanding the impact of parental time on the child’s weight outcome. Presence of the former which directly concerns this study is much scantier. In fact the search for this documentation led to the discovery of only two studies (You, 2005; McIntosh et al., 2006). Both of these are related in that they all utilize the same data and explore the effect of parental time, and work spill over on BMI. Inferences on endogeneity are implied but not exactly tackled. Major differences between two studies are in the methodologies.

Deviating from earlier works on time allocation and children’s outcomes, You (2005) incorporates children along with parents as part of the household decision making process concerning non market time allocation. Other works such for example Apps and Rees (2001) assume that children’s have no influence on the household decisions. Following a game theoretical means of the Stackleberg game structure, You (2005) assumed that parents act as leaders and the child as a follower in time allocation process to health attainment. The resultant solution is a Pareto optimal point at which the parents enjoy the gains achieved from their children’s health, partly contributed to by the time use decisions made by the children. Empirical analysis following this formulation involved the estimation of a system of equations that included the children’s health production technology, parents’ actual time spent with their children, along with several other decision-related variables. Suspecting simultaneous equation bias brought about by endogeneity of right hand side variables and correlated error terms, the author adopted iterated 3SLS as the estimator. For robustness, she compared these results with those

generated by the iterated seemingly unrelated regression (ITSUR) method. While the latter provided more significant results, it did not account for endogeneity in the system. The SUR method is advantageous for its ability to correct for correlated residuals between equations and yield efficient estimators even in small samples (Zellner, 1962; Kmenta & Gilbert, 1968). Instrumental variable methods such as 2SLS provide required estimates for endogeneity. However, it is important to note that 3SLS is more asymptotically efficient. But in single equations the 3SLS estimator is less robust given the inconsistency created should IV assumptions of a predetermined variable fail in any equation (Green, 2003).

McIntosh et al., (2006) took a more complicated approach of ratios of linear relationships of weight and height squared to unveil the relationship between parental time and children's BMI. In part, the approach was responsible for their adoption of the non linear seemingly unrelated regression (NLSUR) technique. The other reason was due to the possible existence of cross equation correlated errors in the system. Like ITSUR, NLSUR does not account for misspecification in any equation or endogeneity that could be due to other causes such as simultaneity between equations, which if present can have damaging consequences for results.

Possibly more efforts of dealing with endogeneity of parental time and childhood obesity are observed in works concerning time away from children, most particularly in the form of maternal employment. Primarily, employment time reduces the actual time invested in children. Endogeneity in these studies occurs mainly in the form of unobserved heterogeneity. Majority of these studies utilize longitudinal data (e.g., the

National Longitudinal Survey of Youth (NLSY)) the use of which can so easily take advantage of the various techniques that correct the endogeneity problem. For example, the work of Anderson, Butcher and Levine (2003) that sought explain the effect of maternal employment and child overweight dealt with this kind of bias from various routes. Amongst these was the use of long differences to control for unobserved impact of the mother's behavior during the lifetime of the child; sibling differences at a point in time to account for the unobserved mother's behavior; sibling differences at the same age to account for unobserved mother's work intensity; and instrumental variables (IV) to control for any variable unobserved heterogeneity. An extensive set of IVs was employed including state unemployment rate, child care regulations, child care wages, welfare benefit levels, and status of welfare reforms in the country. Results from this study revealed that IV results were not that different from point estimates suggesting little presence of omitted variable bias. This work found that mother's work intensity especially for the privileged promoted childhood overweight.

Ruhm's (2008) investigation on the same relationship between the mothers and adolescents encountered similar problems. In tackling the potential omitted variable bias due to correlation of maternal work hours and child outcome error term, he included many covariates as possible of the former to ensure it's orthogonality with the later. Additionally, the author adopted the child's birthday; the mother's year prior to employment; and employment status in the calendar year after assessment to further control for time and time invariant correlated unobserved factors. His findings also revealed that maternal employment greatly affected obesity for advantaged children and

that the growth in childhood obesity may be dependent on factors that are common causes of obesity to both the mother and the child.

In the same light, Chia (2008) employed Canadian data from the National Longitudinal Survey for Children and Youth (NLSCY) to tackle mechanisms between the mothers' labor supply and the probability that the child will be overweight. This particular work involved linking children's activities and mothers' work intensity to weight outcome. Similar to works mentioned above, Chia attempted to address the problem of endogeneity due to unobserved factors. However, only use of the sibling difference model was possible to correct for unobserved family fixed factors. Endeavors to apply instrumental variable (IV) method were unsuccessful. IVs that were adopted to proxy for the mother's work hours were provincial childcare policy variables, provincial unemployment rates, and actual and predicted maternal wages. All turned out to be non-predictors of mothers' work hours. Results from this study indicated that increased work intensity of the mother upon return to employment after the birth of a child was associated with increases in childhood obesity.

Somewhat different is the work of Cawley and Liu (2007) who directed their research to the effect of maternal employment on time child diet and physical activity and subsequently to obesity. Their study utilized data from the American Time Use Survey (ATUS). Attempts to correct for the presence of unobserved heterogeneity led them to adopt the instrumental variable approach, with state employment as the choice of an instrument. Findings revealed some evidence of endogeneity, given that corresponding F-value exceeded the critical Stock-Yogo values. In addition, it was found

that employed mothers spent significantly less time cooking, eating and playing with their children and were more likely to purchase meals outside the home.

Clearly, works on actual time spent with child have been less extensive in exploring the subject of parental time and children's weight outcomes and less rigorous in dealing with the bias that might result from potential endogeneity of the two variables. Given that both approaches are important in drawing conclusions about the effect of the mother's time on childhood obesity, it becomes necessary to also explore and correct for any possible presence of endogeneity between actual time the mother spends with children and children's weight outcome, which is what this study attempts to do.

Theoretical model

Decisions concerning a parent's time inputs and time costs to promote a child's healthy development are well placed among household production models. These studies have been instrumental in the assessment of various parental time choices as they regard children's health in terms of cognitive development (e.g. Datcher-Loury, 1988; Blau & Grossberg, 1992; James-Burdumy, 2005; Ruhm, 2008), illness (e.g. Pit & Rosenzweig, 1990), birth weight and deaths (e.g. Ruhm, 2000; Maitra, 2004) and most recently obesity (e.g. You, 2005; McIntosh et al., 2006; Ruhm, 2008; Scholder, 2007).

Within this theory, economic models seeking to explain children's developmental outcomes rely heavily on concepts from Becker's (1965) theory of allocation of time and or Grossman's (1972) framework of health production. Accordingly, underlying principles of these models argue that a child's health status is a

non-market commodity produced and directly enjoyed by the household. The commodity is generated via a health production technology to which the family allocates non-market time and market goods and services in an environment that is also constrained by available total time and income resources. The best possible input combination of time and goods that produces the desired level of health product is achieved via a utility maximization procedure.

Some like Becker (1965) have assumed a unitary household behavior with members having identical preferences and pooling their incomes to achieve these (e.g., Dickie, 2005). Although following this approach is advantageous for welfare analyses, it has several implications when considering an individual parent. The fact is that it becomes difficult to disentangle the impact of a one parent's resource allocation towards the health of their children, given that every parent has similar preferences. Moreover, many studies have indicated that parents exhibit inequalities when allocating resources; for example a given parent's income and the intra-distribution of household resources impact the amounts of time devoted to children, depending on their health needs, gender and age (e.g. Pit & Rosenzweig, 1990). Thomas (1990), Bourguignon, Browning, Chiappori, & Lechene, (1993) and Lundberg, Pollak & Wales (1997). It is argued that changes in an individual parent's income are important, regardless of whether such gains are a result of income transfers or market wage increases, after the value of time is taken into account. These alterations will induce the family to reallocate time and market goods within and across household production activities. Families will substitute away from the time- and goods-intensive activities when the value of time is high. Because the

health production of children is a time consuming activity, parents will change time inputs depending on whether or not it is regarded as a time-intensive product.

These failings are the reason why other researchers have supposed non-unitary household behavior when explaining children's health outcomes (see Pit & Rosenzweig, 1990). Non-unitary household models exist in several forms. They are linked together by the fact that they all consider that individual household members have different preferences and vary on how they reconcile these differences to reach a particular goal. Settling these differences can be achieved in co-operative bargaining manner (McElory & Horney, 1981; Lundeberg and Pollack, 1993) or non-cooperative bargaining way (Carter & Katz, 1992) or in a general collective way (Chiappori, 1992, 1997; Apps & Rees, 1997).

This work adopts a theoretical structure similar to the general collective model (Chiappori, 1992; Apps & Rees, 1997; 2001). The interest is to account for individual preferences in resource allocation rather than test for the distribution powers within the household. The latter is what many applications of the model have centered on. Consequently, sharing rules or welfare weights do not appear in this model. The framework could be regarded as having an inefficient outcome⁶. Given that we have data for a single time period, the structure adopted is static.

Consider a three person household constituting of a mother (m), a father (f), and a child (c), whose health status is H . All household decisions are made by the

⁶ The collective model assumes resolving differences within the household always attains a pareto optimal –efficient outcome. For such a point to be attained, there must be there must exist a unique sharing rule for members in the household (Chiappori, 1992)

parents. H is produced by the household via a technology to which parents allocate time and other goods expressed as;

$$H = h(t^m, t^f, \vartheta, \mu) \quad 2.1$$

where h is a function that defines the allocation of parental time t^m and t^f used to produce children's health (H), given the household characteristics (ϑ) that comprise of the child's personal characteristics and family characteristics; and unobserved health endowment known to the parents and the child that cannot be seen by the researcher (μ). This equation displays the technical relationships that are the primary concern of this study. The actual time mothers spend with their children adds to health by reducing obesity risk such that $\delta h / \delta t^m \leq 0$. The challenge lies in having consistent estimates about the function, given that the conditioning of parental time on the child's health endowment does not account for endogeneity. The presence of μ has the capacity to affect endogenous t^m in addition to creating a contemporaneous correlation between the predictor and error term. It is assumed that the function h has decreasing marginal productivity.

Assuming that parents exhibit egoistic preferences then each parent will derive utility from only own consumption of a composite market good (z) whose price is one, child health (H) and leisure (l^i); $i = m, f$. The supposition of the composite good is based on the fact that the data are cross-sectional thus households face the same prices. Given this, the mother will allocate her resources to maximize the utility function;

$$U^m = u(z, H, l^m) \quad 2.2$$

where u is a strictly quasi-concave, increasing and continuously differentiable function defining her own consumption of market goods, child health and leisure. However her allocation process must take into consideration of father's and child utilities that must exceed their respective reservation wages \bar{u}^f and \bar{u}^c such that;

$$U^f = u^f(z, H, l^f) \geq \bar{u}^f \quad 2.3$$

$$U^c = u^c(z, H) \geq \bar{u}^c \quad 2.4$$

The mother's decisions are further constrained by amount available time and incomes both of which are combined to go give a full income constraint represented as;

$$z + \sum_i w^i(t^i + l^i) = \sum_i(w^i T + A^i) = Y; \quad i = m, f \quad 2.5$$

Y is the full income earned from the market time (T) at the respective parental market wages (w^i) and exogenous/unearned income A^i . It also represents money spent on the consumption of a vector of household goods z whose price is one, parental time t^m and leisure l^i whose prices are wages.

The maximization of equation 2.2 subject to 2.1, 2.3, 2.4, and 2.5 yields reduced-form unconditional demands of parental decision variables of time allocations to children t^i , leisure l^i , and market goods z as functions of all exogenous variables in the model. For the sake of relevancy only the demand function for mother's time is given below;

$$t^m = \varphi(w^m, w^f, A^m, A^f; \vartheta, \mu) \quad 2.6$$

The above function implies that time mothers spend with their children is dependent on parental wages, parental exogenous income, household characteristics and an unobserved health endowment. The equation represents a typical demand function that

satisfies all relevant theoretical restrictions of Slutsky symmetry, adding-up, homogeneity and negativity. However, it is only the adding-up condition that has been consistent with empirical modeling. Substituting equation 5 into 1 yields a reduced demand equation for health; in this case the weight status of the child determined by similar factors and can be expressed as;

$$H = h(w^m, w^f, A^m, A^f; \vartheta, \mu) \quad 2.7$$

As long as mothers' time with their children and health status of those children are continuous variables, then OLS estimations of either of the reduced form equations 2.6 and 2.7 above provide consistent estimates of t^m and H , since μ are distributed independently of wages, incomes etc.

However, such analyses do not answer the central concern of this work, which regards the association between health status and parental time input described by production function 2.1. The effect of μ to t^m and H demands that one use instrumental variables. The proper set of such factors should enter the mothers' time function 2.5, but not the production function 2.1. The existence of 2.6 provides us with choices from a set of instrumental variables (IVs), which are the exogenous variables (income, wages etc.) related to endogenous mothers' time spent with their children but not to health status. The availability of exogenous variables presents the exclusion restriction needed to identify parameters of the health production function 2.1. Reduced form equation 2.6 is thus the starting point of our empirical estimation and is used to determine the relationships in structural equation 2.1. Given the joint determination of the parental input and child outcome, equations 2.6 and 2.1 will be estimated as a system.

Empirical methods

This work follows empirical structure laid down by Rosenzweig and Schultz (1983). The two instrumental variables used to estimate the impact of mothers' inputs to children's birth weight. Adopting function 2.6 assumes that we have all relevant data. Unfortunately, this is not so, as data on wages are lacking; thus variables w^m and w^f must be dropped.

In addition, very few parents reported non-earned incomes to facilitate estimation. However, many provided individual annual total income Y^i . Earlier studies using the same data set assumed this to be exogenous in the short run. This work supposes the same and the variable is used to replace the parental non-earned incomes. Due to the potential of self-selection bias between working and non-working mothers, mothers' total income is excluded.

Furthermore, given the extensive nature of family resources, the IV set is augmented to include parental work-family variables, in particular the fathers' work to family spillover variable that reflects the demands on the amount and quality of time that parents invest in their children. The spillover of parental work into family activities is randomly distributed among households and thus assumed to be independently distributed of μ .

Considering the above statements, equation 2.5 is transformed into 2.8. Variable S^f represents the fathers' work spillover as the additional IV. Since this study focuses on mothers' time spent with their children, fathers' time with children (t^f) is dropped from the equation leading to 2.9.

$$t^m = \varphi(Y^f, S^f, \vartheta, \mu) \quad 2.8$$

$$H = h(t^m, \vartheta, \mu) \quad 2.9$$

Assuming linear relationships of the mother's actual time spent with the child and child health production functions, the empirical system of equations is specified as;

$$t^m = \beta_{10} + \beta_{11}Y^f + \beta_{12}S^f + \sum_{i=1}^n \beta_{1i}\vartheta_i + \varepsilon_1 \quad 2.10$$

$$H = \beta_{20} + \beta_{21}t^m + \sum_{i=1}^n \beta_{2i}\vartheta_i + \varepsilon_2 \quad 2.11$$

whereby the β s represent coefficients associated with empirical estimation. $i = 1, \dots, n$ represents the number of household characteristics related to children's weight status and time allocation. ε_1 and ε_2 are the error disturbance terms associated with each equation. This system consists of two equations, two dependent variables and two excluded IVs.

Estimating any system of equations demands a qualification for identification of each equation. Equation 2.10 is already identified by the fact that it is a reduced form equation. In determining the identification of the child health equation, we draw from the exclusion criteria of the order condition, which requires that the number of predetermined variables excluded from an equation be at least as large as the endogenous variables included (Green. 2003). The number of endogenous variables included is one ($= t^m$), while predetermined variables are two ($= Y^f, S^f$). Thus, equation 2.11 is qualified as over identified by the number of excluded IVs. It is possible that the predictability of one of these variables is zero, in which case equation 2.11 would be just identified. Satisfying the order condition will usually ensure that the rank condition is met but not always. The rank condition of identification would require that there exist at least one non zero determinant of order $(M-1)(M-1)$ of coefficients of

variables excluded from 2.11 but included in 2.10. M would be number of endogenous equations and variables. In this case, we have a 1×1 matrix which means that β_{11} or β_{12} must be at least no zero.

This specified system resembles a recursive structure/triangular system in which case the matrix of coefficients of endogenous given 2.10 and 2.11 is;

$$\begin{array}{l} \text{Equation 9} \\ \text{Equation 10} \end{array} \begin{array}{|c|c|} \hline t^m & H \\ \hline 1 & 0 \\ \beta_{21} & 1 \\ \hline \end{array}$$

As long as the error disturbances are not correlated, i.e. $cov(\varepsilon_1, \varepsilon_2) = 0$, any equation using an OLS estimation will produce consistent estimates. However, this is unlikely as relationships such as these are never fully specified. Thus, error terms ε_1 and ε_2 will be correlated through the effect on endogenous mothers' time spent with the child causing further inconsistent estimates. The problem can be controlled by use of an IV estimator, which can be from a limited information method or full information method.

In view of these problems and goals, this work adopts two-stage least squares (2SLS) method. This is a type of limited information least squares method that is able to consistently estimate over identified equations and determine the appropriateness of IVs. Suitability of 2SLS is based on the fact that there exists endogeneity between two dependent variables. This work will determine whether the phenomenon exists, using Durbin-Wu-Hausman tests, whose null hypothesis assumes that mothers' actual time is exogenous. The test follows a χ^2 distribution with k degrees of freedom equal to number of endogenous regressors. A rejection of the null indicates the presence of endogeneity.

Mechanically, 2SLS works in two stages. In the first stage, all exogenous variables in the system are regressed on t^m to obtain its predicted values (t^{m*}). t^{m*} is used as the IV to predict the impact of maternal time on child's weight status. The method is robust against specification errors and problems associated with multicollinearity. In guarding against specification errors, 2SLS works on one equation at a time without taking into account other equations in the structure and thus stopping the spread of errors throughout the system. However, its superiority over other IV estimators is limited to small samples.

Although 2SLS method offers several advantages, it assumes independent and identically distributed (i.i.d.) errors. If this assumption is violated, then its power to produce the most efficient estimates breaks down. Consequently, for robustness the 2SLS estimates are contrasted with those from alternative IV estimators, including limited information maximum likelihood (LIML), Fuller (k) and the generalized method of moments (GMM). If the residuals are heteroskedastic, then GMM better estimator. GMM takes into account non-i.i.d errors by attaching a weight that corrects for the behavior. If instruments are weak the LIML provides more meaningful information than 2SLS or GMM (Hahn, Hausman & Kuesteiner, 2004). Fuller-k-estimators are modified versions of the LIML estimators. While for LIML $k=1$, the liml eigen value for Fuller is $-k = \lambda - (\alpha/N - L)$. L is the number of excluded instruments and N is the number of sample observations. α is a user specific constant which has been suggested to be equal to 1. It is also stated that Fuller performs better than 2SLS when instruments are weak yet also assumes i.i.d errors. In general, while IV estimators strive at achieving

consistent estimates, their results are not unbiased (Fuller, 1977; Baum, Schaffer, & Stillman, 2003, 2007; Donald & Newey, 2001).

If father's income and work to family spillover are suitable IVs, then they must pass all relevant empirical tests. Obviously, none of these IVs should be redundant in the first stage, i.e., they should significantly predict mothers' time spent with their children. In determining the validity of the choice IVs in the first stage, this study uses the F-test of joint significance (Bound, Jaeger & Baker, 1995). However, other tests such as Partial R^2 (Bound, Jaeger & Baker, 1995), and Shea's Partial R^2 (Shea, 1997) exist. The null hypothesis of the F-test is that the excluded instruments do not predict mothers' time spent with their children. The alternative assumes otherwise. The significance of this χ^2 distribution test would imply that the excluded IVs are relevant. The test, along with the other tests discussed, can be misleading given that it could turn out to be significant, even though not all IVs are significant (Baum, Schaffer, & Stillman, 2007). These checks are further criticized for their lack of critical values for weak IVs. Staiger and Stock (1997) suggested to consider an IV weak if the first stage F-statistic < 10 .

Therefore in addition to this, tests of under and weak identification of excluded IVs are also employed. Tests of under identification determine if the excluded instruments are relevant, i.e., if they are correlated with the endogenous mothers' time spent with their children. The null hypothesis is that the equation is under identified, otherwise the alternative is assumed to be true. Tests are either the Anderson's canonical rank correlation, Lagrange multiplier (LM) test (Anderson, 1951), and Cragg-Donald Wald statistic (Cragg & Donald, 1993) that assume i.i.d error or the Kleibergen -Paap

rank statistic (Kleibergen & Paap, 2006), which assumes non i.i.d errors. The first two are applicable under 2SLS. The second is relevant for Fuller (k) and LIML, while the third is applicable under GMM. A rejection of the null means that equations are identified and instruments are important predictors. But this does not rule out the presence of weak correlation.

Whenever excluded IVs are only weakly correlated with the endogenous regressor, weak identification results. The above estimators will provide poor results, some more than others (LIML is the most robust). Tests based on Cragg and Donald F-statistic for i.i.d errors (for 2SLS, Fuller(k), LIML) and Kleibergen-Paap rank F-statistic for non i.i.d errors (for GMM) help in deducing incidence of the phenomenon. The decision rule is based Stock and Yogo's critical values developed for various k-estimators and also for GMM.

The exclusion of both income and fathers' work to family spillover suggested an over identified system. This is the case if none of these variables are redundant in predicting mothers' time with their children. In this regard, checks of over identifying restrictions must be applied. Basically, these tests determine if the instruments are valid. The study will employ two types of tests including Hansen's J-statistic (Hansen, 1982) for GMM when errors are non i.i.d. and Sargan's Statistic (Sargan, 1958) for 2SLS when errors are assumed i.i.d. The null hypothesis is that instruments are uncorrelated with the error term and that they are correctly excluded. Rejection of the null means otherwise and creates suspicion regarding the choice IVs. If one of the IV is insignificant in the first stage, then these tests will be rendered irrelevant.

This work takes advantage of STATA's `ivreg2` procedure which incorporates all these statistical tests and can enable deduction of valid IV. Two types of estimations are conducted (i) involving only children's and parental personal characteristic as right hand side variables and (ii) addition to (i) children's and parental behaviors specifically children's eating food from restaurants, children's breakfast behavior, and the parents' breakfast and exercise behavior are included. Being aspects of both maternal time and health, there is reason to believe that information from these might reduce on the predictability of IVs in the 2.9 and thus reduce the impact of mothers' time.

Data

Sample

The data for this study comes from the same source as that used McIntosh et al. (2006) and You (2005), which is the Parental Time, Role Strains, Coping, and Children's Diet and Nutrition project performed at Texas A&M University. The project was conducted on about 300 households in the Houston Metropolitan Statistical Area (MSA) between 2001 and 2002. Data was gathered through administration of surveys on various issues concerning health, nutrition, work, time allocation, earnings and expenditures; and taking anthropometric measurements of children aged 9-11 and 13-15 years. Parents' provided self-reported data on their height and weight. Families of children aged 12 years were not included due to the onset of puberty at that age. Information was collected from both single and dual-headed families. This particular work focuses on only the later. For more details regarding the procedures of the project

we refer the reader to McIntosh et al. (2006). This study seeks to understand the effect of mothers' time spent with their children on those children's weight status, while exploring and tackling unobserved heterogeneity. The focus is on the pool of children and adolescents rather than their sub-categories. The reason is that the sub-groups provided no significant results regarding the association between mother's time and child health when IV methods were applied. The total sample constituted 226 but the presence of missing variables reduced to 193 observations. This analysis is based on the latter. Below we describe each variable included in the model. A brief presentation of their description and corresponding statistics can be found in Tables 2.2 and 2.3, respectively

Dependent variables

Based on the system of equations, the dependent variables include the mother's actual time spent with the child and the health outcome (H), which in this case is the weight status of the child.

Mothers' actual time spent with their children t^m represents the average time in minutes the mothers spent with their children on an average day. The variable was computed based on time diary data obtained over a two-day period. The benefits of using time diary data are well known (Juster & Stafford, 1991). Parents were provided diary charts and asked to indicate activities in which they had engaged, how much time was spent in each activity as well as where and with whom this time spent for each day. The time spent with their children is regarded as that difference between total time present in

a day and the time the parent does not spend with the child. This variable is representative of that time primarily spent with child whereby the parents' attention is directed towards their children. Children may also be in the presence of their parents but as secondary beneficiaries of that parental care, given that parent might be engaged in another task of higher priority. In this case, parents would consider spending time with their children a secondary activity. It must also be stated that this amount of time is not a reflection of quality time, which would require taking into account the type of activity the mother was engaged in with the child. While such information is very meaningful, it would reduce the sample substantially, making it difficult to pursue empirical analysis.

The measure of weight status utilized in this study is the body mass index (BMI) of the children. The variable was generated as the body weight in kg divided by the height in meters squared of the children. Scientifically, the measure is considered a valid and reliable indicator of weight status (Dietz & Robinson, 1993). Based on the BMI-for-age growth charts, a child may be classified as being underweight for BMI value between 85th and 95th percentiles and obese for BMI values equal or greater than 95th percentile (CDC, 2009b). For reasons of maintaining a sizable sample, this work favored the continuous measure as computed above over the categorical approach to BMI.

Independent variables

All together, independent variables refer to household characteristics. However, they fall into two groups including those that form the potential excluded instrumental variables (IVs) and those that do not.

The *non-IV household characteristics* comprise the children's and parents' variables, some of which are behaviors that define the household's obesity enhancing environment. All these factors can influence the children's weight status and the parent's time input, therefore are included in both the health input equation and weight status equation.

The child specific variables considered include gender, race, level of maturity, age and dietary behaviors such as breakfast, eating food from restaurants and level of physical activity. These factors relate readily with parental preferences for time allocation and obesity. While mothers are generally seen as equally caring all of their children, a handful of studies suggest that they tend to interact more with the same sex children, especially among adolescents. For example, Tucker, McHale and Crouter (2003)'s work on two parent families with adolescents indicated that mothers spent more time with daughters, likewise fathers spent more time with sons. Similar results were found by Starrels (1994). On one hand, allocation of time from the parent's side may be influenced by shared interests or nurturing of similar roles. On the other hand, children may seek out the same sex parent, based on the activity they wish to pursue. Comparable findings regarding parental time preferences and infants can be found in Belsky (1979).

In terms of the *age* of children, studies have also indicated that mothers tend to spend more time with younger children compared to older children. For example, Bryant and Zick (1996) found that on average mothers spent 0.25 hours more with younger children compared to older ones. Likewise, it is also known that weight status increases with age in children. Although physical growth is also affected by the age squared of

that individual, this work purposely leaves this variable out to minimize on the effects of multicollinearity brought about by presence of both aged squared and the age of the child. Age of the child is included as months of age.

A lot remains to be learned about the distribution of parental time by *race/ethnicity*. Literature concerning such relationships provides few results. It is possible that parents may allocate time differently due to customs and traditions. Consequently, the inclusion of race variables is to capture these culture differences. Unlike parental time, research has found that increases in overweight among children differs by race with Hispanic and Mexican American children being more susceptible while white American children being least susceptible (e.g. Ogden et al., 2010). In this study, the race of the children is characterized by three separate dummy variables indicating as to whether one is black, white or Hispanic. However, in the empirical model, the child being black is excluded, given that it is regarded as base.

Children's behaviors included those dietary and activity practices that directly affect weight outcomes in children. Dietary behaviors contribute to the energy intake into the body while activity practices contribute to its expenditure by the body. Taken together, energy intake and expenditure determine the body weight outcome. While we consider this a direct relationship between children's BMI and behaviors (given that children are not part of the decision making process), it is possible that this may not be the true association. Instead, the real process may be through a choice or allocation mechanism similar to that described for parental time above; in which case children would undertake the behavior after considering available alternatives in terms of costs as

well as benefits. Several of the practices adopted for study are from nutritional, behavioral and medical literature. In the case of *breakfast*, increasing evidence from both cross-sectional and longitudinal studies suggests that the behavior contributes to reducing weight status (e.g. Gibson & Sullivan, 1995; Barton et al., 2005; Fiore et al., 2006). Using NHANES III data Fiore et al. (2006) found that adolescents who had breakfast were shielded from obesity. Likewise, Barton et al. (2005)'s ten year study found a negative association between the frequency of having breakfast and BMI. In our study, breakfast intake is considered as the estimated number of days per week children undertake the behavior. The effect of *physical activity* on weight status in children has been widely studied. The practice burns energy and leads weight loss. The direction of its impact is expected to remain the same in this study. Here children were simply asked to indicate whether they had participated in the activity for at least 30 minutes five days a week and or not. A dummy variable was coded 1 for 'yes' responses and 0 for 'no' responses. *Eating food from restaurants* is expected to increase obesity due to restaurant meals' higher fat content and larger portion sizes. The factor was captured as the as the number of times over the past seven days the children practiced the behavior.

The specified children's behaviors can also influence or be a reflection of the parents' time choices and demands by their children. Take for example the case for breakfast, some parents regard this to be a very important meal of the day and will make time to ensure that their children partake of the meal before leaving the house. In a recent blog entitled Parents talk back (2009), one parent stated that she did not mind if her child skipped lunch, but she considered breakfast to be a non-optional meal and

would be willing to force her child to eat the meal. In yet another parent poll, as much as 19% of parents contacted indicated that they always had breakfast with their children, while 28% usually did the same and 40% sometimes eat breakfast with their children (Highlights Parents.com, undated).

The *non-IV parental variables* included are both mothers' and fathers' weight statuses. The importance of these factors is that they partially account for children's genetic susceptibility to obesity, as has been well demonstrated within economic, medical and socio-behavioral literature. For example, Anderson, Butcher and Levine (2003) found that mothers' weight status had a substantial impact on children's weight status. Others have found similar results (McIntosh et al., 2006; You, 2005). Studies on how parental weight status influences their allocation of time to children are nearly nonexistent. You (2005)'s findings found a non-significant relationship between the two variables. Since the model specification allows for its inclusion, this study is interested examining the relationship further. In this model parental weight statuses appear as the BMI calculated in the same manner as that for the child. An adult is considered underweight if the corresponding BMI < 18.5; healthy weight if the BMI is 18.5 < 24.9; overweight if the BMI is 25.0 < 29.9 and obese if the BMI < 30 (CDC, 2009b).

In addition, the model includes *parental age* in years and college-level education (yes= 1, 0 otherwise). These factors demonstrate resource capabilities of the household. According to (Bryant & Zick, 1996), an increase mothers' age tends to reduce her time spent with children. This could be a reflection of priorities of the children's needs or age of last birth. It may also be due to reduced energy levels in the parent and increased

competing demands between work and family. The impact of parental age on childhood obesity has gone largely ignored. Some studies have linked parental age to power differences between spouses (McIntosh et al., 2006; You, 2005). However, age when coupled with education is representative of accumulation of wealth/resources over life cycle, increasing access to healthful resources (Ross & Wu, 1996). What this suggests in our case is that older, better educated parents are likely to be richer and may be more capable of providing health-enhancing resources to counter obesity. Including both age and education captures this effect. This information also suggests a possible interaction factor between the two. However, preliminary analysis found such a factor to be insignificant and thus it was dropped.

By itself, *parental education* stands out as one of the most influential factors in resource allocation to health improvement. It attached to the human development capacity of the parent. Several studies have determined that highly educated mothers allocate more time to their children because they perceive greater benefits to the healthy development (e.g. cognitive development) of their children (Guran, Hurst & Keaney, 2008; Bryant & Zick, 1996; Liebowitz, 1974; Sandberg & Horferth, 2001). This justifies why it should be included as a covariate in mothers' time equation. The role of education in explaining health outcomes development has been strongly related to improvement in health knowledge and accounting for health enhancing background factors (Hannan, & Wendling, 2010; Wolfe & Behrman, 1987). This association causes one to consider it as a covariate in the both the time and children's health regression. Only mothers' education is included as the as the father's education was found to be redundant.

Other parental variables that might influence obesity behavior of the child include the *mother's physical activity, breakfast patterns* and *eating out habits*. The first two behaviors were captured in the same manner as they were for the children. Eating out habits is included as the number of times mothers' eat away from home.

Based on equation 2.8, the *excluded instrumental variables (IVs)* comprise fathers' total income and father's work spillover that do not enter into the children's health production function 2.9.

Fathers' income was computed based on various information concerning earnings received by fathers. Parents provided data on weekly and/or monthly earnings from various work activities. These values were transformed into individual annual earnings from work and summed, along with any non-earned income to create the measure of total income. Income measures such as these are subject to various problems, the most common being measurement errors, given that most people rarely report their true incomes. A second reason has to do with the potential endogeneity between health status and income. Specifically, children's health outcome and income are jointly determined, making income an unsuitable IV. Parents with healthier children may participate more in work activities, increasing their incomes. At the same time, increased incomes may cause parents to invest in more health services for their children. In addition, the variable is subject to measurement. One may choose to ignore the problems based on justifiable reasons or correct for it by using instrumental variables (e.g., Ettner 1996). By assuming exogeneity of income, this work ignores the endogeneity problem.

Only the fathers' work to family spillover was adopted as an IV. The same variable for mothers was found to be a redundant predictor of mothers' time with children and children's health outcome. The variable was generated from scale 6 work and family experiences listed in Table 2.1. These experiences reflect physical and mental exhaustion and inability to participate in parenting activities. Parents were asked to rank themselves on a scale of 1 to 5 representing the level of agreement with which they encountered these experiences. A 1 indicated strongly agree whilst 5 indicated strongly disagree. These rankings were analyzed using a common factor analysis procedure. For each of these analyses, the factor loadings and scores are presented below.

Table 2.1: Father's Work to Family Experiences

Experience	Factor Loading	Score
a. I experience conflicts between my work responsibilities and my family responsibilities	0.48759	0.13996
b. I sometimes miss out on the pleasures of being a parent	0.52171	0.17701
c. I worry about the effects my job may have on my children	0.61212	0.22343
d. My problems at work spill over into my family.	0.65882	0.22897
e. I feel stressed out by my work.	0.70238	0.31069
f. I feel frustrated by my job	0.5757	0.185

Cronbach's alpha = 0.9995; Variance explained = 104%

Each of the variables loaded well in same direction exceeding the set value of 0.30 in this case meaning that they formed the same scale. The value of Cronbach's alpha very high nearly close to 1 the maximum attainable limit while variance explained by variables in the scale above 100%. Father's work spillover for each child was calculated based on, respective ranks that parents attached to their experience. This scale

deviates from that developed by McIntosh et al., (2006) and You (2005) by including experiences e and f otherwise it is similar in experiences a to d.

Summary statistics

Summary statistics for all variables used in this study are presented in Table 2.3. The mean BMI of children in the sample is 20.76 Kilograms/meter² with lightest child weighing 14.33 Kilograms/meter² and the heaviest child weighing 45.97 Kilograms/meter². However, these are not based on the CDC's percentile charts for classifying children's body weight, so it is not possible to determine whether the child is obese or not.

Statistics also indicate that on average, mothers' time spent with their children on a typical day is 107.43 minutes. Some mothers spent no time at all with their children, while others spent as much as 539.50 minutes or approximately 9 hours a day. The variation in time allocations from the mean is quite high, indicated by CV value of 97%.

Regarding household characteristics, means of the dummy variables (coded as either 1's or 0's) represent the proportion of those respondents with a score of 1. Thus, 12% of all children are Hispanic, 79% are white, 48% are girls while 59% indicated that they are mature. 67% of children in this sample indicated that they exercised for 30 minutes at least five days a week. The fraction of mothers who did the same is much lower in our sample registering only 36%. However, most mothers in this sample had received some college education, the corresponding proportion of which is 69%.

On average children's age was 143.26 months showing very little variation from the mean at 18.2%. Mean ages of parents appear to be very close with a difference of about 2.34 years although the dads appear to be much older than the mothers on average. The very small variations in CV suggest most parents are very close to mean. Likewise the mean BMI of both parents are very close, averaging 25.38 Kilograms/meter² for mothers and 27.70 Kilograms/meter² for fathers. By CDC standards for adults, these figures fall within the overweight category which could suggest that children are more susceptible to overweight. However, some parents in this sample are also underweight with BMI's of close to 18 Kilograms/meter² or obese with BMI close to 46 Kilograms/meter². Although the average number of times children eat from a restaurant is less than one (=0.78 time/sevens days), some children obtain food from the same as many as 8 times. Trends in breakfast habits between children and parents are very close with respective means indicating 5.66 and 5.16 days per week. Some children take advantage of this kind of meal all week long. Similarly, some parents do the same.

On average, most fathers earn 80,177.16 dollars a year with some as receiving as little as 600 dollars, while others reported as much as 283,044.00 dollars a year. The average income of this sample is much higher than recorded national average of 50,000 dollars in 2002 when the survey was done. This suggests the households in this sample have relatively high socio-economic status. The mean score of fathers' work to family spillover is 2.29, which was near the midpoint on the scale. However, the CV is very low suggesting that most parents' spillover indicator is close to the mean value.

Empirical results

Test of endogeneity

As mentioned earlier the use of IV is based on the suspect of endogeneity of mothers' time spent with children. The Durbin-Wu-Hausman test from systems estimation, including fathers' income and work to family spillover as IVs, indeed indicates that this is so. The test statistic is 7.12 with a corresponding p-value of 0.007, implying that we should reject the null hypothesis for exogeneity of mothers' time. The significance of the test remained after dropping the redundant income variable and upon adding more household characteristics. The corresponding values in this case are 8.27 and 6.16 and p-values are 0.004 and 0.013 respectively.

First stage results

The second column of Table 2.4 gives the first stage OLS estimations when income and spillover are used as IVs. Results indicate that while fathers' work to spillover significantly predicts mothers' actual time spent with their children. A one unit change in fathers' work to family spillover leads to increase in mothers' time by 22 units. However, the income coefficient is redundant, suggesting that it is not an IV this case. Findings by You (2005) also indicate no significant relationship between mothers' time with their children and fathers' income in the pooled sample. However, others including Kimmel and Connelly (2007) found a complementary causal link between the mothers' child care time and her husbands' income suggesting some form of specialization on the mothers' part. But then again these authors used longitudinal data

rather than cross-sectional data as in our case. The corresponding F-statistic of the excluded instruments is 5.36, which although significant, falls below the suggested critical point of 10 by Stock and Yogo (1997). This signifies weak IVs, possibly brought about by the insignificant income variable. Based on theory, the decision is to drop income.

The significant effect of fathers' work to spillover on mothers' time spent with their children was maintained upon re-estimation of the system. The third column of Table 2.4 gives these results. The strength the variable as an IV increased to a great degree with the F-statistic reaching 13.11, greater than the set Stock and Yogo critical value of 10. The direction of its impact remained the same with a slightly higher magnitude of the coefficient. That is, a one unit increase in fathers' work to family spillover leads to increases in mothers' time with their children by 24 units. This effect of spillover is expected, given the fact that earlier works have suggested that stressful work reduces energy levels. In this case, a high level of job demands depletes the energy levels of fathers both mentally and physically, which causes them to be less involved with their children. In this situation, mothers are forced to increase on childcare time to compensate for the father's unavailability.

Education of the mother also appears to be a very important factor in determining the time spent with the child. Findings indicate that a mother's receipt of college education increases time spent with her child by 41.6 units. These results are similar to earlier findings by Guran, Hurst and Keaney (2008) and Liebowitz, (1974) who found

that more educated mothers spent more time with their children. Their studies related more to the human capital development of the child.

These same relationships are maintained upon adding behavior variables, whose first stage results are shown in Table 2.6. The only notable difference is the slight decrease in the F-statistic to 13.08 due to the IV, which is still above the set minimum cut point of 10. Information from children's and parents' habits had no effect on mothers' time allocation to their children.

Second stage regressions

Results are presented in Tables 2.5 and 2.7. In the former household characteristics are limited to children's and parent personal characteristics in the equation and the latter adds behaviors to this equation.

It can be observed from Table 2.5 that there is consistency across all estimators with GMM slightly out performing other's methods. Mother's actual time allocated to the child is shown to significantly reduce the child's weight status. This result is similar to other findings by McIntosh et al. (2006) and You (2005), although their results were based on sub-groups of children by age. This effect of mothers' time on weight status has been associated to their availability to prepare and monitor nutritious meals for children as well as discourage sedentary activities. Evidence concerning working mothers shows that they lack time to make nutritious meals or supervise children's eating those meals (Cawley & Liu, 2007). Also, children with employed mothers spend a substantial amount of time watching TV compared with children of non-working

mothers, which in turn promotes obesity (Fertig, Gloom & Tchernis, 2009). Although You (2005)'s own findings demonstrate the opposite in the pooled sample, results showed that fathers' meal time preparation decreased weight status of 13-15 year olds.

Other important variables affecting children's BMI include children's age, parental weight status and fathers' age. Increase in children's age by one month results in an increase in their weight status by over 0.07 kilograms/ m² in all estimators. The same positive relationship is exhibited with parents' weight status, but with the impact of the mothers' BMI being more pronounced than that of fathers.' In the case of fathers' age, older fathers are likely to promote reduction in weight status of the children compared to younger ones. That is, a one year increase in fathers' age will decrease children's weight status by over 0.16 kilograms/ m². All other variables are insignificant.

All tests of IVs based on second stage regressions are consistently significant. The significant under identification test indicates that fathers' work spillover is a relevant and valid IV. The null for weak identification is rejected at the 15% maximal IV and LIML size and at 30% maximum and relative fuller bias based on the Stock and Yogo. Thus, the impact of fathers' spillover in indentifying the effect of mothers' time spent with their children on a global scale (pooled sample) is quite strong.

Upon adding the children's and parents' habits as exhibited in Table 2.7, the same direction of relationships seem to persist. 2SLS, LIML and fuller(k=1) show consisted results most probably because they assume i.i.d. error. Using these methods, the impact of mothers' time spent with their children is reduced slightly in both magnitude and significance (i.e., significant at the 10% level). Similarly, all other

coefficients are reduced in size. The relationship involving mothers' breakfast consumption becomes significant at 5% level. In other words, the mothers' ability to eat breakfast will result in a reduction in the weight status of their children.

The GMM estimations, however, differ by showing mothers' time spent with their children is significant at 5% level of significance. With exception of parental weight statuses, the influence of all other important variables is unchanged. Mothers' and fathers' BMIs are now significant, but only at 10% level. As with the other estimators, the size of the coefficients falls. All other variables are not important. These differences in estimators could be due to heteroskedasticity brought about by introducing the additional factors.

Concluding remarks

This study set out to examine the effect of mothers' time with their children on children's weight status, while controlling for unobserved factors. Unobserved factors have the ability to cause mothers' time to be endogenously correlated with children's weight status distorting any meaningful interpretation. Using cross sectional data, this work employs and corrects for the problem, using IV estimation methods. In particular, this work utilized 2SLS methods, whose results were compared with those from LIML, $\text{fuller}(k=1)$ and GMM for robustness. Based on a theoretical model, the choice of IVs included income and fathers' work to family spillover.

Results indicate that the impact mothers' time spent with their children is endogenous. It was also found that fathers' work to family spillover increases mothers'

time with their children, which in turn reduces children's weight status. Fathers' work to family spillover was found to be a valid and relevant IV for mothers' time spent with their children, passing all relevant tests and was robust across all estimators. The negative relationship between mothers' time spent with their children was consistent with earlier results that did not use IV estimations and were based on sub-group samples. Previous studies did not find the same relationship in pooled samples, possibly because it was being masked by effects of unseen factors.

Along with fathers' work to family spillover, this study finds mothers' college education to be a significant determinant of the mothers' allocation time to their children. Regarding children's weight status, important factors include children's age, parental weight status, fathers' age and mothers' breakfast habits.

Policy

Findings clearly demonstrate an interaction between the parental work, family time and childhood obesity. While fathers' job demands have no direct influence on children's health on a global level, their impact is channeled through the mothers' time allocation to their children. Because mothers continue to have most of the child care responsibilities in families, alternations in time spent with their children are bound to have a substantial impact on their children's well being.

Results from this study emphasize the need for reforms that integrate parental work demands and children's health needs. Central to these reforms should be parental work flexibility and paid leave to make available more time to mothers and fathers to

share in the task of childcare. Such reforms are more necessary today, given the changing American family structure. More children are being raised in family where both parents work full time compared to 40 years ago. This means a reduced work-family balance for the parents and reduced quality time in the provision of childcare, especially for working mothers (Council of Economic Advisers, 2010).

Aspects of work flexibility take on various forms, including picking one's own work schedules, flexibility in the work place (e.g., working at home given today's internet availability), and reduced work hours with low penalties for shorter hours. The existence of these practices offers some degree of control over work activity to the parents such that they can spend more time with their children when needed. Furthermore, these benefits are not limited to the parents, but extend to business organizations in terms of decreased costs associated with turnover, absenteeism, and lower productivity (Kornbluch, 2004; Sloan Work and Family Research, 2005; Cooperate Voices for Working Families, 2008).

Likewise, the provision of paid parental leave makes it possible for parents to spend quality time with their children with fewer worries about their work. These occasions are very important, given that parental time contributes greatly to the healthy development of children. One state that has enacted a comparable policy is California, whose paid family leave program reimburses employees that have recently had a child. The program is for both fathers and mothers, making it easier for them to deal with spillover and crossover effects between spouses. However, it is important that this

regulation be extended to parents with adolescents. Moreover, its adoption by other states would improve children's health.

Overall, few U.S. organizations have adopted such family-friendly policies. A major reason is that firms differ in cost-benefit structures and in the degree of competition they face. Companies experiencing less competition tend to shy away from such policies (Council of Economic Advisers, 2010). In addition, there is lack of economic information regarding benefits and costs associated with these policies, such that many tend to overestimate the costs of adopting them and have little information about their potential benefits. This deficiency in data is also the major problem for the researcher, leading an incomplete understanding of the problem. Aside from cost-benefit information, there exists little literature pertaining impacts of these family-friendly regulations in terms of productivity, turnover, health, and childcare, further limiting sound policy formulations. If these policies are to be considered in the future, it is important that these information limitations be addressed. In line with this work, future studies about the links between parents' work flexibility patterns and paid family leave and children's weight status would better inform policy makers as they attempt to combat children's obesity through alteration of work policies.

CHAPTER III

BEHAVIORS AND CHILDHOOD OBESITY

Introduction

It is well known that behaviors and lifestyles are major contributors to the weight status and overall health of the individual. Consequently, understanding children's behavioral patterns might provide opportunities for addressing the current obesity tendencies. The fact is that once these behaviors are adopted they may continue through adulthood, which can affect long-term health and weight status (e.g. Gordon-Larsen, Nielson & Popkin, 2003; Mikkila, Raasanen, Raitakari, Pietinen, & Viikari, 2005).

Obesity is an energy imbalance condition that results when more calories are consumed than can be expended by the body. This makes nutrition and physical activity behaviors central to the development of obesity. This chapter explores the effect of three practices by children including breakfast consumption and fast food consumption, specifically eating food or drink bought from a convenient store on children and adolescents' weight outcomes. The first two behaviors are important inputs of nutrient intake (Nielson & Popkin, 2003; Rampersaud, 2009) while the third is considered vital in the modulation of leptin and ghrelin hormones essential in the regulation of body weight and metabolism (TaHERi et al., 2004). Patterns of the above behaviors have varied overtime among children which could explain changes in prevailing weight outcomes.

Breakfast is considered to be the most important meal of the day offering nutritional, cognitive, and health benefits to the body (Miller et al., 1998; Rampersaud, 2009). The importance of breakfast for weight status possibly lies in its contribution to nutritional adequacy and dietary behaviors. By consuming breakfast, children and adolescents attain a high proportion of total daily energy that cannot be compensated for by consuming other meals (Nicklas, Reger, Myers, & O'Neil, 2000; Skinner et al., 1985; Morgan, Zabik, & Stampley, 1986; Sjoberg, Hallberg, Hoglund, & Hulthen, 2003; Sampson, Dixit, Meyers, & Houser, 1995). These studies have determined that the total daily energy intake of breakfast eaters is higher than that of breakfast skippers. High energy intake at breakfast has been associated with lower BMI (Summerbell, Moody, Shanks, Stock, & Geissler, 1996).

Children and adolescents who skip breakfast are likely to have poor diet habits that may promote the development of obesity. Breakfast skipping is linked to increased frequency of eating snacks (Dubois, Girard, Kent, Farmer & Tatone-Tokuda, 2009; Wolfe & Campbell, 1993) and reduced incidence of having meals (Sjoberg et al., 2003) both of which are associated with gain in weight. According to Toschke, Chenhoff, Kolestzko, and Von Kries (2005), meal frequencies in children were found to be inversely related to BMI while Francis, Lee and Birch (2003) found that girls who snacked more had higher fat intakes which contributed to the increased in body weight.

Yet a recent review of literature concerning breakfast patterns suggests the rate of skipping breakfast among children and adolescents is at its highest-ranging from 10% to 30% depending on the age, gender, and ethnicity (Rampersaud, 2009). An earlier

study had also established a decline in breakfast consumption of 5% to 20% by preschoolers and adolescents between 1965 and 1991 (Siega-Riz, Popkin & Carson, 1998). Overall, research concerning breakfast and obesity has been diverse, constituting cross-sectional, longitudinal and clinical studies (Rampersaud et al., 2005). But findings remain inconsistent across these studies. Among cross-sectional studies, some have found an inverse association regarding breakfast consumption in children and adolescents with weight status. For example Gibson and O'Sullivan (1995) found that BMI was lower for children that frequently ate breakfast, while Fiore et al., (2006) found that eating breakfast every day or some days during the week was protective against high BMI for children who had obese parents. However, other works (e.g. Vagstrand et al., 2007) have found no relevant association between breakfast and BMI. Longitudinal findings concerning the same variables have also shown a conflicting pattern. Based on a sample of 2,379 girls from 10 year, Barton et al. (2005) found that frequency of having breakfast was linked to lower BMI. Similarly, Niemeier et al., (2006) found an inverse association between reduced breakfast intake and bodyweight. However, Berkey et al., (2003) found varying results after examining the effect of breakfast on 1,400 children over one year period. Their results indicated that the BMI of obese children who ate no breakfast was lower than that of other obese children who had breakfast, while normal weight children who never had breakfast gained weight compared to that of other normal children that had breakfast every day. A study by Affenito et al., (2005) also had mixed findings. Initially, breakfast consumption among African American and white girls was found to be predictive of lower BMI, after controlling for demographic factors.

However, the relationship disappeared when subjected to controls for parental education, physical activity and energy intake. This inconsistency in findings only suggests the need for more studies.

Unlike breakfast consumption tendencies, trends specifically relating to the consumption of food from convenience stores were not readily available. However, developments concerning fast food consumption, for which convenient stores are a category, show upward trend in consumption among adolescents. Using data from a nationally representative study, Nielsen et al. (2002) found that intakes of high energy snacks and food from vending machines, restaurants, and fast food establishments had increased between 1977 and 1996 among adolescents. A similar pattern was found by French, Lin and Guthrie (2003) in their investigation concerning the consumption of soft drinks among children aged 6 to 17. Findings from this study revealed an increased share of soft drink intake from fast food places. A connection between fast food and obesity is that the former's leads to high energy intakes (Paeratakul, Ferdinand, Champagne, Ryan & Bray, 2003). This is made worse by the present day portion sizes, which have increased over time (Nielsen removed comma & Popkin, 2002).

Research pertaining fast food consumption and adolescents' body weight status has tackled a range of issues, a majority of them being environmental. Such aspects have included store proximity (e.g. Jeffery, Baxter, McGuire & Linde, 2006; Davis & Carpenter, 2009), store access, availability and costs (e.g. Powell, Auld, Chaloupka, O'Malley, & Johnston, 2007; Powell & Bao, 2009), sedentary behavior specifically TV viewing (e.g. Utter, Nuemark-Sztainer, Jeffery & Story, 2003), and family

characteristics, including parental practices and home environment (e.g. Boutelle, Fulkerson, Neumark-Sztainer, Story & French, 2006). Few of these studies have centered on nutritional practices (e.g. Taveras et al., 2005; Huang, Howarth, Lin, Roberts & McCrory, 2004; Niemeier et al., 2006; Boutelle et al., 2006). For example, Neimeier et al., (2006) attempted to capture the impact of fast food on weight status over a 5 year period. They found that fast food intake was predictive of increased BMI when transitioning to adulthood. However, many of these studies have either concentrated on fast food from restaurants or taken fast food place as an aggregate. Other than a recent study by Galvez et al., (2009), which attempted to underscore the link between convenience store and children's weight outcomes, we are not aware of any other similar study. Galvez et al., (2009)'s work was based on proximity of stores and their results showed that children living within one block of the store were more likely to have a higher BMI. This study looks at direct impact of food consumption from convenient store on children's weight status.

It is highly suggested that insufficient sleep is the cause of several health problems, including obesity in children and adolescents. Adolescents should sleep for a minimum of 8-9/hours a day (National Sleep Foundation (NSF), 2006). However, several findings suggest a decline in amount of sleep among adolescents over time. For example research by Gupta, Mueller, Chan, and Meininger (2002), found that average sleep time of child aged 11-16 to be 7.68hrs. Adding to this are findings of the recent sleep in America polls from the NSF (2006) showed that a high school child slept an average of 6.9 hours while a sixth grader that had only 8.4 hours which is below the

sufficient amount required. The same poll also indicated sleep insufficiency increased with increase in BMI of the child.

Overall, literature concerning the effect of sleep duration on adolescent weight change is very limited. What is more disturbing is the inconsistency in findings especially for adolescents aged at least 10 years and above (Patel & Hu, 2008). One study by Landis and Parker (2007) attempted to score the effect of decreased total sleep by focusing sleep complaints. Their study found that adolescents experiencing sleep complaints were overweight and that lighter sleep and less sleep were associated with BMI. Likewise, Gupta, Mueller, Chan, and Meininger (2002) revealed that obese adolescents significantly experienced less sleep than non obese peers and that the odds of being overweight increased for every one hour loss in sleep. Other works with similar findings include that by Snell, Adam, and Duncan (2007). But Knutson (2005) found that relationship to be consistent among boys and not among overweight girls in a national representative study. Even then sleep was weakly associated with BMI. Eisenmann, Ekkekakis and Holmes (2005) also found a similar relationship in boys but not girls. Their results were based on Australian Health and Fitness survey of children aged from 7 to 15 years. Several reasons have been attached these observed differences. Among them are differences in measures of sleep duration (Knutson & Lauderdale, 2007), differences in development and sleep characteristics (Knutson, 2005). However, it could also be that the effect of sleep on obesity girls may is negligible. By investigating the effect of sleep duration, I seek to add to the existing literature and further explore the relationship between sleep and adolescent obesity.

Previous works concerning the above behaviors have looked at single behavior at a time. This study considers their multiple behaviors in an effort to score their joint significance in affecting children's weight status while accounting for contextual factors. Achieving this requires that one chooses appropriate methodologies. Thus the next section presents the theoretical framework adopted. The corresponding empirical framework is presented following this. There after the data and matching statistics are presented. This is followed by empirical results, a discussion on policy and concluding remarks.

Literature

Theoretical framework

A number of theories explaining behavioral practices and how they impact weight outcomes have been proposed in sociological, psychological and medical literature. Those that have been adopted and are common within obesity research were discussed by Baranowski et al., (2003). A characteristic amongst these frameworks is that they contain factors that influence an individual's decision making behavior which in turn affects weight change. By including these factors along with the behavior variable in research, the role of that particular behavior and mediating variables can be identified. This in turn is helpful in designing effective interventions against obesity.

Obesity is caused by a myriad of factors thus understanding it requires a multidisciplinary approach. The fact that we seek to explore several obesity related causes begs for more of this approach. One conceptual model that suits this purpose

well is the Ecological Systems Theory (EST). Originally proposed by Bronfenbrenner (1979), the model has been adopted to explain obesity outcomes (Davidson & Birch, 2001; Garry & Swinburn 1997; Gorin & Crane, 2000). The framework is multidimensional integrating multiple levels, multiple organizations, and multiple factors with joint and equal focus on the person, his/her behaviors and the environment to explain health outcomes. The task is to illustrate this framework and its applicability to obesity risk behavior. A brief summary of findings concerning the model and breakfast consumption, fast food consumption and sleep are also presented. Furthermore, other methods examining obesity risk behaviors will be presented.

Ecological systems theory (EST). Bronfenbrenner (1979, 1986) suggested that a human development and behavior is best understood by considering that person within the context of his or her environment. He went on to classify this environment as a system of four nested levels of influence namely the microsystem, mesosystem, exosystem and the macrosystem. The microsystem constitutes the immediate environment in which the child lives and functions. The system contains various organization such as the family, neighborhoods, daycare, and the school, with different structures and factors (e.g. family care practices- diet behavior, parenting lifestyles, family activity, TV-viewing and socio-economic status; school practices- physical activity patters, food patterns and availability and choice of diet, etc.) that directly effects the child. Interactions between those institutions and the child, as well as with other social groups such as the peers and caregivers will determine how this child grows. These interactions are reciprocal that is child behavior can effect and be affected by

components of the microsystem. How the child responds is determined by his or her personal characteristics including biological factors, beliefs, values, knowledge, and attitudes and many more. The mesosystem is a system of microsystems. It characterizes the environment where all the microsystem component interactions occur. For example, relationships between the home and school environments which impact the child.

The exosystem refers to larger social settings including people and places the individual does not interact with often, but will nevertheless impact the development of the person. These settings can be formal or informal. Formal settings such as the parents' work place influence the quality care to the child by affecting incomes, work schedules, leave and stress of the parent. Community institutions such as school district administration and or city government may make decisions that can influence the quality of life of the family and the child (Davies, 1999). Informal settings can be the parents' social networks and extended family that might influence on the parents' decisions made about their children.

The macrosystem is the widest environment and is remote from the person. It encompasses a variety of influences including government regulations, culture, resources, economy, wars, religion, etc. Changes in these factors e.g. economic recession, global reorganization, or welfare laws may impact the lives of families and eventually affect the development of the child. For example, changes in the economy may cause company relocation to another country and force the parent to take up other time consuming jobs, reducing the time spent with their children, which in turn affect children's development (Davies, 1999). Bronfenbrenner's conceptual framework helps

us understand the complex nature of transactions that influence development of the individual. Not only do the systems affect the child's behavior thus health outcome, but the systems themselves will change as their components are replaced or altered.

EST and childhood obesity. Application of the ecological systems theory to the development of obesity in children and adolescents has involved researchers taking up multiple environmental influences (e.g. family, school, community, societal) from the various levels of influence along with individual factors (e.g. sex, age) to account for obesity risk behaviors that jointly and directly affect weight outcomes (Davidson & Birch, 1999; Gorin & Crane, 2000). Obesity risk behaviors include dietary patterns, sedentary behaviors and physical activity. According to the framework by Davidson & Birch (1999), the influencing variables are grouped in three levels as the child's characteristics, including gender, age and familial susceptibility to weight status; parenting lifestyles and family characteristics such as parental weight status, nutritional knowledge, parent encouragement of physical activity, etc; and community, demographic and societal characteristics. Under this ecological system model, obesity risk behaviors are viewed as affecting and being affected by parental and community factors. At the same time, their impact in causing risk in obesity is determined by child's characteristics. Clearly the relationship is a multifaceted one. Thus, understanding the impact of risk behaviors on weight status requires a consideration of their determinants, which taken together, contribute to the development obesity.

For instance in examining the effect of breakfast behavior on obesity, it is necessary that one includes the various factors that shape its nature thus contributing to

disparities in weight status. Major children's characteristics that have caused differences in breakfast patterns include age and gender. Findings from several studies suggest that breakfast skipping increases with age (e.g. Timlin, Pereira, Story, & Neumark-Sztainer, 2008; Barton et al., 2005; Rampsaud et al., 2005; Delva, O'Malley, Johnson, & Racial, 2006; Siega-Riz, Popkin & Carson, 1998). The behavior is worse if the child is female than male. One study by Timlin et al., (2008) that sought to investigate breakfast eating and weight change of teens over a 5 year period found that younger teens ate more breakfast than did older teens. In this study girls were found to skip breakfast more than boys. An earlier study by Siega-Riz, Popkin and Carson (1998) found a similar pattern. That is, breakfast consumption decreased with increase in age among older adolescents and adolescent boys were more likely to have breakfast compared to girls of the same age. Although not mentioned by Davison and Birch (2001), a number of other personal factors have been found to cause variation breakfast patterns and could possibly contribute to obesity. These include being a minority (Dweyer, 2001; Affenito et al., 2005), having more autonomy over food choices (Videon & Manning, 2003), making poor lifestyles such as smoking (Keski-Rahkonen, Kaprio, Rissanen, Virkkunen and Rose, 2003), being physically inactive (Aanio, Winter, Kujala & Kaprio, 2002), dieting to lose weight (Barker, Robinson, Wilman & Barker, 2000), and not being hungry (Shaw, 1998). Equally important is the knowledge of importance of breakfast. Butcher-Powell, Bordi, Borja, Cranage, & Cole (2003) found that beliefs that breakfast was necessary to get one's nutritional requirement significantly contributed to children's breakfast consumption.

There are also several parental lifestyles and family characteristics that affect breakfast patterns of children and adolescents. Pearson, Biddle and Gorely, (2009) reviewed the effect of parent and family environment on breakfast. Their analysis revealed overwhelming evidence about the effect of family structure on breakfast. In general children who come from two parent families were more likely to consume breakfast compared to those from nontraditional homes. Possibly this is due to limited parental control over meal pattern in the nontraditional homes (Stewart & Menning, 2009). Additional findings by Pearson, Biddle and Gorely (2009), which related to other factors such as the parental breakfast consumption, parental presence, and socio-demographic characteristics including parental education, employment, socio-economic status, and socio-deprivation remained mixed. Other mechanisms through which family characteristics can influence breakfast patterns are through family meals specifically family dinner (Fulkerson, Kubik, Story, Lytle, & Arcan, 2009; Woodruff & Hanning, 2009); family connectedness (Mellin, Neumark-Sztainer, Story, Ireland, & Resnick, 2002); providing particular breakfast foods, mother's modeling, and home rules towards breakfast (Dejong, Lenthe, Horst & Oenema, 2009), and parental involvement (Stewart & Menning, 2009). According to Stewart & Menning (2009), nonresident father involvement was found to increase the frequency of having breakfast in children.

Different community and societal factors e.g. school dietary and physical programs neighborhood safety, availability and access to recreation facilities, convenience food and restaurants and many more can have different impact on breakfast patterns. According to the EST their impact is directed through parental and family

characteristics. However research regarding the impact of these factors on breakfast is limited. One study by indicated that skippers of school breakfast had no time to take advantage of the meal or were not hungry (Reddan, Wahlstrom & Reicks, 2002). In another study dealing with disadvantaged community decreased the odds of adolescents having breakfast but increased their chances of developing obesity in adulthood (Merten, Williams, & Shriver, 2009).

Similarly, children's characteristics of age and gender have been found to be important predictors of difference in fast food consumption among children and adolescents. Bowman, Gortmaker, Ebbeling, Pereira, and Ludwig (2004) found that fast food consumption among children aged 4 to 19 years, increased significantly by age and male gender. He attributed the effect of age to the fact that adolescents had more autonomy, more disposable income, more access to fast food places due to employment, and were more susceptible to fast food advertising. A similar trend was found by Paeratakul et al., (2003). Other personal characteristics factors that might sway fast food consumption include the television viewing and student employment (French et al., 2001) and preferences for unhealthy food, playing in the sports team, concern about one's weight and use of weight control techniques (Bauer, Larson, Nelson, Story, & Neumark-Sztainer, 2009). However, Bauer et al., (2009) found the latter two factors are applicable to girls only. The influence of parental and family characteristics on fast food consumption is linked to the availability of unhealthy food at home, peer's concern for eating health food and mother's encouragement to eat health food (Bauer et al., 2009, French et al., 2001). In both of these studies, teens whose home environment provided

unhealthy foods were more likely to consume fast foods. With the exception of the first variable, all factors are significant for boys in the study by Bauer et al., (2009).

Fast food store availability and proximity of location and availability of vending machines in the neighborhood and school are among the major community factors associated with increased fast food or drink consumption among adolescents (Jago et al., 2007; Wiecha et al., 2006; Galvez et al., 2009). Increased consumption is also blamed on reduction in the prices of fast food. Children who are in areas promoting price reductions are likely to consume more fast foods. According to French et al., (2001) a reduction in prices of high sugar snacks in several schools increased their consumption in adolescents by up to 93%. Another factor attributed to variation in fast foods consumption is fast food advertising on television (Story & French, 2004). Powell, Szczypka & Chaloupka (2007) determined that fast food was the most frequently viewed food product category, comprising of 23% of all food related advertisement in adolescents. This advertising translates into purchases. Utter, Scraag & Schaaf (2006) found that children and adolescents who watched TV more frequently were more significantly likely to consume commonly advertised fast foods, which included soft drinks, hamburgers and French fries.

In the case of sleep patterns, overwhelming evidence indicates that sleep decreases with age. For example, a study by Iglowstein et al., (2003), which sought examine age specific variation in sleep duration from infancy to late adolescence over a 21 year period, established that sleep decreases with age. However, findings concerning gender remain unclear. Some studies have found that girls need more sleep compared to

boys (Yacheski, 1994). Others have found no such differences (Lee, Mcenany, & Weekes, 1999). Yet others have found the gender differences to be on important on weekends versus week days or vice versa (Mercer, Merrit & Cowell, 1998; Laberge, Petit & Vitaro, 2001). Both these studies suggested the sleep variations to be the role of puberty rather than gender. Additional studies have found puberty as the cause of sleep differences among adolescents by Andradei et al., (1993). Similarly, findings concerning race remain conflicting as some have found it important (e.g. Spilsbury et al, 2004; Hale & Do, 2007) and others have found it not important in causing sleep patterns among children.

The most documented evidence of parental impact on children's sleep is through their regulation of the sleeping and waking times of children. Children and young adolescents are more likely to have parents set bed time and wake time, while for older adolescents, parental influence will most likely be at waking time (Carskadon, 1990). Besides this work, no other studies were found on the influence of parents on adolescent sleep.

Community and societal factors affecting sleep patterns in adolescents could be associated with the day of the week (Andradei et al., 1993; Lee, Mcenany, & Weekes, 1999), school environment such as early school schedules and nature of semesters (Andradei et al., 1993, Carskadon, 1990); curfews for students attending boarding school and employment (Carskadon, 1990); and location differences in terms of urban versus rural area residence (Louzada & Menna-Barreto, 2002) or inner city versus urban area (Hale & Do, 2007).

Summary of empirical findings concerning EST, breakfast patterns, fast food consumption and sleep in children and adolescents

Overall, the empirical application of EST to obesity research is limited, possibly due to the complex nature of obesity-related behaviors. Some studies examined here focused on obesity prevention (DeMattia & Denney, 2008), transportation issues (Lopez-Zetina, Lee & Friis 2006); and multiple factor analysis (e.g. Gable & Lutz, 2000; Hawkins, Cole & Law, 2009; Jones, Okely, Gregory & Cliff 2009).

Application of the EST framework to the behaviors that concern this study and adolescents in particular is much rarer. Nearly all of the encountered works were directed towards fast food store availability and the neighborhood environments. For example, Reidpath et al., (2002) sought to examine the relationship between socio and environmental determinants of obesity in Australia, based upon the ecological concept. Their methods involved relating social economic status (SES) and the density of fast-food outlets. What they found was that people living in areas of low SES experienced 2.5 times the exposure to outlets than people in the wealthiest areas. However, their study fell short of connecting this relationship directly to weight status of individuals due to lack of individual level data.

Researchers have attempted to address this limitation by collecting individual data. An example is Crawford et al., (2008), who obtained body weight data in order to investigate the link between exposure to fast food outlets in neighborhoods and child and parental obesity. In general, their findings revealed that proximity to stores did not result in higher BMI. Children and their parents with at least one store within a 2 kilometer

radius had lower BMI compared to those that were further off. The father's odds of being overweight increased with each additional kilometer to the nearest store. A comparable result was obtained by Jeffery, Baxter, Maguire and Linde (2006) in a related study of adults over 18 years of age. Using a wide range of data, they found that while body weight status (in form of BMI) was linked to the frequency of eating fast food, but BMI was independent of restaurant proximity; in addition, the direction of the result for men was in the opposite direction in men. In other words, exposure to restaurants did not result in increased body weight. They attributed this to several reasons including the possible homogeneity of restaurants, imprecision in analysis of fast food and exposure, and probable minor contribution of fast food to obesity. In these studies, ecological theory is more of an orientating concept rather than explanatory process.

In investigating the impact of breakfast, some researchers have relied on approaches other than EST. An example of one such study is O'Dea and Willson (2006), who utilized the socio-cognitive theory and theory of planned behavior to assess the associations and interactions between adolescent students' diet patterns, personal factors, cognitive and environmental factors and their BMI. Key breakfast variables were breakfast consumption patterns, breakfast quality and food variety. Findings from this study revealed that breakfast quality to be important influencing student's body weight.

Several others have not followed theoretical frameworks (e.g. Neimeier et al., 2006; Berky et al., 2003; Fiore et al., 2006; Affenito et al., 2005; Barton et al., 2005; Merten, Williams & Shriver, 2009). Of all these studies, only Merten, Williams &

Shriver (2009)'s work considered the individual in addition to personal factors, bodyweight and breakfast behavior. The study sought to track the effect of breakfast consumption patterns on weight outcomes from adolescence to adulthood. Selected contextual variables were community economic disadvantage, family-level socio-economic status, and parents' presence at home during the morning. Findings from their study indicated that residing in disadvantaged communities increased the odds adolescents not eating breakfast and increased their chances for chronic obesity. Parental presence in the morning was an important factor in influencing regular breakfast consumption, which was also a predictor of regular breakfast consumption by parents. Regular consumption of breakfast during adolescence and young adulthood also provided considerable protection from obesity.

All of the studies examined regarding the relationship between sleep and obesity in children and adolescents were non-theoretical. Analyses in these studies were based on hypothesized relations that had to be validated. However, these studies utilized sleep hours, using varying methods. Knutson (2005) based his results on a self-reported measure hours of sleep, while Landis and Parker (2007) based theirs on sleep hours collected via laboratory-based polysomnography. Gupta et al., (2002) took advantage of the actigraph measurement technique to estimate the total sleep time and sleep disturbances of children. These two variables were used to study the effect of sleep on weight outcome. Furthermore, Snell, Adam and Duncan (2007) used time diaries to arrive at the total sleep time of children aged 0-12 years. While differences in results might be attributed to methods, they could also be due to variety of factors that affect

sleep variation, but not controlled for by the methods. According to Carskadon (2002), adolescent sleep is influenced by a wide range of factors that are biological, behavioral, social and psychosocial in nature. The fact that these studies do not consider theoretical frameworks limits the identification relevant variables. Results from these studies must be regarded with caution.

Other socio-theories assessing the effect of obesity risk behavior on weight status of children

Behavioral learning theory (BLT). This framework is an extension of the learning model applied to human behavior. Within BLT, the motivation to perform a behavior is a disinclined physiological drive for example the reduction in hunger. The process is one that involves stimuli-response associations and memory of the individual. Behavioral change occurs randomly whenever a stimulus is applied. Due to memory of the associations, responses will reoccur due to similar stimuli.

An applied version of the model to obesity is the behavioral economics model that assumes that behavior is a result of costs and benefits. Benefits reinforce behavior and their value differs among individuals. Obese children find more reinforcing value from food those non-obese children (Hill et al., 2009; Temple et al., 2008; Clark, Dewey & Temple, 2010). For example, Temple et al. (2008) observed that overweight children found food more reinforcing and consumed more high energy foods than did their non-obese peers. Overweight children were less likely to participate in sedentary activities compared to eating food. Reinforcing value relates to how hard the individual is likely to

work to gain access to food rather than the alternative. In determining if reinforcing behaviors predict BMI, Hill et al. (2009) took a longitudinal approach and found the expected result that indeed relative reinforcing value predicts increased in BMI in children.

Because of such reinforcing values, the theory can be used in control of obesity by increasing reinforcing values of non-obesity-encouraging behaviors. However, its overall application is challenging as results require exceptional control of behavior.

Social cognitive theory (SCT). SCT has been frequently used when it comes to understanding obesity risk behavior in children and adolescents and interventions (e.g. Gortmaked et al., 1999; Golan & Weizman, 2006; O’Dea & Wilson 2006; Sharma, 2006; Sharma, Wagner & Wilkerson, 2006-2007). Originally, it incorporated quite comprehensive cognitions and environmental factors into models of health related behaviors. The model encompasses a wide range of concepts used to explain dietary and physical activity behavior. Among these concepts are self-efficacy, which is the confidence that one will be able to perform a specific behavior under a variety of circumstances; skill, which relates to the ability to practice a particular behavior; and outcome expectancies as a result of performing a particular behavior. Along with these are environmental concepts that emphasize modeling of behavior and availability of reinforcers of behavior and also the notion of self-control and regulation that cause change in behavior.

Most recently, O’Dea and Wilson (2006) adopted that framework to predict the relationship between socio-cognitions, nutrition factors and socio-economic status with

childhood obesity. Diet-related factors included breakfast consumption and food variety. Their findings suggested that children from lower socio-economic background were more likely to have higher BMI because they received no breakfast or had poor quality breakfast. Also, children with high variety of foods were more likely to have high self-efficacy related to eating healthy foods, which had a positive effect on BMI. Overall, much remains to be learned about SCT concepts and dietary or physical activity decisions and their effects on obesity. There is substantial concern about their poor prediction of behavior, especially in children. It is not clear if this is due to inappropriate application, unreliable measures, or the fact that they are too cognitive to capture behaviors in children. In dealing with this, SCT concepts should be applied to obesity risk decisions, where children exert most control to facilitate the predictability of social cognitions (Baranowski et al., 2003).

Theory of planned behavior (TPB) and theory of reasoned action (TRA). TPB is an extension of TRA. The basis of TRA is to explain relationships between attitudes and behavior. TRA posits that a person is more likely to perform a behavior when she or he intends to perform it. The level of intention varies among individuals. It is higher among those who have a more positive attitude towards and stronger perceived subjective norms about that behavior. The attitude towards the act is an interactive function of strength of the person's beliefs and values about expected outcomes. A drawback for the theory is that it does not account for behaviors that are out of one's control. TPB corrects this by adding that the intention to perform is influenced by perceived behavioral control.

TPB has been shown to account for a significant amount of variation in intentions involving dietary and physical activity behaviors, but falls short of directly associating behavior with BMI. Instead, in applying it to childhood obesity, researchers identify several of such behaviors that are strongly associated with obesity and then make an argument for their meaningfulness based on this. An example of this is in the work of Fila and Smith (2006), Kaseem, Lee, Modeste and Johnston (2003), Kyle, Kami, and Ihuoma, (2010), and Andrews, Silk and Eneli (2010), who used THB to explore healthy eating behaviors in youth and who use the same to effect. Their case was based on the fact that changing poor diet habits would reduce obesity. The nature of both TRA and TPB has provided very promising results, making it attractive to researchers.

Transtheoretical model and stages of change. This particular theory combines theories and concepts from clinical psychology. Its concepts include the pro and cons of undertaking a behavior; self efficacy, which is the confidence of performing that behavior and processes of change. Emphasis of the theory is the stages of change under which behavioral change may occur. Although there is disagreement on the number of stages, most common ones used in research are precontemplation, contemplation, planning or preparation, action and maintenance (Prochaska & DiClemente, 1982, 1986; Greene et al., 1999).

As much as the theory has been applied to understand and manage childhood obesity risky behaviors (Beckman, Hawley & Bishop, 2006; Rhee et al, 2005), it has been associated with several methodological problems. One is that people have different stages of change for a particular diet or physical activity. In addition, people are not

always aware why they may choose certain practices or behaviors, making it difficult to classify them. The presence of such problems calls for more research into this theory especially in comparing those who are at risk of obesity with those at no risk of obesity.

Knowledge attitude behavior model (KAB). The central focus of this framework is the accumulation knowledge, which in turn changes attitude and then behavior. In other words, attitude can alter obesity risky behavior that in turns alters BMI. An assumption by the theory is that people are rational. However, there are concerns that not all people are rational. The fact that there is no standard definition of knowledge is also another problem. This has made it difficult to distinguish it from skills. Furthermore, this model's concepts contained in the model are part of other larger frameworks. These short comings make inadequate and questions its relevancy (See Baraowski et al., 2003).

But despite such criticism, KAB has been used to explain diet and physical activity behavior in children. For example, Thomson et al., (2001), used the framework to explain the level of physical activity in children; while Lin, Yang, Hang & Pan (2007) used the same to assess diet behavior. More specifically, Gordon (2001) employed the concepts with a reflection of obesity in children. His findings indicated that knowledge and attitudinal factors had far less impact on obesity than activity related behavioral factors.

In summing up, literature proposes several frameworks that can be sued to explain the effect of behavior on obesity of children. Concepts in one framework may overlap with concepts in another. In addition, each theories has own emphasis, strength

and weaknesses. Choice of particular framework may depend on the question that researcher seeks to answer; in this study it is EST.

Empirical methods

Model specification

As put by ecological systems theory (EST), obesity risk behaviors are determined by a wide range of child's personal characteristics and factors from other social contexts including the parental/family and community environments. In turn, these risk behaviors along with child characteristics directly alter the child's weight status. However, EST also suggests a feedback loop from children's health status to behavior. These relationships can be expressed as

$$X = x(H, A, Z, \theta); \quad 3.1$$

$$H = h(A, X); \quad 3.2$$

where X is the child's obesity risk behavior such as having breakfast, consuming fast food (in particular eating foods from convenient store) and sleeping; A is the individual characteristics, Z represents family/parental characteristics associated with the child; θ represents community/societal factors and H is the child's weight status. By specifying such a relationship, it assumed that only the obesity risk behaviors and personal characteristics have direct impact. It is possible that there exist other factors that affect the child's weight status directly. These factors are assumed to be unobserved.

In many cases, the above relationships are transformed via multilevel or a hierarchical method that is considered the most suitable empirical technique for

examining behavior within the social hierarchies (Mason, Wong & Entwisle, 1983-1984; Heck & Thomas, 2008; Bryk, & Raudenbush, 1992; Boyle, Georgiades, Racine, & Mustard, 2009). The mechanism assumes that the outcome for an individual is driven by fixed effects and variability of factors within and between contexts. However, the data requirements for this technique cannot be met by this study.

Instead this study adopts an alternative but equally appropriate strategy in which equations 2.1 and 2.2 are considered as a system, given the nature of ecological systems. Health outcomes and behavior processes are integrated and occur together. As seen above, obesity risk behavior is both a response and covariate in the system. Health outcomes also follow in the same manner by impacting behavior. Consequently, it becomes necessary to consider the two as single structure. In particular, the structure comprises of 4 regressions, three of which represent the obesity risk behaviors of breakfast consumption (X_1), convenient store food consumption (X_2) and sleep (X_3) and one which represents the weight status of the child (H). A potential drawback is that the data lack information on community characteristics, so variable θ is excluded from the system.

Empirically equations 3.1 and 3.2 can be transformed as;

$$X_i = \beta_{i0} + \beta_{i1}H + \sum_{j=1}^J \beta_{ij}A_{ij} + \sum_{r=1}^R \beta_{ir}Z_{ir} + \varepsilon_i; \quad i = 1,2,3 \quad 3.3$$

$$H = \alpha_{i0} + \sum_{j=1}^J \alpha_{ij}A_{ij} + \sum_{i=1}^I \alpha_i X_i + \varepsilon_H; \quad 3.4$$

error terms ε_i and ε_H are assumed to be normally distributed i.e. $\varepsilon_i \sim N(0, \sigma_i^2 I)$ and $\varepsilon_H \sim N(0, \sigma_H^2 I)$ and capture information the unobserved factors in the regression. $r = 1 \dots R$ denotes the number of parental and family factors in vector Z , whose size differs from

behavior to the next. For example, the number of parental and family factors affecting breakfast consumption differs from that affecting fast food consumption from convenience stores or sleep in children. Similarly, $j = 1 \dots J$ represent the number of factors in vectors A , which also remain defined as before and may differ in size depending on the outcome. $I = 3$ is the number of obesity risk behaviors. In this structure, obesity behaviors $X_i = (X_1, X_2, X_3)$ and weight status H are dependent variables, while others are independent or predetermined.

Most specifically considering previous literature and available data on personal; family and parental variables; and community variables, the empirical system to be estimated can be specified as below;

$$\begin{aligned}
 X_1 = & \beta_{10} + \beta_{11}H + \beta_{12}HIS + \beta_{13}WH + \beta_{14}GD + \beta_{15}AG_c + \beta_{16}MT + \beta_{17}EX + \\
 & \beta_{18}DT + \beta_{19}ADT + \beta_{110}DTxADT + \beta_{111}Y_m + \beta_{112}EDUC_m + \beta_{113}ENC_m + \beta_{114}BF_m + \\
 & \beta_{115}EDUC_d + \beta_{116}AG_d + \beta_{117}BF_d + \varepsilon_1
 \end{aligned} \tag{3.5}$$

$$\begin{aligned}
 X_2 = & \beta_{20} + \beta_{21}H + \beta_{22}HIS + \beta_{23}WH + \beta_{24}GD + \beta_{25}AG_c + \beta_{26}MT + \beta_{27}MC + \\
 & \beta_{28}JB + \beta_{29}Y_m + \beta_{210}PM_m + \beta_{211}PM_d + \varepsilon_2
 \end{aligned} \tag{3.6}$$

$$\begin{aligned}
 X_3 = & \beta_{30} + \beta_{31}H + \beta_{32}HIS + \beta_{33}WH + \beta_{34}GD + \beta_{35}AG_c + \beta_{36}MT + \beta_{37}TS + \\
 & \beta_{38}Y_m + \beta_{39}EDUC_m + \varepsilon_3
 \end{aligned} \tag{3.7}$$

$$\begin{aligned}
 H = & \alpha_1 + \alpha_2X_1 + \alpha_3X_2 + \alpha_4X_3 + \alpha_5BMI_m + \alpha_6BMI_d + \alpha_7HIS + \alpha_8WH + \alpha_9GD + \\
 & \alpha_{10}AG_c + \alpha_{11}EX + \varepsilon_H
 \end{aligned} \tag{3.8}$$

Details concerning each variable listed in the equations are provided in the data selection and summarized in Table 3.1.

Issues in estimation

Fitting systems of equations has for long been discussed within statistical, economics and econometrics literature (e.g. Green, 2005; Angrist, 2001, Heckman 1978; Amemiya, 1978; Zellner, 1962; Blundell & Smith, 1989) and has most recently gained attention in epidemiological studies (e.g. Zohoori & Savitz, 1997). Overall, research indicates that such estimations face several problems including identification of the system, simultaneity and unobserved factors.

System identification. Identification is the prerequisite for statistical inference about an underlying structure. This requires that necessary rank and order conditions be satisfied. Of the two, the former is considered sufficient and can easily be determined in small structures. However, in large models, the procedure of determining the rank is usually formidable. Meeting the order condition is usually enough for identification. Thus, this is what is determined here. Concisely, the order condition demands that the number of predetermined variables excluded from an equation be at least as large as the endogenous variables included in it (Green, 2003: pp392). The endogenous variables constitute the all dependent variables. Taking the respective equations it can be deduced that for:

3.5 the predetermined variables excluded are $JB, MC, PM_m, PM_d, TS, BMI_m, BMI_d,$

$EDUH_m$ and the endogenous variables included is X_1 and H ;

3.6 the predetermined variables excluded are $EDUH_m, EDUC_m, EDUC_d, TS, AG_d,$

BMI_m, BMI_d, EX and the endogenous variables included are X_2 and H ;

3.7 predetermined variables excluded are $EDUH_m, EDUC_m, EDUC_d, AG_d, JB, MC, PM_m, PM_d, BMI_d, EDUH_m EX$ and endogenous variables included are X_3 and H ;

3.8 predetermined variables excluded are $EDUH_m, EDUC_m, EDUC_d, AG_d, MC, PM_m, PM_d, TS, Y_m$ and endogenous variables included are X_1, X_2, X_3 and H .

Judging from above, the number of excluded predetermined variables exceeds the endogenous variables included in each equation. By the exclusion principle, each equation and thus the system are over identified. Furthermore, an established rule of thumb for identification states that the entire model is identified if every equation has its own predetermined variable (Green, 2003: pp393). The above model clearly exhibits this tendency. Each equation has at least one unique predetermined variable.

Simultaneity. This relates to the joint dependency between weight status and the obesity risk behavior. That is, obesity behavior will alter weight outcomes, at the same time weight status may cause change in behavior. EST itself suggests this simultaneous relationship potentially exists. For example recent findings on sleep and weight status on one hand indicate that weight causes sleep problems (e.g. Must & Strauss, 1999; Dietz, 1998) and other hand show that insufficient sleep might cause increase in weight children (Chaput & Tremblay, 2007; Landhuis, Poulton, Welch, & Hancox, 2008). The same feedback relationships have not yet been supported for breakfast consumption, and are yet to be explored for consumption of fast food.

In the present study, we examine this possible association by using H as covariate in X_1, X_2 and X_3 equations. A test of simultaneity is conducted, using Hausman test whose null hypothesis assumes that X_1, X_2 and X_3 are exogenous. That is,

there is no simultaneity between weight status and obesity risk behaviors. However, if it turns out to be significant, then there is joint determinacy between these variables. It is on this basis that we include variable H in equations 3.5-3.8. However, because of the many covariates in each of obesity risk behavior equation, H may offer no meaningful information, in which it will be dropped.

Simultaneity between child weight status and obesity risk behavior means X_1, X_2 and X_3 are no longer independently distributed from ε_H . Similarly, H is no longer independently distributed of $\varepsilon_1, \varepsilon_2$ and ε_3 . OLS regressions would be inappropriate and would result in biased estimates. The situation can be handled by use of instrumental variables. In this case it is considered that any unique predetermined variable in the respective equation can act as an appropriate instrument.

Unobserved factors. Unobserved factors arises due to the unmeasured factors captured by error terms $\varepsilon_1, \varepsilon_2, \varepsilon_3$ and ε_H that contributed to the child weight status and behavior respectively. Sometimes these variables are omitted due to costs of data collection, other times they may not have been observed by the researcher but observed by the child. Regardless of the reason, it is likely that error terms are will be correlated due to the fact that the child's choice in behavior is dependent on unseen factors related to both the behavior and weight status. This problem is also rectified by use of instruments.

Choice of estimator

A number of techniques exist for examining systems of equations. Some are limited information methods such as OLS and two stage least squares (2SLS). Others are full information methods such as three stage least squares (3SLS), full information maximum likelihood (FIML) and generalized methods of moments (GMM). The choice depends on the sample and problems being addressed in the estimation. In light the above drawbacks, the study adopts a 3SLS estimation model. The estimator is an instrumental variable (IV) technique that accounts for joint dependency of endogenous regressors and cross-equation error term correlations to ensure consistent estimates and improvement in asymptotic efficiency. The process involves a first stage ordinary least squares estimation (OLS) in which endogenous behavior variable is predicted by the set of predetermined variables. The predicted values are appropriate instruments independent of the error terms. They are then regressed on child weight status using generalized least squares, while incorporating covariance matrix for the errors of a combined response.

However it is important to note that instruments can be weak and may produce worse estimates compared to those produced by OLS. In order to detect this, other full information estimators may be applied. However, this is left is for another time.

Data

Sample

The sample is drawn from a pool of cross sectional data from the Parental Time, Role Strains, Coping, and Children's Diet and Nutrition project, which involves about 300 households in the Houston Metropolitan Statistical Area (MSA). The project was approved by the internal review board Texas A&M University and commenced between 2001 and 2002. Briefly, the study included administering surveys on various issues concerning health, nutrition, work, time allocation, earnings and expenditures from parents and one child; and taking anthropometric measurements of children aged 9-11 and 13-15 years. Parents reported their own weight. Parental interviews were done via the telephone and self administration while children were personally interviewed. Part of information collected related to obesity enhancing and mediating behaviors, socio-economic environment and parenting styles which are the central to this investigation. Data was gathered from both single and dual-headed families, although this particular study focuses on only the later. Details of project can found in McIntosh et al. (2006).

This study considers the effect of behaviors on childhood obesity in three cases including both children and adolescents (i.e. 9-15 year olds), on children alone (i.e. 9-11 year olds) and on adolescents alone (13-15 year olds). The reason for sub-categories of child versus adolescents is due to marked differences in physiological growth patterns that may affect weight status and are influenced by nutritional status and physical activity (see Rogol, Clark & Roemmich, 2000). The lack of consideration of children aged 12 years is due to the onset of puberty. The total sample for this study consisted of

228, 122 and 106 households for 9-15, 9-11, and 13-15 year olds respectively. However, missing observations reduced the sub-samples to 187, 97 and 93 in that order. Consequently, regressions are based on the later. What follows is a detailed description of variables pertaining to this study; a corresponding summary representation can be found in Table 3.1 in Appendix A part II.

Dependent variables

As mentioned earlier, these include the child's breakfast consumption (X_1), buying food from the convenience or grocery store (X_2), and sleep (X_3) patterns and weight status (H). The description provided is tied to the survey questionnaires utilized by McIntosh et al., (2006).

Breakfast consumption (X_1) was captured the practice based on the history and frequency of the behavior. Specifically, the child was asked how many days of the week she or he consumed breakfast. This was used as a reflection of breakfast behavior of that respective child. The use of frequencies to capture breakfast patterns is a usual practice (Rampersaud, 2009; Perason, Biddle, & Gorely, 2009). The behavior may be assessed in other ways such as dietary surveys and 24 hour dietary recall. The adoption of one method over another depends on the issue at hand and available resources. For example, if assessing of dietary/nutrient intake for breakfast is desired, then 24 hour recall is the appropriate method. However, the method is subject to recall errors and is very expensive to undertake. Alternatively, history and frequencies thought associated with

limited information and recall bias, are quick to conduct, may reflect usual dietary patterns and long term habits.

Similarly history and frequency of *convenient store food consumption* (X_2) was used as the measure of fast food consumption. In this case the child was asked to recall how many times she or he had bought food or snacks from a grocery or convenience store during the last 7 days. The use of frequency as indicator of intake of fast food is also not new. For example, Pereira et al., (2005) categorized food behaviors based on the incidence with which people ate food from fast food places.

As mentioned earlier, information on sleep patterns is usually captured in hours. In this case children were asked to note down their wake and sleep times. However, the technique yielded few responses and thus could not be used to facilitate any meaningful estimation. Furthermore, the method required recall times creating potential recall bias. Consequently, an alternative measure of sleep sufficiency (X_3) was adopted as a proxy for sleep. In particular, children were asked if they had gotten enough sleep, with possible responses of yes=1 or no=0.

The indicator of a *child's weight status* (H) used in this study is the body mass index (BMI). The variable was calculated as the body's weight in kg divided by the height in meters squared. Although BMI does not measure body fat directly, it is highly correlated with several factors that directly capture fatness and, thus deemed a valid sign of obesity in children and teens (Dietz & Robinson, 1993). Furthermore, the indicator is favored due to its reliability. Based on the BMI-for-age growth charts, a child may be classified as being underweight for BMI value less than 5th percentile, healthy weight for

BMI value between 5th and 85th percentiles, overweight for BMI value between 85th and 95th percentiles and obese for BMI values equal or greater than 95th percentile (CDC, 2009b). Rather than use these categories, this study considers the continuous measure as computed as above. The reason is that it would greatly increase the sample size.

Independent variables

The framework emphasizes three categories of independent variables as Individual-specific variables, parental and family characteristics and community characteristics. Descriptions for community characteristics are disregarded because due to the lack of data. The adoption of variables in model is based on available data and prior literature concerning obesity risk behaviors and weight status in children.

Individual specific variables. These include the age (AG_c), in months, gender (GD), and maturity (MT) of the child. In addition, race specific dummy variables are added, categorizing the child as Hispanic (HIS), white (WH) and black (BLK). However, the later is used a base and thus not included in the estimation. Given that all factors are independently correlated with behaviors and weight status, they are included in the four equations of the system.

The inclusion of other individual factors is particular to the specific equation due to its relationship with the dependent variable in question. Of importance to this study is the child's genetic susceptibility to obesity. Clinical and non clinical studies have shown the mother's and father's weight status are important reflectors of the genetic transmission or heredity of obesity to children (Ebbeling, Pawlak, & Ludwig, 2002;

Whitaker et al., 1997). Thus, the mother's body mass index (BMI_m) and the father's body mass index (BMI_d) are considered as personal indicators of this genetic susceptibility to obesity. The computation of each parental BMI is similar to the way child BMI is calculated. These two factors are part of the child weight status equation (H).

Dieting in children and adolescents is a key deterrent to breakfast consumption or a promoter of breakfast skipping (e.g. Baker et al., 2000). To capture its influence, a dieting variable (DT) reflecting diet behavior, along with the age of dieting (ADT) and their interaction ($DT \times ADT$), were included in the breakfast consumption regression (X_1). Dieting is captured with a response of "yes" if the child indicated that she or he diets and with a response of "no" if otherwise. Thus, DT is a dummy variable of 1 = yes and 0 = no. ADT relates to the age in years when child began dieting. For those who have never dieted the corresponding age value was 0. The interaction term is the product of both the dieting behavior and age of dieting.

Money received from parents for chores done at home (MC) and the child having a job (JB) were the additional individual factors in consumption of foods from the convenient store (X_2). Both factors give more purchasing power to the child to acquire whatever he or she may want which includes food related items. Furthermore, the factors are dummy variables with 1 capturing the fact that that the child was a recipient of monetary benefits for chores performed at home or having a job, otherwise 0.

Aside from the natural personal factors, the sleep equation (X_3) includes dummy variables TS which represents the parental regulation of the child's sleep period, an

individual factor not included in the other models. Children were asked to indicate “yes” if parents let them make their own decisions about what time they went to bed on week nights and otherwise “no.”

Parent and family characteristics. Literature cites several parental and family characteristics that may alter behaviors of children, although in several cases findings have remained mixed. This study adopts a number of factors related to parental lifestyles, and parental capacities and socio-economic status such as education, age, and income that can affect the resource distribution. Because of differences in family roles, moms (*m*) and dads (*d*) might have differing effects on child obesity behavior, thus are considered separately.

Parental education is considered to be a determinant in the breakfast consumption (X_1), although some have found it to be important and others not (see Pearson, Biddle & Gorely, 2009). The same is also considered to be important to child sleep (X_1). The level of parental education was categorized as having attained a high school diploma or less ($EDUH_m$) and ($EDUH_d$) or having some college education or college degree ($EDUC_m$) and ($EDUC_d$) for the mom (*m*) and dad (*d*), respectively. However, not all categories appear in the regression. The former is taken as a base in the breakfast regression, while the latter is considered as base the sleep regression. Furthermore, only maternal high school education appears in X_3 ; this is because father’s high school education was redundant. The same reasoning explains the exclusion of mother’s age. The importance of parental age in the breakfast consumption model is captured by adding the father’s age (AG_d).

To capture the impact of socio-economic status on childhood obesity behavior, parental total income was added to each of the (X_1) , (X_2) , and (X_3) regressions. The total income level of each parent constitutes an annual sum of earned and unearned incomes. Earned income included the sum of salaries, wages and commissions received from employment throughout the year. Unearned income included all monies received from food stamps, welfare, social security, unemployment compensation, worker's compensation, personal and joint compensation, pensions or annuities, care of foster children, cash scholarships, fellowships and stipends, child support and other sources. Although both mothers and father's incomes were considered as important to household behavior, only the mother's income (Y_m) is included in this analysis due to the same reasons that led to the ruling out of father's high school education and maternal age in other equations.

The model also includes several parental life styles relating to food and diet behavior. The first of these relates to the parents' frequency of encouraging the child to eat a low fat diet (ENC_m) included in breakfast consumption X_1 and consumption of food from convenience/other store X_2 regressions. The variable is an indicator of the parents concern for the child to eat healthy. Basically, parents were asked to rate themselves as whether they "never," "very seldom," "occasionally," "frequently" or "very frequently" encourage their child eat a low fat diet. Responses were ranked from 1-5. From these replies, a dummy variable was constructed with 1 reflecting the first three categories and 0 reflecting the last 2. The same factor for father is not included because very few fathers responded to this question.

The second parental lifestyle is the breakfast consumption patterns, which has been found to promote increased consumption in children. The variable is included as BF_m and PM_d for the mother and father, respectively. As in the case of children, the variables captured the number of days a week a parent consumes breakfast.

The final parental lifestyle variables related to the consumption of food from the convenient store are the mother's (PM_m) and the father's (PM_d) habits of eating food prepared outside the home. Each parent was asked recall how many times they purchased and brought fast food home a week. Bauer et al., (2009) and Boutelle et al. (2006) indicated that adolescents in homes, where parents brought fast foods home, were more likely to have increased their intake fast foods, which in our case is food from convenient store.

Summary statistics

Descriptive statistics of all variables are provided in the Tables 3.2, 3.3 and 3.4 of Appendix A part II; with N signifying the number of observations per variable, Std.dev signifying the standard deviation and CV representing the coefficient of variation. CV measures the percentage variability within the variable and computed as the standard deviation over the mean time 100%. Average means for those variables coded as 0 or 1 represent the proportion of that variable in the sample.

Dependent variables. It can be observed that the on average, children and adolescents aged 9-15 have breakfast 5.66 days per week, which approximates 6 days/week. The minimum and maximum values of breakfast consumption are 0 and 7,

respectively, meaning that some children did not have breakfast at all while others did take advantage of breakfast consumption throughout the entire week. But a closer look between children 9-11 years and adolescents 13-15 years indicates that the former take advantage of breakfast consumption more frequently than the latter. Mean consumption frequencies are approximately 6 and 5 days in a week, respectively. The variability in breakfast behavior of the whole group is 33.76% higher than 23.17% for children aged 9-11 years, but lower than 43.65% for those aged 13-15 years. These findings are comparable to earlier research, which found that older children consume less breakfast than younger ones.

Consumption of food from convenience stores differed greatly among children and adolescents, with some obtaining food up to 8 times in a week, while others obtaining none. The average number of times is less than 1, i.e. 0.78, and the variability in the behavior is quite substantial, registering 177.37%. The practice appears to be more popular in adolescents compared to children. The average number of times is 1.07 and 0.57 respectively, which is an approximate ratio of 1:2 for adolescents to children in that order.

Similarly, adolescents indicated having less sufficient sleep compared to children aged 9-11 years. Respective means are 0.67 and 0.9 for adolescents and children, corresponding to a proportion of 67% and 90% of adolescents and children. Again the variation in pattern in adolescents appears to be twice that of children. While these results might suggest increased potential risk to obesity in adolescents, they might also be an indicator of sleep problems brought about by excessive weight. This is because the

two are considered to have an endogenous relationship. This remains to be seen in the empirical analysis. However, overall sleep variation around the mean is 50% for sample of 9-15 year olds.

The average BMI of the children and adolescents is 20.73kg/m^2 . The variability in weight status is not that far from the mean, showing 23.06%. As expected, adolescents weighed more than children with mean BMI being 22.20 and 19.53 kg/m^2 , respectively. However, there was not much difference in variability recording 22.70% and 21.79% respectively.

Independent variables. Among individual characteristics there is not much difference in variation between 9-11 year olds and 13-15 year olds when it comes to gender, age and race if the child is of white. On the other hand maturity and race if the child is Hispanic varies greatly. In the case of maturity children age 9-11 are nearing the puberty growth which might explain the high variations compared to 13-15 year olds.

Variations in factors that serve as proxies for the susceptibility of the child to obesity did not differ that much between the two groups. My results indicate that mothers' BMI is 24.97kg/m^2 and 25.84 kg/m^2 for 9-11 and 13-15 year olds, respectively, with corresponding variations being 20.47% and 21.94% in that order. Likewise, the mean BMI of fathers is 27.8 kg/m^2 and 27.54 kg/m^2 with associated variations at 14.96% and 14.61%, respectively. What is also notable is that these figures are not that different from averages associated with all children, which register at 25.42 kg/m^2 for mother and 27.64 kg/m^2 for the father. What can be said is that these weight statuses are outside cut-off level for healthy weight and may suggest an increased risk of obesity in this sample

of children and adolescents. According CDC classification indicates adults are considered underweight if their BMI is < 18.5 ; healthy weight if their BMI is > 18.5 but < 24.9 ; overweight if their BMI is > 25.0 but < 29.9 and obese if their BMI is ≥ 30 (CDC, 2009b).

Of all the child specific behaviors influencing childhood obesity, dieting factors demonstrated the greatest variability in all samples. Unlike previous literature, this study finds dieting practices to be more common in children compared to adolescents. Average values of this behavior indicate a score of 0.13 (13%) for 9-11 year olds, while it is 0.9 (90%) for 13-15 year olds. Calderon, Yu and Jambazuan (2004) found incidence of dieting increased with age. Fifteen percent of their sample indicated to have dieted by age 11. By age 14, the proportion of dieters was 84%. A similar tendency was found by Maloney et al., (1989) who discovered a progressive trend in prevalence of dieting from children in the 3rd to 5th grades. Clearly this kind of inclination is different from what is found here and in our case suggests increased prone to obesity in children. Likewise the associated variability is for each group in 257.34% and 353.03% respectively. Variation in dieting is closely related with some children having started the behavior within the same year of commencement the study. The tendency of the behavior for the 9-11 olds is not that different from the mean of the children as a whole.

The data also show that children receive more money rewards for doing jobs at home than do the adolescents. The means for these two groups are 0.85 and 0.74 in that order. The average for all the children is 0.80. With regard to work, adolescents were

more likely to have a job compared to children. Corresponding means for these two groups are 0.26 and 0.45. Such a tendency is expected, given that parents may encourage children to perform work at home rather than work away from home, while adolescents have more freedom in deciding whether to take on the additional responsibility of a job. The fact that both practices put money in the hands of the children suggests that they could promote obesity.

On average, mothers of 9-11 year olds earned \$24785.11 with mothers of adolescents earning more than mothers of children per a year. Within each group, some earned over 150,000 dollars per year, while others nothing at all. Such differences signal resource inequality in household resources, which could affect the parenting styles and obesity risk behavior by children.

The proportion of parental high school education for mothers averaged the same for all of the mothers in the sample and those in the subsamples at 8% (0.08) for high school and 69% (0.69) for college. However, differences are seen in the variations from the mean. By contrast, father's college education differs slightly across the three groups, showing 64%, 57% and 61% for 9-11 year olds, 13-15 year olds and 9-15 year olds, respectively. Given this, it can be said that a greater proportion of mothers in this sample had a college education than did fathers.

In all three groups, breakfast consumption behavior is more frequent practiced by mothers compared with fathers; however, both parents of adolescents were the less likely to practice this behavior than parents of children. This might suggest a stronger influence by the mother on children than by the father. Minimum and maximum values

of 0 and 7 consumption tell us that while some parents may skip breakfast, others take advantage of the meal seven days a week.

Statistics indicate that mothers of adolescents show less concern when it comes to the frequency of advising their children to eat low fat diets. Mean values for ENC_m variable were 0.29 (29%) for 13-15 year olds compared to 0.28 (28%) for 9-11 year olds. Overall, fathers purchased and brought meals more frequently to the home compared to mothers in all categories. The tendency in fathers was more prevalent in home of 9-11 year olds. A look at mothers across all three groups indicates the opposite. Mothers of adolescents practiced this behavior more frequently than mothers of children aged 9-11 years. This result might suggest that fathers' influence may be stronger for children, while mother's influence might be stronger for adolescents when it comes to promoting fast food consumption by children. However, such a conclusion remains to be seen; other factors must be taken into account.

Empirical results

As mentioned earlier, the inclusion of weight status in obesity risk behavior equations 3.5-3.7 depends on whether there is a simultaneous relationship between the variables. The three children's obesity risk behavior equations include breakfast consumption (X_1), consumption of food from convenient/grocery stores (X_2), and sleep sufficiency (X_3); as well as one health outcome equation of weight status of the child (H). The Hausman test of simultaneity about the residuals of X_1 , X_2 and X_3 when added as regressors in H are shown in Table 3.5. According to results, tests on breakfast

intake and consumption of fast food are significant at 5% and 10% level; thus the two obesity risk behaviors exhibit simultaneity with weight status and thus H was included in equations 3.5 and 3.6, while dropped from 3.7. However, the importance of H in equation 3.5 ceased to be significant after the 3SLS analysis, which prompted its removal from that regression. For more on this analysis please refer to Appendix B.

3SLS estimation involves 1st stage regressions in which obesity risk behaviors are predicted based on individual and family factors that influence a given risk factor. The second stage involves a 3SLS estimation of the H based on predicted behaviors, while at the same time taking into account joint determinacy and correlated errors with other regressions. Consequently, the following results are presented based on the 1st stage OLS estimates for each obesity risk behavior and 2nd stage 3SLS estimates for the child weight models. For tabular results please refer to Appendix A, part II.

Children's breakfast consumption model

Results for the breakfast consumption model are shown in Table 3.6. To begin with, it should be noted that results from the regressions for the 9-15 year olds and 13-15 year olds are slightly different from those for 9-11 year olds. The difference lies in the exclusion of the ENC_m variable from the latter. The reason for this omission is due to the redundancy that made the regression worse in terms of significance; consequently it was dropped. That aside, it can be observed that all regressions are significant, although that of 9-11 year olds is significant only at the 0.1 level.

Overall, there is little consistency across regressions. Among the individual factors, it is the age of onset of dieting behavior that appears to be a consistently significant determinant of breakfast consumption in 9-15 year olds and 13-15 years old. A one year increase in age of the child will significantly lead to a reduction in breakfast consumption by 0.095 days for all children and adolescents and 0.134 days for adolescents only. The same variable was insignificant for children, although it was in the same direction as its relationship with breakfast in the other two groups. Age of the child was also a significant determinant, but was significant in all children and adolescents. For every one month increase in the age at which child starts to diet, breakfast consumption falls by 0.08 days. Other personal factors including race, specifically whether the child is black or white, gender in particular the child being a girl, dieting, and exercising had no influence on the behavior. However, the direction of their relationship with breakfast behavior shows consistency with prior literature (see, Siega-Riz, Pokin & Carson, 1998; Timlin et al., 2008; Rampsaud et al., 2005; Keski-Rahkonen et al., 2003; Aanio et al., 2002; Barker et al., 2000; Videon & Manning 2003).

Parental characteristics also show consistent relationships across all regressions. However, the most consistently significant determinant of breakfast behavior is the mother's frequency of encouraging low fat food consumption in all children and adolescents and in adolescents only. In other words, children and adolescents will consume less breakfast, if the mother does not encourage low fat foods.

Equally important is the parental education level, although this is only significant in the whole sample. A mother's having college education will reduce breakfast

consumption in 9-15 years old by 0.58 days, while the same level of education by fathers will result in increased breakfast consumption by 0.62 days in 9-11 year olds. This finding is comparable to that of Videon and Manning (2003) who found that college parental education promoted breakfast skipping, although only in adolescents. The same finding regarding mothers is in contrast to that of Siega-Riz, Pokin and Carson (1998), who found that mother's college education significantly increased breakfast consumption of children and adolescents aged 1-18 years, but was not important in adolescents aged 11-18 years.

A notable surprise is the insignificance of parental breakfast behavior on children's breakfast behavior, especially that of the mother. Some studies (e.g., Keski-Rahkonen et al., 2003) have shown that mother's eating of breakfast will significantly increase breakfast intake in children. While the relationship found in the present study is consistent with such findings, it is not important at all in children or adolescents for that matter. Possibly this may be issue of sample size or measurement.

Convenient store food consumption model

Results associated with the convenience store consumption model are presented in Table 3.7. Like in the case of breakfast there are differences in regressions of 9-15 year olds and 13-15 year olds; and children aged 9-11 years. In the case of aged 9-11 years, the child having a job and food purchase by the father were insignificant and highly distorted the regression in terms of significance; as result JB and PM_d were disregarded. All regressions are seen to be significant at 5% level with $p > \chi^2$ being

0.0002, 0.0003 and 0.005 for 9-15 year olds, 9-11 year olds and 13-15 year olds, respectively.

As in the case of breakfast consumption, consistency of significant results is greater between 9-15 years than adolescents aged 13-15 years. A noteworthy finding in the study is quite the pronounced effect of weight status on buying food from a convenient/grocery store. Basically, a unit increase child BMI will cause an increase in eating fast food from convenience in all children and adolescents by 0.11 times and in children by 0.18 times. Change in weight status in adolescents has no impact on this particular behavior.

Personal characteristics of race and gender are also important in influencing the behavior. That is, being Hispanic or white results in increased consumption of fast food from the convenience store in children only, while being white will promote this habit among all children and adolescents. Female adolescents are less likely to practice the behavior, given that girls will reduce consuming fast food from the store by 0.57 times/week compared with boys.

Results also show that money obtained from chores done at home has no influence on buying food from these stores. But having a job away from home encourages the behavior in pool of children and adolescents by 0.36 times more frequently. However, this effect can only be associated with adolescents given that none of the children had a job away from home. As stated earlier, having a job provides money resources in the control of the adolescent, enabling him or her to acquire fast food. Thirteen to fifteen year olds are likely to be more prone to this habit, given the

fact that eating outside the home increases during adolescence (Lin, Guthrie & Frazio, 1999). In addition, work places for adolescents are mostly fast food places, which put them in close proximity to fast food. These reasons, coupled with increased independence and autonomy in adolescence, can explain why jobs promote this behavior.

The effect of parental characteristics, as captured maternal total income, shows that increases in income promotes this habit among children and adolescents. A subgroup analysis also indicates that this effect is important for adolescents, but not for children. The impact of income on promoting fast food habits in children remains largely an undocumented phenomenon, which limits understanding of its impact. Most of the evidence regarding high income received by working mothers suggests it represents a lack time for food preparation and a preference for convenience foods (e.g. see Bowers, 1999). Possibly this may lead them to encourage their children to obtain fast foods as a substitute for one or more meals of the day.

Along with maternal income is the mother's purchase of convenience foods for home consumption, which is significant in all children and adolescents. Again subgroup analysis indicates that effect is most important among adolescents compared to children aged 9-11 years. It is argued here that children may easily be influenced by parental lifestyle. As such bringing fast food home may induce the teenager to behave that way.

Sleep model

Only regressions from the all children and adolescents aged 9-15 and adolescents aged 13-15 are significant showing $p > \chi^2$ of 0.0045 and 0.02, respectively, as can be seen in Table 3.8. Sufficiency in sleep for children aged 9-11 years is determined by data aside from that considered in this regression. The insignificance of the regression could also be an issue to functional forms, which can affect the predictability and magnitude of the coefficients. Linear models, as assumed to be the correct approach in this study, may be insufficient in depicting determinants of sleep in children. These functions can be transformed into advanced relationships via Box-Cox transformations (Box & Cox, 1964).

Consistent relationships in the model are parental characteristics, including the mother's income and high school education. Both relationships are important in children aged 9-15 and 13-15 years, but with differences in the level of significance. More specifically, an increase in the mothers' income is will reduce sleep in all children and adolescents at 10% level of significance, while the effect will occur in adolescents at 5% level. The effect of income on sleep in children is a rare finding in literature. But similar to Smaldone, Honig and Byrne (2009), our finding is contrary to earlier results (e.g. American Academy of Neurology, 2007). Findings by American Academy of Neurology (2007) from a study performed on children aged 4-10 indicated that children from low income homes had more sleep problems than children from higher income homes.

Having a high school education increases sleep sufficiency in both children and adolescents at 5% level of significance, while the same will occur in adolescents only at 10%. In relation to earlier attempts, Dasch, Raviv and Gruber, (2000) found that increases in education promoted high sleep quality in terms of increased percentage of adequate sleep and reduced number of waking. While the measure used in this study may provide one measure of sleep, it does not exactly reflect quality. It is seen as simple and subjective. What is regarded as sufficiency from one child may be different for another. This study was not able to control for such differences. Thus, comparability with prior studies may be limited.

Consistent with other literature is the finding that sufficiency is sleep decreases with age. Many such as Daseh, Raviv and Gruber (2000), Smaldone, Honig and Byrne (2009), and Spilbury et al., (2004) found a similar result under different samples. However, the same result was not found in sub group analysis in this study. In addition, the maturity of the child appears to have increase sleep sufficiency in adolescents. This variable has been given little attention in research on sleep; consequently not much can be inferred at this point. Unlike prior studies, this study found no significant influences of race or gender on sleep.

Child weight status model

Results for the child weight status model are shown in Table 3.9. All regressions are significant at 5% level with $p > \chi^2$ being 0, 0004 and 0.01315 for all children and

adolescents, children only, and adolescents only. This implies that all of the significant independent variables perform well in the prediction of child's BMI.

It can be observed that considering all children and adolescents, breakfast consumption and buying fast food from the convenience or grocery stores strongly predict childhood obesity in children. More specifically, increasing breakfast consumption by 1 day/week will decrease the BMI of the child by 0.15 units. This effect is more important for adolescents than children, given that breakfast consumption is insignificant in subgroup analysis of 9-11 year olds. This result reiterates earlier findings that have found such behaviors to have very negative effects in children (e.g. Gibson & O'Sullivan 1995; Fiore et al., 2006; Barton et al., 2005; Neimeier et al., 2006).

Consuming fast food from the convenience or grocery stores results in increased obesity of all children and adolescents. A onetime increase in the obtaining food from convenience stores a week promotes gains in weight status by 0.01 kg/m². But in this case the negative impact is mostly experienced by children aged 9-11 that adolescents. A onetime increase in the obtaining food from the convenience store by this group would lead to increased BMI by approximately 0.05 kg/m². Like in the case of breakfast these findings are consistent with earlier results (e.g. Neimeier et al., 2006; Taveras et al., 2005; Huang et al., 2004; Berkey et al., 2003).

This study finds that increases in parental BMI increased the susceptibility to obesity in both children and adolescents. However, the mother's impact is more pronounced compared to the father's. The same effect, however, is not seen in subgroup analysis of 9-11 year olds and limited to fathers in 13-15 year olds. Along with these

variables is the effect of race. Being Hispanic or white reduces the susceptibility to obesity in all children and adolescents and in children alone. Other factors including sleep, gender, exercise, maturity and age of the child were insignificant.

Concluding remarks

In summing up above findings, it can be said that dieting behaviors, breakfast consumption, and fast food consumption from convenient stores are very predictive of obesity in children as whole. However, their importance depends on the age group. While breakfast was important in altering the weight of teenagers, fast food consumption was not. Instead, this was far more important for younger children.

Both breakfast and fast food consumption habits were found to be simultaneous with gain in weights of the child. However, in case for breakfast, information from weight status was unimportant. Instead, the practice was predicted by others personal and contextual factors involving breakfast, including age of child, parental education, and encouragement from the mother to adopt healthful eating habits. This was not so for fast food consumption. While this risk behavior was found to cause increases in weight status, the reverse is also true. This result emphasizes the need for a two way intervention, that is while, on one hand, assists the child to control gains in weight as such, on the other hand, it should also be target change in her behaviors in general.

The influence of sleep turned out to be non significant. Possibly none of the individual and contextual factors were good instruments/predictors, especially in young children. It is also possible that the measure of sleep utilized by the study was poor given

its subjective nature. Most studies concerning sleep measure it in terms of hours slept. Using this variable would have greatly affected sample size given that only few children indicated how many hours they had slept. However, it is also possible that model construction to reveal the impact of sleep was poor. Some studies utilized much more complicated methods representing the sleep cycles and patterns, but this would require much more detailed data not available in this case. The bottom line is that impact of sleep on obesity needs to be studied further.

Policy

Findings from above reinforce the importance of diet behaviors in childhood obesity policies. The rates of childhood obesity remain a huge public health concern. Most recent updates on childhood obesity policy contained in National Conference of State Legislatures (NCSL, 2010) indicate a range of policy approaches that have been considered, including procedures on BMI control, physical activity education in schools, school wellness policies, raising awareness, nutrition education, school nutrition legislation, trans-fat in school foods, diabetes screening and many more. The approach is commendable for its holistic nature in considering the person and the environment. However, nearly half the states are yet to consider these policies. Of those states that have considered them, only a few have gone ahead to enact a selected number of these regulations.

Most states that have enacted the policy have dedicated their efforts to school nutrition programs. According to the Center for Health Improvement (CHI, 2010), the

School Breakfast Program (SBP) was permanently enacted in 1975 to boost nutritional needs of students from poor families. Under the program the government offers cash subsidies to schools for the total cost of breakfast for students under 130% of federal poverty and partially meets that of students up to 185% of poverty (USDA, 2010), it largely remains underutilized. Findings by Gleason (1995) indicated that only 19% of students participated in this school breakfast program. Similarly, Gross et al., (2004) found that participation in the program was 11%. A more recent study by Bartfeld, Kim, Ryu & Ahn, (2009) indicates that only 35% ate school breakfast, although the figure rose to 42% when findings were limited to schools where only school breakfast was provided. Consequently, there is need to increase participation rates remains high priority.

Overcoming this problem will require policies that address the current barriers to the program. Among these is the social stigma associated with the program. That is, it targets low income households and children who don't want to be viewed as poor. The program requires breakfast to be served very early and some children don't have time to eat this meal. In addition, the reduced prices are still unaffordable to poor students. Some schools experience logistical problems in terms of staff to supervise meal administration and changing bus schedules. Furthermore, students' partaking in this breakfast is further limited by the parental understanding of the program, given that some mothers view the breakfast meal as the responsibility of the family (McDonell et al., 2004).

Making the program universally free has contributed to this the goal by removing some of the barriers and increasing participation rates (Lent, 2007; Bernstein,

McLaughlin & Crepinsek, 2002). However, adoption of the policy has been limited to some states and needs to be promoted elsewhere. A huge challenge is that schools need funding from the state is to enable them to be institute such program. Some states place requirements that schools need to have a certain proportion of student before they can eligible for the program which has stopped several schools from accessing the program. For example, Texas, which was central study area for this work, the Texas education code requires that the school contain at least 10% of students who are eligible under criteria set by the national school breakfast program.

Aside from instituting such a program, it is important that policies make provisions for continuous sensitization of parents and children about the health benefits of the program possibly through the school. This based on the fact that parental education seemed to strongly predict the behavior. In addition, increasing funding for schools to meet logistical needs will foster further breakfast participation. Justification of such funds may be strengthened by research concerning costs and benefits of breakfast program and childhood obesity expenditures. As more data on expenditure of childhood obesity becomes available, it will enhance such studies

In terms regulations of consumption of fast foods by children, current policies are directed towards control of access times, distribution points, and nutrition quality of competitive foods and beverages on school grounds. In addition to this, replacing the foods in vending machines that are of poor nutrition quality is a priority (NCSL, 2010). Again only a few states have adopted the regulations.

Beyond efforts to change the school environment, others have been directed towards the market. Among these are nutrition labeling in restaurants to assist children, parents and individuals make healthy choices, abolishing food advertising aimed at children, and increases in taxes of high fat content snacks (Cawely, 2006; Kuhler, Golan, Veriyam & Crutchfield, 2005). However, expectations are such that they will not lead to change behavior. Benefiting from the first plan would require that information be presented in manner that children and parents can understand it. The second, the aim is to reduce or halt children's preferences for high fat foods by means of adding 'fat taxes' to such foods. The last proposition is somewhat risky, given the fact that there is a tendency for firms to absorb all tax increases, leaving the price of food and thus behavior unchanged. This kind of intervention is beneficial only if the firms pass the tax to the consumer, that way the child and parent will substitute healthy foods for high priced non-nutritious foods. But in all these cases there is need for research especially directed towards children's responses to such policies to determine their effectiveness. Lastly, like in the case of breakfast policies, instituting such plans is very expensive. However, the cost is likely necessary and is lower than that created by an even greater obesity epidemic in children and society.

CHAPTER IV

CONCLUSIONS

This chapter summarizes the purpose and findings of this research. Primarily this dissertation set out to evaluate the effects parental time and children's behaviors on changes on children's weight status that are considered as major causes of the condition. The two aspects cause changes in weight in various ways. This study investigates these links in a different approach compared to prior research. Given the differences in their processes of impact the two causes are investigated separately.

The source of data aiding these investigations is the micro-level data from Parental time, Role strains, Coping and Children's Diet and Nutrition project on about 300 households in the Houston Metropolitan Statistical Area. Samples are limited to two parent families with one child.

The importance of actual parental time use and its effect obesity is studied in Chapter II. Over the past 30 years changes in parental time have paralleled changes in childhood obesity suggesting that the former are to blame for the latter. Economic studies examining the association have come to a major conclusion that mother's time spent with the child reduces the condition. However, studies focusing on the mother's actual time with the child have ignored the effect of unobserved factors can lead to biased results. Examining and correcting for the issue constituted the major focus of this chapter. Instrumental variables were adopted as the means of correcting problem. The task was to identify variables meeting all relevant criteria in a theoretical and empirically

consistent way. Such variables impact the mother's time allocation decision but not the child's health outcome.

The household production model formed the basis for deriving a potential reliable instrument variable set to facilitate empirical modeling. This set of variables influences parental input, but do not enter the production function. This makes it possible to obtain information about an underlying health technology without bias.

The potential instrument set considered of wages, non earned income and any household characteristics that had no impact of health outcome but will affect child health. Due to data limitations, wages were excluded and parental unearned incomes substituted along with annual incomes. In addition, father's work to family spillover that represents a resource and time capacities were included. This is what constituted the instrumental variable set.

Empirical investigation involved joint estimation of both the mother's actual time with the child and child's weight status. That is, the former is used to produce an estimate of mother's time spent with their children to study the impact of mother's time on obesity. Thus, this system of equations consisted of one reduced form equation of mother's time allocation and one structural equation of child health.

In addition, the empirical investigation called for certain estimation issues to facilitate statistical inference and reduce any bias. To avoid self-selection bias between non working and working mothers, mother's income was dropped. Identification of the system was based the excluded instrument(s) and endogeneity brought about by correlated errors was tackled through adoption an estimator that would minimize that

bias. Instrumental variable techniques (2SLS) were used empirically investigate the causal link of concern, while testing for relevancy of instruments. Results were compared with those from other IV estimators including LIML, Fuller(k) and GMM.

Findings revealed that the more time a child spent with the mother led to a less gain in weight status. In this regard, results were similar to those of earlier findings by McIntosh et al., (2006) and You (2005) although both are on smaller sub samples. Evaluation of the same causal link on pooled sample in one study (i.e. You, 2005) yielded no results. Possibly the pronounced impact of unobserved factors shadowed the observation of this association and the best way would be by use of IV methods.

Father's work to family spillover emerged as a suitable IV for mother's time with the child meeting all relevant criteria. The higher the father's work to family spillover, the more the time spent with the child. Its strength was not reduced upon adding obesity health enhancing or discouraging environments, except for suspected white noise. Earlier explorations of a similar variable had found it to directly affect child weight in smaller sub samples. However, the same impact was not found in much larger pooled sample. It is possible that when considering children as whole father's work to family spillover is an IV rather than a direct covariate. Its impact on changes in weight status is only through its influence on mother's time with the child.

Father's income was not found to affect changes mother's actual time with the child. Such a finding can be attached to the gendered traditional role expectations. Mothers view themselves as primary care takers of the children and will always presume this role that regardless whether parents earn high incomes or not. While mothers might

cut back on work hours to spend time with the child, father's are less likely to so. However, the direction of causation shows that unit change in father's income will reduce mother's time with the child indication that the two might be substitutes.

Other important drivers of child weight status were parents' weight statuses, age of the child, and father's age. Increases in the first two variables, leads to increases in the child weight status. Increase in the father's age leads to reduction in BMI of the child. Education level of mother appeared to be the only other important factor contributing to mother's allocation time with child.

The above results and explanations are limited to the short run information given the nature of cross sectional data. It is important future research consider similar investigations, but in the long run to establish if the role of father's work spillover as IV is sustained or not under such circumstances. Moreover, such analyses would facilitate the use and comparisons of results from fixed effect methods that utilize longitudinal data.

In addition this study considered linear relationships of variables. Future work might consider use of other functional forms using the same methods as used here to see if such relations of IV are maintained. Furthermore, the measure of father's work spillover used in this study is based on combination of several experiences associated with work-family roles. It is suggested prospective works consider decomposing this variable into individual factors that might provide more information on the link between parental time and childhood obesity. Finally, this work minimized selection bias between working and non working mothers by dropping mother's income. Forth coming

works might consider using other methods such as the Inverse Mills Ratio to deal with the problem.

The effect of children's obesity risk behavior was dealt with in Chapter III. Behaviors that formed the central focus were breakfast practices, consumption of fast food from convenient stores and sleeping patterns. The aim here was to jointly evaluate the impact of these practices, while taking into account contextual factors.

The theoretical framework guiding conceptualization and empirical modeling of the factors and children's weight outcomes was ecological systems theory. Based on this model, the obesity risk behaviors and child weight outcomes were modeled as a system of four equations. This study also attempted to evaluate the presence of interaction between weight status and child practices.

Empirical investigation demanded that we consider identification, presence of simultaneity and correlated errors in the system. Checks of identification revealed an over identified system. Checks for simultaneity revealed that breakfast habits and fast food consumption were simultaneous with child weight status. This study then chose to include weight outcomes in the two respective equations with the reservation that if it turned out not be significant it would be dropped. Correlated errors were controlled by choosing 3SLS methods which also controls for simultaneity.

Results revealed that impact of weight status on breakfast was not significant. Instead information on breakfast habits was provided by age of the child, years of dieting, mother's and father's college education, and the mother's encouragement of the child to have a healthy diet. Thus weight status was dropped from this equation;

however, the results remained the same upon re-estimation. The case of fast food consumption was however different as child's weight status contributed greatly to this behavior in child of whole sample and in those 9-11 years. Other important factors included gender, race, having a job, mother's income, and mother's habit of bringing purchased food home. There were difference in effects of these factors between 9-11 year olds and 13-15 year olds with the latter showing more effects. Findings concerning sleep patterns also showed differences among age group with the regression of 9-11 year olds being inefficient. Important factors affecting sleep included age of child, mother's income and mother's high school education.

Overall children's weight status was affected by breakfast and fast food consumption habits. Increasing breakfast consumption habit by one day would result in reduction in body weight of the child. However, increases in fast food consumption would result in the increase in body weight of the child. Such associations were consistent with prior literature. Nevertheless, the relationships break down in subsamples, with 9-11 year old being affected by fast food consumption, while 13-15 year olds being affected by breakfast patterns. Other important factors influencing child BMI included the parent's BMI and the race of the child. That is, being white or Hispanic would reduce gains in body weight of the child.

Policy issues were discussed in view of the results with emphasis on nutrition regulations directed towards childhood obesity. The most common of policy was found to be school breakfast program which even today is still characterized by low participation rates nationwide. This low participation is contributed to by several

barriers including stigmatization, unaffordable reduced costs, non conducive program schedules and school logistical constraints. Some solutions included making breakfast free for all, completely removing reduced priced meals, and increased school funding to assist in running the program. Policies regarding fast food consumption instituted limited serving food at particular times and nutritional quality of competitive foods. Outside school policies have been proposed to regulate open market to direct change in behavior. Some of these pertain nutritional labeling on restaurants, abolishing food advertising aimed at child, taxing foods high calories and reconsidering bans on companies that may supply food that makes people fat. Many of these laws have not been enforced probably due to associated high costs. However such costs are low compared to having sick children and an obese society.

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APPENDIX A

Part I. Tables for Chapter II

Table 2.2: Description of Variables in the System

Variable	Unit
<i>Dependent Variables</i>	
Body Mass index (BMI) of child	Kilograms/meter ²
Mother 's actual time spent with child	Minutes
<i>Independent Variables</i>	
<i>Household characteristics</i>	
If child is Hispanic (=1, otherwise 0)	0 or 1
If child is white (=1, otherwise 0)	0 or 1
Gender (1= female, 0= male)	0 or 1
Maturity	0 or 1
Age of child	Months
If child exercises at least 30 minutes a day	0 or 1
Body Mass Index (BMI) of Mother	Kilograms/meter ²
Body Mass Index (BMI) of Father	Kilograms/meter ²
Father's age	Years
Mother's age	Years
If Mother attended college	0 or 1
Number of times the child bought food from restaurant in past 7 days	Count
Number of days/week child has break fast	Days/week
Number of days/week mother has break fast	Days/week
If mother exercises 30 min five times a week	0 or 1
Number of times the mother eats out per week	Count
<i>Instrumental variables (IV)</i>	
Father's total income	Dollars
Father's work to family spill over	Factor

Table 2.3: Summary Statistics of Variables in the System

Variable Descriptions	N	Mean	Std. Dev	Min	Max	CV
<i>Dependent variables</i>						
BMI of child	227	20.76	4.82	14.35	45.97	23.22
Mother's actual time with child	202	107.43	98.62	0	539.50	91.80
<i>Independent Variables</i>						
<i>Household characteristics</i>						
If child is Hispanic (=1, otherwise 0)	224	0.12	0.33	0	1	270.72
If child is white (=1, otherwise 0)	224	0.79	0.41	0	1	52.34
Gender (1= female, 0= male)	227	0.48	0.50	0	1	104.28
Maturity	220	0.59	0.49	0	1	84.18
Age of child	227	143.26	26.08	108	180	18.20
if child exercises at least 30 minutes a day	226	0.67	0.47	0	1	69.93
BMI of Mother	224	25.38	5.40	17.59	46.20	21.26
BMI of Father	226	27.70	4.09	17.63	45.78	14.75
Father's age	226	44.81	5.38	32	69	12.00
Mother's age	225	42.47	4.67	31	53	10.99
If Mother attended college	225	0.69	0.46	0	1	67.35
Number of times the child buys food from restaurant	227	0.78	1.33	0	8	170.83
Number of days child has break fast	226	5.66	1.91	0	7	33.78
Number of days mother has break fast	225	5.19	2.36	0	7	45.48
If mother exercises 30 min five times a week	225	0.36	0.48	0	1	133.63
Number of times the mother eats out	225	1.55	1.44	0	14	92.75
<i>Instrumental variables (IV)</i>						
Father's total income	202	80177.16	48283.61	600	283044.00	60.22
Father's work spill over	226	2.99	1.05	0	5.92	35.09

Note: N= number of observations for variable; Std. Dev= Standard Deviation; Min= Minimum; Max= Maximum; CV= Coefficient of variation

Table 2.4: First Stage OLS Regression of the Mother's Time Spent with the Child against IVs and Family Specific Control Variables

Variables	OLS	
<i>Independent Variables</i>		
Intercept	2.17E+02 (0.031) **	1.81E+02 (0.076)**
if child is Hispanic	7.19E+00 (0.809)	2.21E+01 (0.48)
If child is white	2.73E+01 (0.24)	1.96E+01 (0.418)
Gender	1.76E+00 (0.891)	1.00E+01 (0.45)
Maturity	-19.6708 (0.34)	-1.93E+01 (0.374)
Age of child	-0.40124 (0.329)	-5.18E-01 (0.23)
if child exercises at least 30 minutes a day	-2.74E+01 (0.055) **	-2.30E+01 (0.118)
BMI of Mother	2.56E-01 (0.837)	-1.21E-01 (0.926)
BMI of Father	-1.95E+00 (0.281)	-1.51E+00 (0.406)
Father's age	4.98E-01 (0.78)	2.53E-01 (0.875)
Mother's age	-2.68E+00 0.202	-1.53E+00 (0.438)
if Mother attended college	3.79E+01 (0.007) **	4.16E+01 (0.004) **
<i>Excluded Instrumental variables (IVs)</i>		
Father's total income	-3.4E-05 (0.812)	
Father's work spill over	2.20E+01 (0.001) **	2.41E+01 (0) **
Number of observations	193	193
F-value	3.01	3.21
Probability >F	(0.0005) *	(0.0003)**

Table 2.4 (Continued)

Variables	OLS	
<i>Test of excluded Instruments (IV)</i>		
<i>F-statistic</i>	5.36	13.11
<i>Probability >F</i>	(0.0055)**	(0.0004) **

Note: P-values are in brackets. * is the level of significance at 5%; ** is the level of significance at 10%.

Table 2.5: Second Stage Regressions of Child Weight Status (BMI) against the Mother's Actual Time Spent with the Child and Family Specific Characteristics

Variables	2SLS	LIML	FULLER(k=1)	GMM
Intercept	1.53E+01 (0.024) **	1.53E+01 (0.024) **	1.47E+01 (0.025) **	1.53E+01 (0.013) **
Mother time with child	-3.05E-02 (0.044) **	-3.05E-02 (0.044) **	-2.80E-02 (0.049) **	-3.05E-02 (0.039) **
If child is Hispanic	-8.84E-01 (0.61)	-8.84E-01 (0.61)	-9.30E-01 (0.581)	-8.84E-01 (0.61)
If child is white	-6.29E-01 (0.65)	-6.29E-01 (0.65)	-6.98E-01 (0.603)	-6.29E-01 (0.639)
Gender	-6.56E-01 (0.38)	-6.56E-01 (0.38)	-6.84E-01 (0.346)	-6.56E-01 (0.36)
Maturity	-1.90E+00 (0.127)	-1.90E+00 (0.127)	-1.83E+00 (0.128)	-1.90E+00* (0.059)
Age of child	7.48E-02 (0.002) **	7.48E-02 (0.002) **	7.55E-02 (0.001) **	7.48E-02 (0.002) **
If child exercises at least 30 minutes a day	-5.74E-01 (0.485)	-5.74E-01 0.485	-5.38E-01 0.499	-5.74E-01 0.494
BMI of Mother	1.56E-01 (0.028) **	1.56E-01 (0.028) **	1.56E-01 (0.024) **	1.56E-01 (0.027) **
BMI of Father	1.76E-01 (0.086)*	1.76E-01 (0.086)*	1.79E-01 (0.071)*	1.76E-01 (0.091)*
Father's age	-1.66E-01 (0.057)*	-1.66E-01 (0.057)*	-1.63E-01 (0.054)*	-1.66E-01 (0.062)*
Mother's age	-5.53E-02 (0.618)	-5.53E-02 (0.618)	-5.12E-02 (0.635)	-5.53E-02 (0.621)
If Mother attended college	1.40E+00 (0.154)	1.40E+00 (0.154)	1.30E+00 (0.167)	1.40E+00 (0.136)
Number of observations	193	193	193	193
F-value	3.39	3.39	3.56	3.2
Probability >F	(0.0002)**	(0.0002)**	(0.0001)**	(0.0003)**

Table 2.5 (continued)

Variables	2SLS	LIML	FULLER(k=1)	GMM
<i>Tests of Under identification for excluded instrument</i>				
Anderson canon. corr. <i>LM</i> statistic	13.105*	13.105*	13.105*	
χ^2 (1) P-value	(0.0003)	(0.0003)	(0.0003)	
Kleibergen-Paap rank <i>LM</i> statistic				13.843*
χ^2 (1) P-value				(0.0002)
<i>Weak Identification for excluded Instrument</i>				
Cragg-Donald Wald <i>F</i> -statistic	13.113 [†]	13.113 [†]	13.113 ^{††}	
Kleibergen-Paap rank Wald <i>F</i> -statistic				14.287 [†]

Note: All P-values are in brackets; ** represents $P < .05$ and * represents $P < .1$

[†]Significant at 10% maximal IV and LIML size and ^{††} Significant at 30% fuller relative and maximum bias of Stock and Yogo critical values.

Table 2.6: First Stage OLS Regression of the Mother's Actual Time Spent with the Child against Child and Parent's Personal Characteristics and Behavior

Variables	OLS
<i>Independent variables</i>	
Intercept	1.87E+02 (0.092) *
if child is Hispanic	2.59E+01 (0.42)
If child is white	2.08E+01 (0.405)
Gender	5.82E+00 (0.664)
Maturity	-22.3773 (0.322)
Age of child	-6.29E-01 (0.168)
if child exercises at least 30 minutes a day	-2.26E+01 (0.129)
BMI of Mother	-4.98E-02 (0.971)
BMI of Father	-1.48E+00 (0.424)
Father's age	2.29E-01 (0.887)
Mother's age	-1.36E+00 (0.492)
if Mother attended college	4.15E+01 (0.006)**
Number of times the child buys food from restaurant	-1.15E+00 (0.825)
Number of days child has break fast	-8.18E-01 (0.831)
Number of days mother has break fast	-2.84E+00 (0.351)
If mother exercises 30 min five times a week	2.46E+01 (0.101)
Number of times mother eats out/week	1.01E+01 (0.122)

Table 2.6 (continued)

Variable	OLS
<i>Excluded Instrumental variable (IV)</i>	
Father's work to family spillover	2.43E+01*
	(0)
Number of observations	193
F-value	2.6*
Probability >F	(0.0009)
<i>Test of excluded Instrument (IV)</i>	
F-statistic	13.08*
Probability >F	0.0004

Note: All P-values are in brackets; ** represents $P < .05$ and * represents $P < .1$

Table 2.7: Second Stage Regression of Child Weight Status (BMI) against the Mother's Actual Time Spent with the Child and Parent's Personal and Behavioral Characteristics

Variables	2SLS	LIML	FULLER(k=1)	GMM
Intercept	1.84E+01** (0.006)	1.84E+01** (0.006)	1.78E+01** (0.005)	1.84E+01** (0.003)
Mother time with child	-2.57E-02* (0.068)	-2.57E-02* (0.068)	-2.35E-02* (0.076)	-2.57E-02** (0.048)
if child is Hispanic	-9.68E-01 (0.561)	-9.68E-01 (0.561)	-1.02E+00 (0.531)	-9.68E-01 (0.588)
If child is white	-6.94E-01 (0.601)	-6.94E-01 (0.601)	-7.56E-01 (0.559)	-6.94E-01 (0.624)
Gender	-8.79E-01 (0.201)	-8.79E-01 (0.201)	-8.93E-01 (0.183)	-8.79E-01 (0.193)
Maturity	-1.87E+00 (0.123)	-1.87E+00 (0.123)	-1.81E+00 (0.126)	-1.87E+00** (0.069)
Age of child	5.91E-02** (0.011)	5.91E-02** (0.011)	5.98E-02** (0.008)	5.91E-02** (0.011)
if child exercises at least 30 minutes a day	-5.06E-01 (0.508)	-5.06E-01 (0.508)	-4.78E-01 (0.523)	-5.06E-01 (0.53)
BMI of Mother	1.36E-01** (0.049)	1.36E-01** (0.049)	1.35E-01** (0.045)	1.36E-01* (0.084)
BMI of Father	1.98E-01** (0.039)	1.98E-01** (0.039)	2.01E-01** (0.032)	1.98E-01* (0.052)
Father's age	-1.55E-01* (0.056)	-1.55E-01* (0.056)	-1.53E-01* (0.054)	-1.55E-01** (0.049)
Mother's age	-5.34E-02 (0.602)	-5.34E-02 (0.602)	-5.04E-02 (0.614)	-5.34E-02 (0.6)
if Mother attended college	1.13E+00 (0.22)	1.13E+00 (0.22)	1.05E+00 (0.238)	1.13E+00 (0.222)
Number of times the child buys food from restaurant	2.62E-01 (0.328)	2.62E-01 (0.328)	2.70E-01 (0.302)	2.62E-01 (0.373)
Number of days child has break fast	-2.11E-01 (0.28)	-2.11E-01 (0.28)	-2.10E-01 (0.271)	-2.11E-01 (0.313)
Number of days mother has break fast	-3.19E-01** (0.042)	-3.19E-01** (0.042)	-3.14E-01** (0.04)	-3.19E-01 (0.122)
If mother exercises 30 min five times a week	1.06E+00 (0.206)	1.06E+00 (0.206)	1.01E+00 (0.218)	1.06E+00 (0.185)
Number of times mother eats out/week	4.65E-01 (0.191)	4.65E-01 (0.191)	4.44E-01 (0.199)	4.65E-01 (0.194)

Table 2.7 (continued)

Variables	2SLS	LIML	FULLER(k=1)	GMM
Number of observations	193	193	193	193
<i>F</i> -value	3.04**	3.04**	3.16**	3.3**
Probability > <i>F</i>	(0.0001)	(0.0001)	(0.0001)	(0)
<i>Tests of Under identification for excluded instrument</i>				
Anderson canon. corr. <i>LM</i> statistic	13.422**	13.422**	13.422**	
χ^2 (1) <i>P</i> -value	(0.0002)	(0.0002)	(0.0002)	
Kleibergen-Paap rank <i>LM</i> statistic				14.023**
χ^2 (1) <i>P</i> -value				(0.0002)
<i>Weak Identification for excluded Instrument</i>				
Cragg-Donald Wald <i>F</i> statistic	13.08 [†]	13.08 [†]	13.08 ^{††}	
Kleibergen-Paap rank Wald <i>F</i> statistic				14.005 [†]

Note: All P-values are in brackets; ** represents $P < .05$ and * represents $P < .1$

[†]Significant at 10% maximal IV and LIML size and ^{††} Significant at 30% fuller relative and maximum bias of Stock and Yogo critical values.

Part II: Tables for Chapter III

Table 3.1: Description of Variables in the Model

Variable	Description	Unit
Dependent variables		
X_1	Number of days/week child has breakfast	Days
X_2	Number of times/week the child buys food/drink from convenient store	Count
X_3	If child has enough sleep (1 = yes; 0 = no)	0 or 1
H	BMI of child	Kilograms/meter ²
Independent variables		
<i>Individual Specific Factors</i>		
BLK^*	If child is black (1 = yes; 0 = otherwise)	0 or 1
HIS	If child is Hispanic (1 = yes; 0 = otherwise)	0 or 1
WH	If child is white (1 = yes; 0 = otherwise)	0 or 1
GD	Gender (1 = female; 0 = male)	0 or 1
AG_c	Age of child	Months
MT	Maturity	
EX	Time the child spends in sports	Hours
DT	If child diets (1 = yes; 0 = no)	0 or 1
ADT	Age of onset of dieting behavior	Years
$DT \times ADT$	Interaction term (if child diets and age of dieting)	
MC	Child receives money for chores done at home	0 or 1
JB	If the child has a job (1 = yes; 0 = no)	0 or 1
TS	If parent let child sleep any time he wants (1 = yes; 0 = no)	0 or 1
<i>Parental factors</i>		
BMI_m	Body mass index of Mother	Kilograms/meter ²
Y_m	Mother's income	Dollars
$EDUH_m$	If highest education attained by mother is high school or less (1 = yes; 0 = otherwise)	0 or 1
$EDUC_m$	If highest education attained by mother college (1 = yes; 0 = otherwise)	0 or 1
ENC_m	If mother does not frequently encourages child to eat low fat diet	0 or 1
BF_m	Number of days/week mother has break fast	Days
PM_m	Number of times/week mother purchases and brings home meals	Count
BMI_d	Body mass index of Father	Kilograms/meter ²
$EDUH_d$	If highest education attained by father is high school or less (1 = yes; 0 = otherwise)	0 or 1
$EDUC_d$	If highest education attained by mother college (1 = yes; 0 = otherwise)	0 or 1
AG_d	Father's age	Years
BF_m	Number of days/week father has break fast	Days
PM_d	Number of times/week father purchases and brings home meals	Count

Note: * BLK, is considered as bases and thus not part of the model.

Table 3.2: Descriptive Statistics of Variables in the Model

Variable	N	Mean	Std. Dev	Minimum	Maximum	CV
<i>Dependent variables</i>						
X_1	227	5.65	1.91	0	7	33.80
X_2	226	0.80	1.40	0	8	175.41
X_3	227	0.79	0.41	0	1	51.21
BMI_c	228	20.77	4.82	14.35	45.97	23.18
<i>Independent variables</i>						
<i>Individual specific factors</i>						
HIS	225	0.12	0.33	0	1	271.41
WH	225	0.79	0.41	0	1	52.19
GD	228	0.48	0.50	0	1	103.80
AG_c	221	0.59	0.49	0	1	83.86
MT	228	143.47	26.22	108	192	18.27
EX	220	1.01	1.09	0	5	107.27
DT	227	0.11	0.32	0	1	278.66
ADT	227	2.53	4.73	0	15	186.87
$DT \times ADT$	227	1.07	3.19	0	14	298.28
MC	227	0.80	0.40	0	1	50.52
JB	227	0.35	0.48	0	1	137.18
TS	226	0.31	0.47	0	1	148.08
<i>Parental factors</i>						
BMI_m	225	25.37	5.38	17.59	46.20	21.22
Y_m	214	25051.04	37369.41	0.00	303000.00	149.17
$EDUH_m$	226	0.08	0.27	0	1	340.69
$EDUC_m$	226	0.69	0.46	0	1	67.14
ENC_m	221	0.29	0.45	0	1	158.72
BF_m	226	5.19	2.36	0	7	45.36
PM_m	226	0.85	0.67	0	4	78.60
BMI_d	227	27.68	4.09	17.63	45.78	14.77
$EDUC_d$	227	0.61	0.49	0	1	80.48
AG_d	227	44.88	5.46	32	69	12.17
BF_d	226	4.61	2.52	0	7	54.59
PM_d	225	1.05	0.82	0	5	77.35

Note: N= number of observations; Std.Dev= Standard deviation; CV =coefficient of variation

Table 3.3: Descriptive Statistics for Children Aged 9-11 Years

Variable	N	Mean	Std. Dev	Minimum	Maximum	CV
Dependent variables						
X_1	121	6.15	1.43	1	7	23.17
X_2	121	0.57	1.06	0	7	185.07
X_3	121	0.90	0.30	0	1	33.32
BMI_c	122	19.53	4.26	14.35	35.30	21.79
Independent variables						
<i>Individual specific factors</i>						
HIS	119	0.15	0.36	0	1	237.88
WH	119	0.77	0.42	0	1	54.40
GD	122	0.48	0.50	0	1	103.76
AG_c	116	0.23	0.42	0	1	182.34
MT	122	120.79	9.60	108	132	7.95
EX	116	0.81	0.84	0	4	103.54
DT	121	0.13	0.34	0	1	257.24
ADT	121	1.93	3.79	0	13	195.77
$DT \times ADT$	121	1.21	3.20	0	13	263.20
MC	121	0.85	0.36	0	1	41.98
JB	121	0.26	0.44	0	1	171.10
TS	120	0.18	0.38	0	1	218.03
<i>Parental factors</i>						
BMI_m	120	24.97	5.11	17.59	46.06	20.47
Y_m	112	19390.93	28989.89	0.00	161199.80	149.50
$EDUH_m$	121	0.08	0.28	0	1	334.55
$EDUC_m$	121	0.69	0.46	0	1	66.64
ENC_m	118	0.28	0.45	0	1	161.18
BF_m	121	5.39	2.28	0	7	42.36
PM_m	121	0.81	0.64	0	3	78.22
BMI_d	121	27.80	4.16	20.08	45.78	14.96
$EDUC_d$	121	0.64	0.48	0	1	74.56
AG_d	121	43.51	5.51	32	69	12.66
BF_d	121	4.65	2.48	0	7	53.35
PM_d	120	1.10	0.89	0	5	81.65

Note: N= number of observations; Std.Dev= Standard deviation; CV =coefficient of variation

Table 3.4: Descriptive Statistics for Children Aged 13-15 Years

Variable	N	Mean	Std. Dev	Minimum	Maximum	CV
Dependent variables						
X_1	106	5.08	2.22	0	7	43.65
X_2	105	1.07	1.69	0	8	158.30
X_3	106	0.67	0.47	0	1	70.54
BMI_c	106	22.20	5.04	14.80	45.97	22.70
Independent variables						
<i>Individual specific factors</i>						
HIS	106	0.08	0.28	0	1	329.85
WH	106	0.80	0.40	0	1	49.94
GD	106	0.48	0.50	0	1	104.34
AG_c	105	0.98	0.14	0	1	14.00
MT	106	169.58	9.67	156	192	5.70
EX	104	1.23	1.27	0	5	103.12
DT	106	0.09	0.29	0	1	311.31
ADT	106	3.22	5.56	0	15	172.95
$DT \times ADT$	106	0.90	3.18	0	14	353.03
MC	106	0.74	0.44	0	1	60.20
JB	106	0.45	0.50	0	1	110.45
TS	106	0.47	0.50	0	1	106.33
<i>Parental factors</i>						
BMI_m	105	25.84	5.67	17.97	46.20	21.94
Y_m	102	31266.07	44123.45	0.00	303000.00	141.12
$EDUH_m$	105	0.08	0.27	0	1	349.88
$EDUC_m$	105	0.69	0.47	0	1	68.03
ENC_m	103	0.29	0.46	0	1	156.75
BF_m	105	4.96	2.43	0	7	48.88
PM_m	105	0.90	0.71	0	4	78.80
BMI_d	106	27.54	4.02	17.63	39.13	14.61
$EDUC_d$	106	0.57	0.50	0	1	87.98
AG_d	106	46.44	4.99	38	65	10.74
BF_d	105	4.56	2.56	0	7	56.28
PM_d	105	1.01	0.72	0	4	71.09

Note: N= number of observations; Std.Dev= Standard deviation; CV =coefficient of variation

Table 3.5: Tests for Simultaneity between Obesity Risk Behavior and Child Weight Status

Child weight status (H)		
Residuals	Coefficient	p> t
X_1	1.95E+00*	(0)
X_2	-1.27E+00**	(0.073)
X_3	-1.00E+00	(0.817)

Note: All P-values are in brackets; ** represents $P < .05$ and * represents $P < .1$

Table 3.6: First Stage OLS Regression of the Effect of Individual and Parental Factors on the Child's Breakfast Behavior

Variables	9-15 year olds	9-11 year olds	13-15 year olds
Intercept	7.63E+00 (0)*	7.09E+00 (0.001)**	7.05E+00 (0.083)*
<i>HIS</i>	-5.12E-02 (0.927)	-5.57E-01 (0.371)	5.82E-02 (0.952)
<i>WH</i>	-8.87E-02 (0.84)	-4.35E-01 (0.436)	1.14E-01 (0.86)
<i>GD</i>	1.36E-01 (0.573)	-1.07E-01 (0.671)	6.55E-01 (0.113)
<i>AG_c</i>	1.78E-02 (0.023)**	-1.11E-02 (0.437)	-6.59E-03 (0.757)
<i>MT</i>	-2.29E-01 (0.57)	3.24E-02 (0.922)	-1.32E+00 (0.351)
<i>EX</i>	6.67E-02 (0.565)	1.68E-01 (0.334)	-5.61E-02 (0.727)
<i>DT</i>	1.02E+00 (0.272)	1.73E+00 (0.27)	9.59E-01 (0.488)
<i>ADT</i>	-9.54E-02 (0.002)**	-2.01E-02 (0.696)	-1.34E-01 (0.003)**
<i>DTxADT</i>	-8.83E-02 (0.376)	-1.80E-01 (0.296)	-1.02E-01 (0.463)
<i>Y_m</i>	2.29E-06 (0.551)	3.35E-06 (0.449)	1.55E-01 (0.793)
<i>EDUC_m</i>	-5.84E-01 (0.019)**	-3.29E-01 (0.221)	-7.57E-01 (0.119)
<i>ENC_m</i>	-5.91E-01 (0.021)**		-9.35E-01 (0.038)**
<i>BF_m</i>	3.37E-02 (0.501)	5.92E-02 (0.367)	3.95E-02 (0.654)
<i>EDUC_d</i>	1.74E-01 (0.431)	6.18E-01 (0.015)**	-1.62E-01 (0.682)
<i>AG_d</i>	2.96E-02 (0.182)	1.60E-02 (0.483)	2.98E-02 (0.484)
<i>BF_d</i>	-3.11E-02 (0.503)	-7.79E-02 (0.132)	3.96E-02 (0.65)
N	186	97	93
χ^2	59.58	22.34	31.04
$p > \chi^2$	(0)**	(0.0991)*	(0.013)*

Note: All P-values are in brackets; ** represents $P < .05$ and * represents $P < .1$

Table 3.7: First Stage OLS Estimation of the Effect of Individual and Parental Characteristics on the Child's Consumption of Food or Drink from the Convenience or Grocery Store

Variables	9-15 year olds	9-11 year olds	13-15 year olds
Intercept	-2.72E+00 (0.026) **	-4.78+00 (0.01) **	1.78E-02 (0.495)
<i>H</i>	1.12E-01 (0.242)	1.86E-01 (0.007) **	1.78E-02 (0.781)
<i>HIS</i>	5.54E-01 (0.247)	1.57E+00 (0.007) **	-2.23E-01 (0.428)
<i>WH</i>	6.88E-01 (0.068) *	1.59E+00 (0.003) **	4.08E-01 (0.428)
<i>GD</i>	7.63E-03 (0.983)	1.05E-01 (0.661)	-5.75E-01 (0.077)
<i>AG_c</i>	-2.71E-01 (0.204)	1.44E-03 (0.914)	1.28E-02 (0.472)
<i>MT</i>	8.72E-04 (0.902)	1.54E-01 (0.621)	-5.39E-01 (0.65)
<i>MC</i>	2.22E-01 (0.373)	-1.60E-02 (0.939)	2.96E-01 (0.481)
<i>JB</i>	3.64E-01 (0.083) *		5.44E-01 (0.09)**
<i>Y_m</i>	9.80E-06 (0.002) **	1.04E-06 (0.685)	1.45E-05 (0.003)**
<i>PM_m</i>	3.12E-01 (0.061)	5.53E-02 (0.658)	4.78E-01 (0.091)**
<i>PM_d</i>	-1.25E-01 (0.312)		-1.82E-01 (0.45)
N	186	97	93
χ^2	36.2	30.98	26.74
$p > \chi^2$	(0.002) **	(0.0003) **	(0.005)**

Note: All P-values are in brackets; ** represents $P < .05$ and * represents $P < .1$

Table 3.8: First Stage OLS Estimation of the Effect of Individual and Parental Characteristics on Child's Sleep Sufficiency

Variables	9-15 year olds	9-11 year olds	13-15 year olds
Intercept	1.29E+00 (0)**	1.16E+00 (0.01)**	-7.72E-02 (0.923)
<i>HIS</i>	-4.06E-02 (0.757)	-1.53E-01 (0.315)	-6.09E-02 (0.784)
<i>WH</i>	6.89E-02 (0.494)	-1.02E-01 (0.453)	7.96E-02 (0.574)
<i>GD</i>	1.11E-02 (0.846)	2.96E-02 (0.642)	-7.08E-03 (0.936)
<i>AG_c</i>	-3.75E-03 (0.04)**	-1.53E-03 (0.666)	3.85E-04 (0.936)
<i>MT</i>	2.58E-02 (0.788)	2.82E-02 (0.734)	7.53E-01 (0.017)**
<i>TS</i>	-2.41E-02 (0.702)	-2.60E-02 (0.751)	-4.36E-02 (0.629)
<i>Y_m</i>	-1.50E-06 (0.096)**	8.98E-07 (0.395)	-3.30E-06 (0.009)**
<i>EDUH_m</i>	2.36E+03 (0.021)**	1.16E+00 (0.311)	-7.72E-02 (0.076)*
N	186	97	93
χ^2	22.24	3.95	18.17
$p > \chi^2$	(0.0045)**	(0.8613)	(0.02)**

Note: All P-values are in brackets; ** represents $P < .05$ and * represents $P < .1$

Table 3.9: 3SLS Estimation of the Effect of Obesity Risk Behaviors on Child Weight Status (*H*)

Variables	9-15 year olds	9-11 year olds	13-15 year olds
Intercept	1.81E+01 (0.001) **	2.81+01 (0.002) **	1.36E+01 (0.147)
X_1	-1.52E+00 (0) **	-2.28E-01 (0.627)	-1.12+00 (0.003) **
X_2	1.02E+00 (0.04) **	4.64+00 (0.001) **	1.18E-01 (0.793)
X_3	2.98E+00 (0.139)	-1.53+00 (0.563)	-1.80E+00 (0.376)
BMI_m	1.16E-01 (0.033) **	2.30E-02 (0.768)	5.42E-02 (0.512)
BMI_d	1.37E-01 (0.075) *	2.30E-02 (0.791) **	2.60-01 (0.032) **
HIS	-2.75E+00 (0.072) *	-8.17E+00 (0.003) **	6.09E-01 (0.803)
WH	-2.58E+00 (0.03) **	8.22E+00 (0.001) **	6.09E-01 (0.67)
GD	-2.30E-01 (0.736)	-6.84E-01 (0.526)	-8.45E-02 (0.924)
AG_c	2.59E-02 (0.281)	-8.46E-01 (0.552)	5.37E-02 (0.255)
MT	-8.22E-01 (0.468)	-1.04E-02 (0.864)	-3.00E+00 (0.384)
EX	2.41E-01 (0.427)	-1.70E-01 (0.811)	-1.57E-01 (0.669)
N	186	97	93
χ^2	50.49	33.93	21.19
$p > \chi^2$	(0) **	(0.0004)**	(0.0315)**

Note: All P-values are in brackets; ** represents $P < .05$ and * represents $P < .1$

APPENDIX B

Stata estimation for parental time and childhood obesity

```

-----
log: c:\data\output5.log
log type: text
opened on: 9 May 2010, 13:13:01

. insheet x1 x2 x3      x4 x5  x6   x7   x8   x9   x10  x11  x12  x13  x14  x15  x16  x17  x18
x19  x20 ///
> x21  x22  x23  x24  x25 x261      x26  x27  x28  x29  x30  x31  x32  x33  x34  x35  x36
x37  x38  x39 //
> /
> x40 x41  x42  x43  x44  x45  x46  x47  x48  x49  x50  x51  x52  x53  x54  x55  x56
x57  x58 x59 ///
> x60  x61  x62  x63  x64  x65  x66  x67  x68  x69  x70  x71  x72  x73  x74  x75  x76 ///
> x77  x78  x79  x80  x81  x82  x83  x84  x85  x86  x87  x88  x89  x90  x91  x92  x93  x94  x95
x96 ///
> x97  x98  x99  x100 x101 x102 x103 x104 using Datafinalt.txt, tab clear
(note: variable names in file ignored)
(105 vars, 294 obs)

. . keep if x30==1
(67 observations deleted)
. ***** variable definitions.....
. *Variable
. *x2   =   Kilo Calories
. *x3   =   Waist circumfrance
. *x4   =   Triceps
. *x5   =   Subscapular Skinfold
. *x6   =   BMI of child
. *x7   =   Father time with child
. *x8   =   Mother time with child
. *x9   =   Father's total income
. *x10  =   Mother's total income
. *x13  =   Father's unearned income
. *x14  =   Mother's unearned income
. *x15  =   BMI of Mother
. *x16  =   BMI of Father
. *x17  =   if child is black
. *x18  =   if child is hispanic
. *x19  =   If child is white
. *x20  =   Gender (1= female, 0= male)
. *x21  =   Maturity
. *x22  =   Age of child
. *x23  =   Age squared of child
. *x24  =   Father' work control
. *x25  =   Mother's work control
. *x26  =   Father's work spill over of full scacle, reverse coded (see McItosh et al 2006)
. *x261 = Father's work spill over of 6 items, no reverse coded item
. *x27  =   Mother's work spill over
. *x28  =   Father's work commitment

```

. *x29 = Mother's work commitment
 . *x30 = If parent is not single = 1, 0 otherwise
 . *x31 = child exercises at least 30 minutes a day
 . *x32 = If child is in sports teams
 . *x33 = if the family exercises at least 30 minutes a day (1, 0)
 . *x34 = Age category of child
 . *x35 = If father works full time
 . *x36 = If mother works full time
 . *x37 = If mother works part time
 . *x38 = If mother is employed
 . *x39 = If highest education attained by Dad was high school or below
 . *x40 = if father attended college
 . *x41 = Father's age
 . *x42 = Mother's age
 . *x43 = If highest education attained by Mum was high school or below
 . *x44 = if Mother attended college
 . *x45 = Houston unemployment rate
 . *x46 = Texas State unemployment
 . *x47 = hours worked by father the previous week
 . *x48 = Hours worked by mother the previous week
 . *x49 = Father's work condition
 . *x50 = Mother's work condition
 . *x51 = Father's work coping strategy
 . *x52 = Mother's work coping strategy
 . *x53 = if child takes medication on regular basis
 . *x54 = If child makes his own decision about what to eat
 . *x55 = Number of times child has a snack per day
 . *x56 = Number of hours child spends in the sport team
 . *x57 = Number of times the child buys food from restaurant
 . *x58 = Number of times the child buys food from convenient store
 . *x59 = if father has more influence in decision making
 . *x60 = if mother has more influence in decision making
 . *x61 = Number of times Mother brings purchased food home
 . *x62 = Number of times father brings purchased food home
 . *x63 = if father frequently makes sure child does not eat junk food
 . *x64 = if father frequently talks to child about health food
 . *x65 = If father frequently encourages child to eat health
 . *x66 = if father likes easy to prepare meals
 . *x67 = if mother frequently makes sure child does not eat junk food
 . *x68 = if mother frequently talks to child about health food
 . *x69 = If mother frequently encourages child to eat health
 . *x70 = if mother likes easy to prepare meals
 . *x71 = Mother work time
 . *x72 = Father work time
 . *x73 = if father drinks
 . *x74 = If mother drinks
 . *x75 = Number of drinks by father per day
 . *x76 = Number of drinks by mother per day
 . *x77 = if father smokes
 . *x78 = if mother smokes
 . *x79 = if child did not have exercise in the last 14 days
 . *x80 = if child had exercise 1-2 days
 . *x81 = if child had exercise 2-5 days
 . *x82 = if child had exercise 6-8 days
 . *x83 = if child had exercise <= 9 days

```

.*x84 = Number of days child has break fast
.*x85 = child watches 2 hours of TV of child
.*x86 = child watches 3 hours of TV of child
.*x87 = child watches 5 hours of TV of child
.*x88 = Hours of sleep
.*x89 = if child has enough sleep dummy
.*x90 = if child did had exercise in the last 14 days
.*x91 = Number of days father has break fast
.*x92 = Number of time father has a snack per day
.*x93 = Number of time a week father takes vitamins, mineral
.*x94 = If father exercises 30 min five times a week
.*x95 = Number of hours father sleeps
.*x96 = Number of times father eats out
.*x97 = Number of times father purchases meals
.*x98 = Number of days mother has break fast
.*x99 = Number of time mother has a snack per day
.*x100 = Number of time a week mother takes vitamins, mineral
.*x101 = If mother exercises 30 min five times a week
.*x102 = Number of hours mother sleeps
.*x103 = Number of times mother eats out
.*x104 = Number of times mother purchases meals
.
.
.*****summary statistics
.
.summarize x6 x8 x9 x15 x16 x18 x19 x20 x21 x22 x261 x31 x41 x42 x44 ///
> x57 x84 x98 x101 x103

```

Variable	Obs	Mean	Std. Dev.	Min	Max
x6	227	20.7573	4.819425	14.35387	45.96822
x8	202	107.4259	98.62186	0	539.5
x9	202	80177.16	48283.61	600	283044
x15	224	25.37871	5.395321	17.59299	46.20335
x16	226	27.70335	4.08548	17.6311	45.77881
x18	224	.1205357	.3263161	0	1
x19	224	.7857143	.4112449	0	1
x20	227	.4801762	.500711	0	1
x21	220	.5863636	.493608	0	1
x22	227	143.2599	26.07576	108	180
x261	226	2.985117	1.047457	0	5.91687
x31	226	.6725664	.4703186	0	1
x41	226	44.81416	5.379052	32	69
x42	225	42.47111	4.665633	31	53
x44	225	.6888889	.4639804	0	1
x57	227	.7797357	1.33202	0	8
x84	226	5.661504	1.912363	0	7
x98	225	5.188889	2.360125	0	7
x101	225	.36	.4810702	0	1
x103	225	1.551111	1.438722	0	14

```

.*correlations.
. correlate x8 x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x31 x44 x57 x84 x98 x101 x103 x9 x261
(obs=183)
. correlate x6 x8 x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x31 x44 x57 x84 x98 x101 x103
(obs=193) (matrices deleted to for reasons of space)

.*=====POTENTIAL INSTRUMENTS.....
.*** x9 x10 x261.
.*****OLS for BMI*****
.*regress x6 x8 x9 x15 x16 x18 x19 x20 x21 x22 x261 x31 x41 x42 x44 x57 x84 x98 x101 x103
.
.*=====IV ESTIMATIONS***.
.*Mother's regression check for IV in father's incomes and father's spillover as VIs first stage
. ivreg2 x6 x15 x16 x18 x19 x20 x21 x22 x31 x41 x42 x44 ///
> (x8 = x9 x261 ), first

```

First-stage regressions-----

First-stage regression of x8:

OLS estimation-----

Estimates efficient for homoskedasticity only
 Statistics consistent for homoskedasticity only

```

                Number of obs =   183
                F( 13, 169) =   3.01
                Prob > F   = 0.0005
Total (centered) SS = 1511459.243    Centered R2 = 0.1879
Total (uncentered) SS = 3460957.156    Uncentered R2 = 0.6454
Residual SS      = 1227401.619    Root MSE   = 85.22

```

x8	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x15	.2564363	1.245617	0.21	0.837	-2.202538 2.71541
x16	-1.948914	1.803242	-1.08	0.281	-5.508696 1.610868
x18	7.190303	29.75979	0.24	0.809	-51.55852 65.93912
x19	27.26611	23.12484	1.18	0.240	-18.38464 72.91686
x20	1.762529	12.87347	0.14	0.891	-23.65099 27.17605
x21	-19.67078	20.55387	-0.96	0.340	-60.24619 20.90463
x22	-.4012385	.4096755	-0.98	0.329	-1.209979 .4075021
x31	-27.40943	14.20611	-1.93	0.055	-55.45372 .6348496
x41	.4976278	1.777447	0.28	0.780	-3.011231 4.006486
x42	-2.677893	2.091733	-1.28	0.202	-6.807184 1.451398
x44	37.91726	13.92338	2.72	0.007	10.43111 65.4034
x9	-.0000341	.0001428	-0.24	0.812	-.0003161 .0002479
x261	21.97593	6.762945	3.25	0.001	8.625203 35.32667
_cons	217.0162	100.0294	2.17	0.031	19.54805 414.4844

Included instruments: x15 x16 x18 x19 x20 x21 x22 x31 x41 x42 x44 x9 x261

Partial R-squared of excluded instruments: 0.0597

Test of excluded instruments:

F(2, 169) = 5.36

Prob > F = 0.0055

Summary results for first-stage regressions

```
-----
Variable | Shea Partial R2 | Partial R2 | F( 2, 169) | P-value
x8       | 0.0597          | 0.0597      | 5.36       | 0.0055
```

Underidentification tests

Ho: matrix of reduced form coefficients has rank=K1-1 (underidentified)

Ha: matrix has rank=K1 (identified)

Anderson canon. corr. N*CCEV LM statistic Chi-sq(2)=10.92 P-val=0.0043

Cragg-Donald N*CDEV Wald statistic Chi-sq(2)=11.61 P-val=0.0030

Weak identification test

Ho: equation is weakly identified

Cragg-Donald Wald F-statistic 5.36

See main output for Cragg-Donald weak id test critical values

Weak-instrument-robust inference

Tests of joint significance of endogenous regressors B1 in main equation

Ho: B1=0 and overidentifying restrictions are valid

Anderson-Rubin Wald test F(2,169)= 3.08 P-val=0.0484

Anderson-Rubin Wald test Chi-sq(2)=6.68 P-val=0.0355

Stock-Wright LM S statistic Chi-sq(2)=6.44 P-val=0.0399

```
Number of observations      N = 183
Number of regressors       K = 13
Number of instruments       L = 14
Number of excluded instruments L1 = 2
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only

Statistics consistent for homoskedasticity only

```
Number of obs = 183
F( 12, 170) = 3.16
Prob > F = 0.0004
Total (centered) SS = 3910.917823      Centered R2 = -0.2098
Total (uncentered) SS = 81268.55573    Uncentered R2 = 0.9418
Residual SS = 4731.581623      Root MSE = 5.085
```

```
-----
x6 | Coef. Std. Err. z P>|z| [95% Conf. Interval]
-----+-----
x8 | -.0339761 .0182228 -1.86 0.062 [-.0696921 .0017399]
x15 | .1753746 .0746248 2.35 0.019 [.0291127 .3216364]
x16 | .1777616 .1103701 1.61 0.107 [-.0385599 .394083]
x18 | -1.250676 1.773158 -0.71 0.481 [-4.726002 2.224649]
x19 | -2.068212 1.495354 -0.14 0.890 [-3.137661 2.724019]
x20 | -.9554068 .7701548 -1.24 0.215 [-2.464882 .5540688]
x21 | -1.991548 1.304221 -1.53 0.127 [-4.547773 .5646772]
x22 | .0775162 .0244009 3.18 0.001 [.0296914 .1253411]
x31 | -.8190142 .905528 -0.90 0.366 [-2.593817 .9557881]
x41 | -.1240856 .1044904 -1.19 0.235 [-.328883 .0807117]
x42 | -.1332837 .1364595 -0.98 0.329 [-.4007395 .1341721]
x44 | 1.383628 1.075279 1.29 0.198 [-.7238798 3.491137]
```

```

_cons | 16.26257 7.805474 2.08 0.037 .9641219 31.56102
-----+-----
Underidentification test (Anderson canon. corr. LM statistic): 10.916
Chi-sq(2) P-val = 0.0043
-----+-----
Weak identification test (Cragg-Donald Wald F statistic): 5.360
Stock-Yogo weak ID test critical values: 10% maximal IV size 19.93
15% maximal IV size 11.59
20% maximal IV size 8.75
25% maximal IV size 7.25
Source: Stock-Yogo (2005). Reproduced by permission.
-----+-----
Sargan statistic (overidentification test of all instruments): 0.534
Chi-sq(1) P-val = 0.4650
-----+-----
Instrumented: x8
Included instruments: x15 x16 x18 x19 x20 x21 x22 x31 x41 x42 x44
Excluded instruments: x9 x261
-----+-----

. ivendog x8

Tests of endogeneity of: x8
H0: Regressor is exogenous
Wu-Hausman F test: 6.84681 F(1,169) P-value = 0.00968
Durbin-Wu-Hausman chi-sq test: 7.12532 Chi-sq(1) P-value = 0.00760.
.
**=====Mother's regression test with only father's spillover as IVs.
. ivreg2 x6 x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44 ///
> ( x8 = x261), first
First-stage regressions
-----+-----
First-stage regression of x8:
OLS estimation
-----+-----
Estimates efficient for homoskedasticity only
Statistics consistent for homoskedasticity only

Number of obs = 193
F( 12, 180) = 3.21
Prob > F = 0.0003
Total (centered) SS = 1779134.891 Centered R2 = 0.1765
Total (uncentered) SS = 3912432.156 Uncentered R2 = 0.6255
Residual SS = 1465121.271 Root MSE = 90.22
-----+-----
x8 | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
x18 | 22.08798 31.17484 0.71 0.480 -39.42717 83.60312
x19 | 19.62849 24.17268 0.81 0.418 -28.06979 67.32677
x20 | 10.03022 13.25767 0.76 0.450 -16.13023 36.19067
x21 | -19.25075 21.60893 -0.89 0.374 -61.89016 23.38867
x22 | -.518061 .4298078 -1.21 0.230 -1.366171 .330049
x31 | -23.00374 14.64079 -1.57 0.118 -51.8934 5.885922
x15 | -.12106 1.295049 -0.09 0.926 -2.676491 2.434371
x16 | -1.514548 1.81972 -0.83 0.406 -5.105276 2.076179

```



```

x41 | .2528086 1.605974 0.16 0.875 -2.916148 3.421765
x42 | -1.528548 1.967962 -0.78 0.438 -5.411791 2.354695
x44 | 41.61266 14.40388 2.89 0.004 13.19049 70.03484
x261 | 24.09006 6.652487 3.62 0.000 10.96317 37.21695
_cons | 181.3349 101.6232 1.78 0.076 -19.19112 381.861

```

Included instruments: x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44 x261

Partial R-squared of excluded instruments: 0.0679

Test of excluded instruments:

F(1, 180) = 13.11

Prob > F = 0.0004

Summary results for first-stage regressions

```

-----
Variable | Shea Partial R2 | Partial R2 | F( 1, 180) | P-value
x8       | 0.0679          | 0.0679      | 13.11      | 0.0004

```

Underidentification tests

Ho: matrix of reduced form coefficients has rank=K1-1 (underidentified)

Ha: matrix has rank=K1 (identified)

Anderson canon. corr. N*CCEV LM statistic Chi-sq(1)=13.11 P-val=0.0003

Cragg-Donald N*CDEV Wald statistic Chi-sq(1)=14.06 P-val=0.0002

Weak identification test

Ho: equation is weakly identified

Cragg-Donald Wald F-statistic 13.11

See main output for Cragg-Donald weak id test critical values

Weak-instrument-robust inference

Tests of joint significance of endogenous regressors B1 in main equation

Ho: B1=0 and overidentifying restrictions are valid

Anderson-Rubin Wald test F(1,180)= 6.16 P-val=0.0140

Anderson-Rubin Wald test Chi-sq(1)=6.61 P-val=0.0102

Stock-Wright LM S statistic Chi-sq(1)=6.39 P-val=0.0115

Number of observations N = 193

Number of regressors K = 13

Number of instruments L = 13

Number of excluded instruments L1 = 1

IV (2SLS) estimation

Estimates efficient for homoskedasticity only

Statistics consistent for homoskedasticity only

Number of obs = 193

F(12, 180) = 3.39

Prob > F = 0.0002

Total (centered) SS = 3975.754576 Centered R2 = -0.1939

Total (uncentered) SS = 85035.71234 Uncentered R2 = 0.9442

Residual SS = 4746.507118 Root MSE = 4.959

```

-----
x6 | Coef. Std. Err. z P>|z| [95% Conf. Interval]
-----+-----

```

```

x8 | -.030504 .0151794 -2.01 0.044 -.060255 -.000753
x18 | -.8838963 1.734486 -0.51 0.610 -4.283426 2.515633
x19 | -.6292462 1.386283 -0.45 0.650 -3.346311 2.087819
x20 | -.6561607 .7472093 -0.88 0.380 -2.120664 .8083426
x21 | -1.895291 1.242724 -1.53 0.127 -4.330986 .5404042
x22 | .0747875 .0237983 3.14 0.002 .0281438 .1214313
x31 | -.5742334 .8215191 -0.70 0.485 -2.184381 1.035914
x15 | .1564786 .0711178 2.20 0.028 .0170902 .295867
x16 | .1755705 .1024031 1.71 0.086 -.025136 .376277
x41 | -.1662381 .0874531 -1.90 0.057 -.3376429 .0051668
x42 | -.0552821 .1109078 -0.50 0.618 -.2726574 .1620931
x44 | 1.396238 .9794619 1.43 0.154 -.523472 3.315948
_cons | 15.34442 6.809689 2.25 0.024 1.997679 28.69117
-----
Underidentification test (Anderson canon. corr. LM statistic):    13.105
                        Chi-sq(1) P-val = 0.0003
-----
Weak identification test (Cragg-Donald Wald F statistic):        13.113
Stock-Yogo weak ID test critical values: 10% maximal IV size    16.38
                        15% maximal IV size      8.96
                        20% maximal IV size      6.66
                        25% maximal IV size      5.53
Source: Stock-Yogo (2005). Reproduced by permission.
-----
Sargan statistic (overidentification test of all instruments):    0.000
                        (equation exactly identified)
-----
Instrumented:      x8
Included instruments: x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44
Excluded instruments: x261
-----

. ivendog x8

Tests of endogeneity of: x8
H0: Regressor is exogenous
Wu-Hausman F test:      8.02226 F(1,179) P-value = 0.00515
Durbin-Wu-Hausman chi-sq test: 8.27867 Chi-sq(1) P-value = 0.00401
.
. ivreg2 x6 x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44   ///
> ( x8 = x261 ), liml

LIML estimation
-----
k      =1.00000
lambda =1.00000

Estimates efficient for homoskedasticity only
Statistics consistent for homoskedasticity only

                        Number of obs =   193
                        F( 12, 180) =   3.39
                        Prob > F   = 0.0002
Total (centered) SS   = 3975.754576      Centered R2 = -0.1939
Total (uncentered) SS = 85035.71234      Uncentered R2 = 0.9442

```

Residual SS = 4746.507117 Root MSE = 4.959

x6	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x8	-.030504	.0151794	-2.01	0.044	-.060255	-.000753
x18	-.8838963	1.734486	-0.51	0.610	-4.283426	2.515633
x19	-.6292462	1.386283	-0.45	0.650	-3.346311	2.087819
x20	-.6561607	.7472093	-0.88	0.380	-2.120664	.8083426
x21	-1.895291	1.242724	-1.53	0.127	-4.330986	.5404042
x22	.0747875	.0237983	3.14	0.002	.0281438	.1214313
x31	-.5742334	.8215191	-0.70	0.485	-2.184381	1.035914
x15	.1564786	.0711178	2.20	0.028	.0170902	.295867
x16	.1755705	.1024031	1.71	0.086	-.025136	.376277
x41	-.1662381	.0874531	-1.90	0.057	-.3376429	.0051668
x42	-.0552821	.1109078	-0.50	0.618	-.2726574	.1620931
x44	1.396238	.9794619	1.43	0.154	-.523472	3.315948
_cons	15.34442	6.809689	2.25	0.024	1.997679	28.69117

Underidentification test (Anderson canon. corr. LM statistic): 13.105
Chi-sq(1) P-val = 0.0003

Weak identification test (Cragg-Donald Wald F statistic): 13.113
Stock-Yogo weak ID test critical values: 10% maximal LIML size 16.38
15% maximal LIML size 8.96
20% maximal LIML size 6.66
25% maximal LIML size 5.53

Source: Stock-Yogo (2005). Reproduced by permission.

Sargan statistic (overidentification test of all instruments): 0.000
(equation exactly identified)

Anderson-Rubin statistic (overidentification test of all instruments): -0.000
(equation exactly identified)

Instrumented: x8
Included instruments: x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44
Excluded instruments: x261

```
. ivreg2 x6 x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44 ///
> ( x8 = x261 ), fuller(1)
```

LIML estimation

k = 0.99444
lambda = 1.00000
Fuller parameter=1

Estimates efficient for homoskedasticity only
Statistics consistent for homoskedasticity only

Number of obs = 193
F(12, 180) = 3.56
Prob > F = 0.0001
Total (centered) SS = 3975.754576 Centered R2 = -0.1292

Total (uncentered) SS = 85035.71234 Uncentered R2 = 0.9472
 Residual SS = 4489.237333 Root MSE = 4.823

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x8	-.027961	.0142297	-1.96	0.049	-.0558507	-.0000714
x18	-.9299642	1.685322	-0.55	0.581	-4.233134	2.373206
x19	-.6981428	1.34398	-0.52	0.603	-3.332295	1.93601
x20	-.683908	.7254111	-0.94	0.346	-2.105688	.7378716
x21	-1.832543	1.204681	-1.52	0.128	-4.193673	.5285876
x22	.0755335	.0231156	3.27	0.001	.0302278	.1208392
x31	-.5384504	.7970293	-0.68	0.499	-2.100599	1.023698
x15	.1561907	.0691622	2.26	0.024	.0206353	.291746
x16	.1792496	.0994269	1.80	0.071	-.0156235	.3741227
x41	-.1634	.0849368	-1.92	0.054	-.3298732	.0030732
x42	-.0511767	.1076735	-0.48	0.635	-.2622129	.1598594
x44	1.299237	.9406808	1.38	0.167	-.5444633	3.142938
_cons	14.65226	6.535629	2.24	0.025	1.842658	27.46185

Underidentification test (Anderson canon. corr. LM statistic): 13.105
 Chi-sq(1) P-val = 0.0003

Weak identification test (Cragg-Donald Wald F statistic): 13.113
 Stock-Yogo weak ID test critical values: 5% maximal Fuller rel. bias 24.09
 10% maximal Fuller rel. bias 19.36
 20% maximal Fuller rel. bias 15.64
 30% maximal Fuller rel. bias 12.71
 5% Fuller maximum bias 23.81
 10% Fuller maximum bias 19.40
 20% Fuller maximum bias 15.39
 30% Fuller maximum bias 12.76

NB: Critical values based on Fuller parameter=1
 Source: Stock-Yogo (2005). Reproduced by permission.

Sargan statistic (overidentification test of all instruments): 0.000
 (equation exactly identified)

Anderson-Rubin statistic (overidentification test of all instruments): -0.000
 (equation exactly identified)

Instrumented: x8
 Included instruments: x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44
 Excluded instruments: x261

```
. ivreg2 x6 x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44 ///
> (x8 = x261), gmm
-gmm- is no longer a supported option; use -gmm2s- with the appropriate option
gmm = gmm2s robust
gmm robust = gmm2s robust
gmm bw() = gmm2s bw()
gmm robust bw() = gmm2s robust bw()
gmm cluster() = gmm2s cluster()
```

2-Step GMM estimation

Estimates efficient for arbitrary heteroskedasticity
 Statistics robust to heteroskedasticity

Number of obs = 193
 F(12, 180) = 3.20
 Prob > F = 0.0003
 Total (centered) SS = 3975.754576 Centered R2 = -0.1939
 Total (uncentered) SS = 85035.71234 Uncentered R2 = 0.9442
 Residual SS = 4746.507118 Root MSE = 4.959

	Robust					
x6	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x8	-.030504	.0147484	-2.07	0.039	-.0594104	-.0015976
x18	-.8838963	1.734891	-0.51	0.610	-4.28422	2.516427
x19	-.6292462	1.339437	-0.47	0.639	-3.254495	1.996003
x20	-.6561607	.7165188	-0.92	0.360	-2.060512	.7481904
x21	-1.895291	1.002338	-1.89	0.059	-3.859837	.0692551
x22	.0747875	.023564	3.17	0.002	.028603	.1209721
x31	-.5742334	.8400219	-0.68	0.494	-2.220646	1.072179
x15	.1564786	.0708923	2.21	0.027	.0175323	.2954249
x16	.1755705	.1038228	1.69	0.091	-.0279184	.3790594
x41	-.1662381	.0889589	-1.87	0.062	-.3405943	.0081181
x42	-.0552821	.1117152	-0.49	0.621	-.2742399	.1636756
x44	1.396238	.9365601	1.49	0.136	-.4393859	3.231862
_cons	15.34442	6.194135	2.48	0.013	3.204143	27.48471

Underidentification test (Kleibergen-Paap rk LM statistic): 13.843
 Chi-sq(1) P-val = 0.0002

Weak identification test (Kleibergen-Paap rk Wald F statistic): 14.287
 Stock-Yogo weak ID test critical values: 10% maximal IV size 16.38
 15% maximal IV size 8.96
 20% maximal IV size 6.66
 25% maximal IV size 5.53

Source: Stock-Yogo (2005). Reproduced by permission.
 NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 0.000
 (equation exactly identified)

Instrumented: x8
 Included instruments: x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44
 Excluded instruments: x261

```

. **=====adding habit variables
. ivreg2 x6 x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x31 x44 x57 x84 x98 x101 x103 ///
> ( x8 = x261), first
Warning - duplicate variables detected
Duplicates: x31

```

First-stage regressions

First-stage regression of x8:

OLS estimation

Estimates efficient for homoskedasticity only

Statistics consistent for homoskedasticity only

Number of obs = 193
 F(17, 175) = 2.60
 Prob > F = 0.0009
 Total (centered) SS = 1779134.891 Centered R2 = 0.2019
 Total (uncentered) SS = 3912432.156 Uncentered R2 = 0.6371
 Residual SS = 1420006.555 Root MSE = 90.08

x8	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x18	25.92753	32.0535	0.81	0.420	-37.33366 89.18872
x19	20.82081	24.92636	0.84	0.405	-28.37416 70.01577
x20	5.818798	13.37828	0.43	0.664	-20.58474 32.22233
x21	-22.37734	22.54061	-0.99	0.322	-66.86376 22.10909
x22	-.6292804	.4542115	-1.39	0.168	-1.525718 .2671571
x31	-22.55798	14.79895	-1.52	0.129	-51.76538 6.649419
x15	-.0497839	1.3562	-0.04	0.971	-2.726398 2.62683
x16	-1.481022	1.846143	-0.80	0.424	-5.124592 2.162549
x41	.2291627	1.610994	0.14	0.887	-2.950316 3.408641
x42	-1.360208	1.977313	-0.69	0.492	-5.262658 2.542241
x44	41.46073	14.79288	2.80	0.006	12.26533 70.65614
x57	-1.154056	5.217346	-0.22	0.825	-11.45107 9.142963
x84	-.8179832	3.83098	-0.21	0.831	-8.378854 6.742887
x98	-2.836767	3.035601	-0.93	0.351	-8.827866 3.154332
x101	24.60016	14.90929	1.65	0.101	-4.825005 54.02532
x103	10.06665	6.470081	1.56	0.122	-2.702785 22.83608
x261	24.34834	6.732275	3.62	0.000	11.06144 37.63524
_cons	186.9564	110.342	1.69	0.092	-30.81589 404.7287

Included instruments: x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44 x57 x84 x98
 x101 x103 x261

Partial R-squared of excluded instruments: 0.0695

Test of excluded instruments:

F(1, 175) = 13.08

Prob > F = 0.0004

Summary results for first-stage regressions

Variable	Shea Partial R2	Partial R2	F(1, 175)	P-value
x8	0.0695	0.0695	13.08	0.0004

Underidentification tests

Ho: matrix of reduced form coefficients has rank=K1-1 (underidentified)

Ha: matrix has rank=K1 (identified)

Anderson canon. corr. N*CCEV LM statistic Chi-sq(1)=13.42 P-val=0.0002

Cragg-Donald N*CDEV Wald statistic Chi-sq(1)=14.43 P-val=0.0001

Weak identification test

Ho: equation is weakly identified
 Cragg-Donald Wald F-statistic 13.08
 See main output for Cragg-Donald weak id test critical values

Weak-instrument-robust inference

Tests of joint significance of endogenous regressors B1 in main equation

Ho: B1=0 and overidentifying restrictions are valid

Anderson-Rubin Wald test F(1,175)= 4.40 P-val=0.0374

Anderson-Rubin Wald test Chi-sq(1)=4.85 P-val=0.0276

Stock-Wright LM S statistic Chi-sq(1)=4.73 P-val=0.0296

Number of observations N = 193
 Number of regressors K = 18
 Number of instruments L = 18
 Number of excluded instruments L1 = 1

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics consistent for homoskedasticity only

Number of obs = 193
 F(17, 175) = 3.04
 Prob > F = 0.0001
 Total (centered) SS = 3975.754576 Centered R2 = -0.0197
 Total (uncentered) SS = 85035.71234 Uncentered R2 = 0.9523
 Residual SS = 4054.168051 Root MSE = 4.583

x6	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x8	-.025661	.0140682	-1.82	0.068	-.0532342 .0019122
x18	-.9680316	1.664862	-0.58	0.561	-4.231102 2.295039
x19	-.6941591	1.326732	-0.52	0.601	-3.294507 1.906189
x20	-.8792019	.6869106	-1.28	0.201	-2.225522 .4671181
x21	-1.870998	1.212699	-1.54	0.123	-4.247844 .5058478
x22	.0590863	.0231967	2.55	0.011	.0136216 .104551
x31	-.5063267	.7653788	-0.66	0.508	-2.006442 .9937881
x15	.1357912	.0689512	1.97	0.049	.0006493 .270933
x16	.1977067	.0960231	2.06	0.039	.0095048 .3859086
x41	-.1552433	.0812499	-1.91	0.056	-.3144901 .0040036
x42	-.053435	.1025016	-0.52	0.602	-.2543345 .1474646
x44	1.127504	.9182867	1.23	0.220	-.6723045 2.927313
x57	.2622471	.2680647	0.98	0.328	-.26315 .7876442
x84	-.2106907	.1949416	-1.08	0.280	-.5927691 .1713877
x98	-.3185389	.156362	-2.04	0.042	-.6250028 -.012075
x101	1.064678	.8423677	1.26	0.206	-.5863319 2.715689
x103	.4650221	.3554923	1.31	0.191	-.2317301 1.161774
_cons	18.35019	6.615457	2.77	0.006	5.384127 31.31624

Underidentification test (Anderson canon. corr. LM statistic): 13.422
 Chi-sq(1) P-val = 0.0002

Weak identification test (Cragg-Donald Wald F statistic): 13.080
 Stock-Yogo weak ID test critical values: 10% maximal IV size 16.38
 15% maximal IV size 8.96

```

                20% maximal IV size      6.66
                25% maximal IV size      5.53
Source: Stock-Yogo (2005). Reproduced by permission.
-----
Sargan statistic (overidentification test of all instruments):    0.000
                    (equation exactly identified)
-----
Instrumented:      x8
Included instruments: x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44 x57 x84 x98
                    x101 x103
Excluded instruments: x261
Duplicates:        x31
-----
. ivendog x8
Tests of endogeneity of: x8
H0: Regressor is exogenous
   Wu-Hausman F test:          5.74052 F(1,174) P-value = 0.01764
   Durbin-Wu-Hausman chi-sq test: 6.16400 Chi-sq(1) P-value = 0.01304.

. ivreg2 x6 x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44 x57 x84 x98 x101 x103 ///
> ( x8 = x261 ), liml
LIML estimation
-----
k          =1.00000
lambda     =1.00000

Estimates efficient for homoskedasticity only
Statistics consistent for homoskedasticity only

                Number of obs =   193
                F( 17, 175) =   3.04
                Prob > F   = 0.0001

Total (centered) SS   = 3975.754576      Centered R2   = -0.0197
Total (uncentered) SS = 85035.71234      Uncentered R2 = 0.9523
Residual SS          = 4054.168051      Root MSE     = 4.583

-----
      x6 |   Coef.  Std. Err.   z  P>|z|   [95% Conf. Interval]
-----+-----
      x8 |  -.025661  .0140682  -1.82  0.068  -.0532342   .0019122
      x18 |  -.9680316  1.664862  -0.58  0.561  -4.231102  2.295039
      x19 |  -.6941591  1.326732  -0.52  0.601  -3.294507  1.906189
      x20 |  -.8792019  .6869106  -1.28  0.201  -2.225522  .4671181
      x21 |  -1.870998  1.212699  -1.54  0.123  -4.247844  .5058478
      x22 |   .0590863  .0231967   2.55  0.011   .0136216  .104551
      x31 |  -.5063267  .7653788  -0.66  0.508  -2.006442  .9937881
      x15 |   .1357912  .0689512   1.97  0.049   .0006493  .270933
      x16 |   .1977067  .0960231   2.06  0.039   .0095048  .3859086
      x41 |  -.1552433  .0812499  -1.91  0.056  -.3144901  .0040036
      x42 |  -.053435  .1025016  -0.52  0.602  -.2543345  .1474646
      x44 |   1.127504  .9182867   1.23  0.220  -.6723045  2.927313
      x57 |   .2622471  .2680647   0.98  0.328  -.26315   .7876442
      x84 |  -.2106907  .1949416  -1.08  0.280  -.5927691  .1713877
      x98 |  -.3185389  .156362  -2.04  0.042  -.6250028  -.012075
     x101 |   1.064678  .8423677   1.26  0.206  -.5863319  2.715689

```



```

x103 | .4650221 .3554923 1.31 0.191 -.2317301 1.161774
_cons | 18.35019 6.615457 2.77 0.006 5.384127 31.31624
-----
Underidentification test (Anderson canon. corr. LM statistic): 13.422
Chi-sq(1) P-val = 0.0002
-----
Weak identification test (Cragg-Donald Wald F statistic): 13.080
Stock-Yogo weak ID test critical values: 10% maximal LIML size 16.38
15% maximal LIML size 8.96
20% maximal LIML size 6.66
25% maximal LIML size 5.53
Source: Stock-Yogo (2005). Reproduced by permission.
-----
Sargan statistic (overidentification test of all instruments): 0.000
(equation exactly identified)
-----
Anderson-Rubin statistic (overidentification test of all instruments): 0.000
(equation exactly identified)
-----
Instrumented: x8
Included instruments: x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44 x57 x84 x98
x101 x103
Excluded instruments: x261
-----
. ivreg2 x6 x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44 x57 x84 x98 x101 x103 ///
> ( x8 = x261 ), fuller(1)

LIML estimation
-----
k =0.99429
lambda =1.00000
Fuller parameter=1

Estimates efficient for homoskedasticity only
Statistics consistent for homoskedasticity only

Number of obs = 193
F( 17, 175) = 3.16
Prob > F = 0.0001
Total (centered) SS = 3975.754576 Centered R2 = 0.0251
Total (uncentered) SS = 85035.71234 Uncentered R2 = 0.9544
Residual SS = 3875.953833 Root MSE = 4.481
-----
x6 | Coef. Std. Err. z P>|z| [95% Conf. Interval]
-----+-----
x8 | -.0235084 .0132581 -1.77 0.076 [-.0494938 .0024769]
x18 | -1.019429 1.625504 -0.63 0.531 [-4.205358 2.1665]
x19 | -.7562061 1.292934 -0.58 0.559 [-3.29031 1.777897]
x20 | -.8934214 .6712065 -1.33 0.183 [-2.208962 .4221192]
x21 | -1.809162 1.18106 -1.53 0.126 [-4.123997 .5056721]
x22 | .0597982 .0226487 2.64 0.008 [.0154075 .1041888]
x31 | -.4775055 .7467561 -0.64 0.523 [-1.941121 .9861094]
x15 | .1350592 .0674071 2.00 0.045 [.0029436 .2671748]
x16 | .2007596 .0937448 2.14 0.032 [.0170231 .3844961]

```

```

x41 | -.1527116 .0793269 -1.93 0.054 -.3081896 .0027663
x42 | -.0504313 .1000928 -0.50 0.614 -.2466095 .145747
x44 | 1.046581 .8872374 1.18 0.238 -.6923724 2.785534
x57 | .2700427 .2617702 1.03 0.302 -.2430175 .7831028
x84 | -.209754 .1906021 -1.10 0.271 -.5833272 .1638192
x98 | -.3143471 .1527199 -2.06 0.040 -.6136726 -.0150215
x101 | 1.00855 .8180796 1.23 0.218 -.5948569 2.611956
x103 | .4444615 .345823 1.29 0.199 -.2333392 1.122262
_cons | 17.79278 6.398389 2.78 0.005 5.252172 30.3334

```

```

-----
Underidentification test (Anderson canon. corr. LM statistic):    13.422
Chi-sq(1) P-val = 0.0002

```

```

-----
Weak identification test (Cragg-Donald Wald F statistic):    13.080
Stock-Yogo weak ID test critical values: 5% maximal Fuller rel. bias 24.09
10% maximal Fuller rel. bias 19.36
20% maximal Fuller rel. bias 15.64
30% maximal Fuller rel. bias 12.71
5% Fuller maximum bias 23.81
10% Fuller maximum bias 19.40
20% Fuller maximum bias 15.39
30% Fuller maximum bias 12.76

```

NB: Critical values based on Fuller parameter=1
Source: Stock-Yogo (2005). Reproduced by permission.

```

-----
Sargan statistic (overidentification test of all instruments):    0.000
(equation exactly identified)

```

```

-----
Anderson-Rubin statistic (overidentification test of all instruments): 0.000
(equation exactly identified)

```

```

-----
Instrumented:    x8
Included instruments: x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44 x57 x84 x98
x101 x103
Excluded instruments: x261

```

```

-----
. ivreg2 x6 x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44 x57 x84 x98 x101 x103 ///
> ( x8 = x261 ), gmm

```

-gmm- is no longer a supported option; use -gmm2s- with the appropriate option

```

gmm      = gmm2s robust
gmm robust  = gmm2s robust
gmm bw()   = gmm2s bw()
gmm robust bw() = gmm2s robust bw()
gmm cluster() = gmm2s cluster()

```

2-Step GMM estimation

```

-----
Estimates efficient for arbitrary heteroskedasticity
Statistics robust to heteroskedasticity

```

```

Number of obs = 193
F( 17, 175) = 3.30
Prob > F = 0.0000

```

Total (centered) SS = 3975.754576 Centered R2 = -0.0197
Total (uncentered) SS = 85035.71234 Uncentered R2 = 0.9523
Residual SS = 4054.168051 Root MSE = 4.583

```
-----
            |            Robust
            |   Coef. Std. Err.   z  P>|z|   [95% Conf. Interval]
-----+-----
            |-----+-----
x8  | -.025661 .0129932  -1.97 0.048  -.0511273  -.0001947
x18 | -.9680316 1.786449  -0.54 0.588  -4.469407  2.533344
x19 | -.6941591 1.417687  -0.49 0.624  -3.472774  2.084456
x20 | -.8792019 .6755122  -1.30 0.193  -2.203181  .4447777
x21 | -1.870998 1.028808  -1.82 0.069  -3.887424  .1454284
x22 | .0590863 .0232318  2.54 0.011  .0135528  .1046198
x31 | -.5063267 .8057614  -0.63 0.530  -2.08559  1.072937
x15 | .1357912 .0785247  1.73 0.084  -.0181145  .2896968
x16 | .1977067 .1016762  1.94 0.052  -.001575  .3969884
x41 | -.1552433 .0787506  -1.97 0.049  -.3095916  -.0008949
x42 | -.053435 .1018677  -0.52 0.600  -.253092  .1462221
x44 | 1.127504 .9222744  1.22 0.222  -.6801203  2.935129
x57 | .2622471 .2943357  0.89 0.373  -.3146402  .8391344
x84 | -.2106907 .2088394  -1.01 0.313  -.6200085  .1986271
x98 | -.3185389 .2061368  -1.55 0.122  -.7225596  .0854818
x101 | 1.064678 .804103  1.32 0.185  -.5113344  2.640691
x103 | .4650221 .3578991  1.30 0.194  -.2364474  1.166492
_cons | 18.35019 6.265533  2.93 0.003  6.069966  30.6304
-----
```

Underidentification test (Kleibergen-Paap rk LM statistic): 14.023
Chi-sq(1) P-val = 0.0002

Weak identification test (Kleibergen-Paap rk Wald F statistic): 14.055
Stock-Yogo weak ID test critical values: 10% maximal IV size 16.38
 15% maximal IV size 8.96
 20% maximal IV size 6.66
 25% maximal IV size 5.53

Source: Stock-Yogo (2005). Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

```
-----
Hansen J statistic (overidentification test of all instruments):         0.000
                                            (equation exactly identified)
-----
```

```
Instrumented:     x8
Included instruments: x18 x19 x20 x21 x22 x31 x15 x16 x41 x42 x44 x57 x84 x98
                                            x101 x103
Excluded instruments: x261
-----
```

```
. log close
    log: c:\data\output5.log
    log type: text
    closed on: 9 May 2010, 13:13:17
```

APPENDIX C

Stata estimations from childhood obesity risk behaviors and childhood obesity

```

log: c:\data\output8.log
log type: text
opened on: 9 May 2010, 13:57:27

. insheet c1 c2 c3 c4 c5 c6 c7 c8 c9 c10 c11 c12 c13 c14 c15 c16 c17 c18
c19
> c20 c21 c22 c23 c24 c25 ///
> c26 c27 c28 c29 c30 c31 c32 c33 c34 c35 c36 c37 m1 m2 m3 m4 m5 m6 m7
m8 m9
> m10 m11 m12 m13 ///
> m14 m15 m16 m17 m18 m19 m20 m21 m22 m23 m24 f1 f2 f3 f4 f5 f6 f7 f8 f9
f10 f11 f12 f13 f1
> 4 f15 f16 ///
> X25 X26 X27 X28 X29 X49 X50 X51 X52 using behaviorcontext.txt, tab clear
(note: variable names in file ignored)
(86 vars, 292 obs)

. keep if c15==1
(64 observations deleted)

.
. *c1 Child number (ID)
. *c2 Triceps (TC)
. *c3 Subscapular Skinfold (SS)
. *c4 BMI of child (H)
. *c5 Waist circumference (WC)
. *c6 BMI of Mother (BMIM)
. *c7 BMI of Father
. *c8 if child is black (BLK: 1=black)
. *c9 if child is hispanic(HIS:1= his, 0= otherwise)
. *c10 If child is white(WH: 1= white, 0 otherwise)
. *c11 Gender (GD: 1= female, 0= male)
. *c12 Maturity (MT)
. *c13 Age of child(AGC)
. *c14 Age squared of child (AGCSQD)
. *c15 If parent isnot single = 1, 0 otherwise
. *c16 child exercises atleast 30 minutes a day (EX30)
. *c17 If child is in sports teams (EXS)
. *c18 Age category of child (0=9-11; 1=13-15)
. *c19 if child takes medication on regular basis(MED)
. *c20 Number of time child has a snack per day
. *c21 Number of hours child spends in the sport team (EX)
. *c22 Number of times the child buys food from convenient store (X2)
. *c23 Number of days child has break fast (X1)
. *c24 if child has enough sleep dummy (X3)
. *c25 if child smokes (SM)
. *c26 dieting(DT)
. *c27 age of dieting (AGT)
. *c28 importance of family dinner(IMD)

```

```

.*c29 frequency of breakfast with family (BFF
.*c30 eating breakfast with family(BF
.*c31 eating breakfast while watching TV (BTV
.*c32 Child picks preferred cereals(BC
.*c33 child receives allowance money for helping on house chores( MC
.*c34 Child has a job (JB
.*c35 Money spent on food and drink away from home (MF
.*c36 if parent let child sleep any time he wants (TS
.*c37 Age category of child (0=9-11; 1=13-15)
.
.
.  *Mother factors
.*m1 Mom income (Ym
.*m2 Mother's age (AGm
.*m3 If highest education attained by Mum was highschool or below (EDUHM
.*m4 if Mother attended college (EDUCm
.*m5 if mother frequently makes sure child doesnot eat junk food (JF
.*m6 if mother frequently talks to child about health food (TH
.*m7 If mother frequently encourages child to eat health (ECN
.*m8 if mother likes easy to prepare meals (EM
.*m9 if mother smokes (MS
.*m10 Number of days mother has break fast (BFm
.*m11 Number of time mother has a snack per day (SKm
.*m12 Number of time a week mother takes vitamins, mineral
.*m13 If mother exercises 30 min five times a week(EXM
.*m14 Number of hours mother sleeps
.*m15 Number of times mother eats out (EOM
.*m16 Number of times mother purchases meals (PMm)
.*m17 Keeps track of sweets(KSm
.*m18 keeps track of snacks
.*m19 Keeps track of high fat food
.
.  *Father factors
.*f1 father's income
.*f2 If highest education attained by Dad was highschool or below (EDUHf
.*f3 if father attended college(EDUHc
.*f4 Father's age(AGf
.*f5 Number of days father has break fast(BFf
.*f6 Number of time father has a snack per day (SKf
.*f7 Number of time a week father takes vitamins, mineral
.*f8 If father exercises 30 min five times a week (EXf
.*f9 Number of hours father sleeps (SHf
.*f10 Number of times father eats out (EOf
.*f11 Number of times father purchases meals (PMf
.
.
. *====inteructions====
.gen y = c26*c27
(1 missing value generated)
.
.
. *====Statistics
.*summarize c23 c22 c24 c4 c6 c7 c9 c10 c11 c12 c13 c21 c26 c27 y c33 c34 m1 m3 ///
> m4 m7 m10 m16 f3 f4 f5 f11
.*summarize c23 c22 c24 c4 c6 c7 c9 c10 c11 c12 c13 c21 c26 c27 y c33 c34 m1 m3 ///
> m4 m7 m10 m16 f3 f4 f5 f11 if c37==1
.*summarize c23 c22 c24 c4 c6 c7 c9 c10 c11 c12 c13 c21 c26 c27 y c33 c34 m1 m3 ///
> m4 m7 m10 m16 f3 f4 f5 f11 if c37==0

```

```
. *=====Bivariate correlations =====
```

```
. correlate c4 c23 c22 c24
```

```
(obs=226)
```

	c4	c23	c22	c24
c4	1.0000			
c23	-0.2562	1.0000		
c22	0.0323	-0.0849	1.0000	
c24	-0.1457	0.1026	0.0205	1.0000

```
. *=====hausman test for endogeneity/simultaneity===.
```

```
. ***whole sample
```

```
. regress c23 c6 c7 c9 c10 c11 c12 c13 c21 c26 c27 y m1 m4 m7 m10 f3 f4 f5
```

Source	SS	df	MS	Number of obs = 188
-----+-----				
				F(18, 169) = 2.92
Model	149.585295	18	8.31029417	Prob > F = 0.0002
Residual	481.684652	169	2.85020504	R-squared = 0.2370
-----+-----				
				Adj R-squared = 0.1557
Total	631.269947	187	3.37577512	Root MSE = 1.6883

c23	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+-----					
c6	-.0072747	.0250904	-0.29	0.772	-.0568057 .0422562
c7	.0784328	.0355414	2.21	0.029	.0082705 .1485951
c9	-.2087728	.6046863	-0.35	0.730	-1.402484 .9849386
c10	-.1799267	.4631322	-0.39	0.698	-1.094196 .7343428
c11	.1722075	.2537319	0.68	0.498	-.3286848 .6730997
c12	-.2825671	.427239	-0.66	0.509	-1.12598 .5608456
c13	-.0145266	.0082497	-1.76	0.080	-.0308124 .0017591
c21	.0898989	.1218053	0.74	0.462	-.150557 .3303548
c26	1.842298	1.05086	1.75	0.081	-.2322058 3.916801
c27	-.1088953	.0353091	-3.08	0.002	-.178599 -.0391916
y	-.1384371	.1119813	-1.24	0.218	-.3594994 .0826252
m1	4.32e-06	3.76e-06	1.15	0.252	-3.10e-06 .0000117
m4	-.5382152	.2928327	-1.84	0.068	-1.116296 .0398661
m7	-.4895448	.299699	-1.63	0.104	-1.081181 .1020912
m10	.0233521	.0596722	0.39	0.696	-.0944467 .1411509
f3	.2155285	.2659371	0.81	0.419	-.3094581 .740515
f4	.0117066	.0250619	0.47	0.641	-.0377681 .0611814
f5	.0128189	.0548737	0.23	0.816	-.0955073 .1211451
_cons	5.769914	1.831791	3.15	0.002	2.153774 9.386053

```
. predict c23_res, res
```

```
(40 missing values generated).
```

```
. regress c22 c6 c7 c9 c10 c11 c12 c13 c21 c33 c34 m1 m16 f11
```

Source	SS	df	MS	Number of obs = 194
-----+-----				
				F(13, 180) = 2.42
Model	61.8014409	13	4.75395699	Prob > F = 0.0050
Residual	354.239796	180	1.96799887	R-squared = 0.1485

```

-----+-----
                        Adj R-squared = 0.0871
Total | 416.041237 193 2.15565408      Root MSE   = 1.4029
-----+-----
c22 |   Coef.  Std. Err.   t  P>|t|   [95% Conf. Interval]
-----+-----
c6 | -.0078873 .0202231  -0.39  0.697  -.0477921  .0320175
c7 | .0080036 .0281251   0.28  0.776  -.0474937  .063501
c9 | .4282038 .4867108   0.88  0.380  -.5321889  1.388596
c10 | .4452 .368739  1.21  0.229  -.2824072  1.172807
c11 | -.3354056 .2069086  -1.62  0.107  -.7436841  .0728728
c12 | .0008918 .3436567   0.00  0.998  -.6772222  .6790058
c13 | .0064084 .0065763   0.97  0.331  -.0065681  .0193848
c21 | .0274447 .0979255   0.28  0.780  -.165785   .2206744
c33 | .2211202 .2714889   0.81  0.416  -.3145899  .7568304
c34 | .4034842 .2234229   1.81  0.073  -.0373807  .8443491
m1 | 9.24e-06 3.26e-06  2.84  0.005  2.81e-06  .0000157
m16 | .3916512 .1754853   2.23  0.027  .0453783  .7379242
f11 | -.1605231 .1357714  -1.18  0.239  -.4284315  .1073852
_cons | -1.098008 1.239045  -0.89  0.377  -3.54293  1.346914
-----+-----

```

```
. predict c22_res, res
```

```
(34 missing values generated)
```

```
.
. regress c24 c6 c7 c9 c10 c11 c12 c13 c21 c36 m1 m3
      Source |      SS      df      MS      Number of obs = 195
-----+-----+-----
      Model | 4.05439449   11  .368581318      F( 11, 183) = 2.38
      Residual | 28.3250927  183  .154781927      Prob > F   = 0.0089
-----+-----+-----
                        Adj R-squared = 0.0726
      Total | 32.3794872  194  .166904573      R-squared   = 0.1252
                        Root MSE   = .39342
-----+-----

```

```

c24 |   Coef.  Std. Err.   t  P>|t|   [95% Conf. Interval]
-----+-----
c6 | -.0058942 .0056199  -1.05  0.296  -.0169824  .005194
c7 | -.0006077 .007749  -0.08  0.938  -.0158966  .0146813
c9 | .0192925 .1358205   0.14  0.887  -.248683   .2872681
c10 | .0985941 .1029622   0.96  0.340  -.1045516  .3017397
c11 | .0017491 .0573226   0.03  0.976  -.111349   .1148473
c12 | .0594291 .095881   0.62  0.536  -.1297453  .2486034
c13 | -.0041263 .0018354  -2.25  0.026  -.0077476  -.000505
c21 | -.0467894 .0269994  -1.73  0.085  -.1000596  .0064807
c36 | -.0454368 .0645043  -0.70  0.482  -.1727046  .081831
m1 | -6.04e-07 7.53e-07  -0.80  0.423  -2.09e-06  8.81e-07
m3 | .2289776 .1062537   2.16  0.032  .0193378  .4386175
_cons | 1.496081 .3324269   4.50  0.000  .8401992  2.151964
-----+-----

```

```
. predict c24_res, res
```

```
(33 missing values generated).
```

```
. regress c4 c6 c7 c9 c10 c11 c12 c13 c21 c23 c22 c24 c23_res c22_res c24_res
```

```

      Source |      SS      df      MS      Number of obs = 186
-----+-----+-----
      Model | 929.360906   14  66.3829218      F( 14, 171) = 4.36
      Residual | 2605.4147  171  15.2363433      Prob > F   = 0.0000
-----+-----+-----
                        R-squared   = 0.2629

```

```

-----+-----
                        Adj R-squared = 0.2026
Total | 3534.77561 185 19.1068952      Root MSE   = 3.9034
-----+-----
c4 |   Coef. Std. Err.   t   P>|t|   [95% Conf. Interval]
-----+-----
c6 |   .126082 .0639448   1.97 0.050  -.0001408  .2523049
c7 |   .257643 .0833705   3.09 0.002  .093075  .4222109
c9 |  -3.000364 1.401053  -2.14 0.034  -5.76595  -.2347772
c10 |  -2.53488 1.135128  -2.23 0.027  -4.775548  -.2942124
c11 |  -1.617992 .6114874  -0.26 0.792  -1.368835  1.045237
c12 |  -1.088309 1.023608  -1.06 0.289  -3.108844  .9322266
c13 |   .0193234 .0264817   0.73 0.467  -.0329497  .0715966
c21 |   .2924289 .3484662   0.84 0.403  -.3954204  .9802782
c23 |  -1.896429 .4453882  -4.26 0.000  -2.775596  -1.017262
c22 |   .8687503 .663101   1.31 0.192  -.4401673  2.177668
c24 |   1.552957 4.231515   0.37 0.714  -6.799775  9.905688
c23_res | 1.954091 .4773898   4.09 0.000   1.011755  2.896427
c22_res | -1.274551 .7068476  -1.80 0.073  -2.669821  .1207193
c24_res | -1.003663 4.320211  -0.23 0.817  -9.531475  7.524148
_cons | 19.03632 7.68316   2.48 0.014   3.870272  34.20237
-----+-----

```

```

. *=====3SLS=====
. *****wholesample
. reg3 (c23 c4 c9 c10 c11 c12 c13 c21 c26 c27 y m1 m4 m7 m10 f3 f4 f5) ///
> (c22 c4 c9 c10 c11 c12 c13 c33 c34 m1 m16 f11) ///
> (c24 c9 c10 c11 c12 c13 c36 m1 m3) ///
> (c4 c6 c7 c9 c10 c11 c12 c13 c21 c23 c22 c24) , 3sls

```

Three-stage least-squares regression

```

-----+-----
Equation      Obs  Parms   RMSE  "R-sq"  chi2    P
-----+-----
c23           186   17  1.632772  0.2031  54.78  0.0000
c22           186   11  1.486348  0.0006  36.25  0.0002
c24           186    8  .3849945  0.1056  22.25  0.0045
c4            186   11  5.004079 -0.3176  48.08  0.0000
-----+-----

```

```

|   Coef. Std. Err.   z   P>|z|   [95% Conf. Interval]
-----+-----
c23 |
c4 |   .0911631 .1075075   0.85 0.396  -.1195478  .3018739
c9 |   .0793232 .6057376   0.13 0.896  -1.107901  1.266547
c10 |   .047597 .4884453   0.10 0.922  -.9097382  1.004932
c11 |   .2189679 .2725562   0.80 0.422  -.3152324  .7531682
c12 |  -.221999 .4121688  -0.54 0.590  -1.029835  .5858369
c13 |  -.0218518 .0097034  -2.25 0.024  -.0408701  -.0028335
c21 |   .0642947 .1185395   0.54 0.588  -.1680384  .2966279
c26 |  1.431348 .9985224   1.43 0.152  -.5257199  3.388416
c27 |  -1.152202 .0369349  -3.12 0.002  -1.876113  -.0428291
y |  -1.197283 .1103871  -1.08 0.278  -3.36083  .0966263
m1 |  1.67e-06 4.18e-06   0.40 0.689  -6.53e-06  9.88e-06
m4 |  -.6898192 .3279371  -2.10 0.035  -1.332564  -.0470743
m7 |  -.6941529 .2933856  -2.37 0.018  -1.269178  -.1191276
m10 | .0395204 .0552598   0.72 0.475  -.0687869  .1478277

```



```

f3 | .1838882 .2471472 0.74 0.457 -.3005115 .6682879
f4 | .035906 .0290732 1.24 0.217 -.0210763 .0928884
f5 | -.0244619 .0512132 -0.48 0.633 -.124838 .0759142
_cons | 6.003232 2.544207 2.36 0.018 1.016679 10.98979
-----+-----
c22 |
c4 | .114732 .0498422 2.30 0.021 .0170431 .2124209
c9 | .5528452 .4779895 1.16 0.247 -.383997 1.489687
c10 | .6929367 .3766178 1.84 0.066 -.0452206 1.431094
c11 | -.268828 .2136733 -1.26 0.208 -.6876201 .149964
c12 | .0085328 .3518587 0.02 0.981 -.6810976 .6981632
c13 | .0008079 .0070598 0.11 0.909 -.0130291 .0146448
c33 | .2375063 .250376 0.95 0.343 -.2532217 .7282342
c34 | .356102 .210483 1.69 0.091 -.0564371 .7686411
m1 | 9.66e-06 3.22e-06 3.00 0.003 3.35e-06 .000016
m16 | .3120714 .1670603 1.87 0.062 -.0153609 .6395036
f11 | -.1227687 .1244669 -0.99 0.324 -.3667193 .121182
_cons | -2.788703 1.221947 -2.28 0.022 -5.183675 -.3937299
-----+-----
c24 |
c9 | -.0402336 .1311611 -0.31 0.759 -.2973046 .2168374
c10 | .068654 .100745 0.68 0.496 -.1288026 .2661107
c11 | .0110564 .0572134 0.19 0.847 -.1010798 .1231926
c12 | .0259723 .0960199 0.27 0.787 -.1622232 .2141679
c13 | -.0037407 .0018297 -2.04 0.041 -.0073268 -.0001546
c36 | -.0258023 .0628776 -0.41 0.682 -.14904 .0974355
m1 | -1.51e-06 9.02e-07 -1.68 0.094 -3.28e-06 2.57e-07
m3 | .2348934 .1023746 2.29 0.022 .0342428 .435544
_cons | 1.286075 .2393746 5.37 0.000 .8169097 1.755241
-----+-----
c4 |
c6 | .1227753 .0592833 2.07 0.038 .0065823 .2389684
c7 | .1636535 .0828243 1.98 0.048 .0013209 .3259861
c9 | -2.793094 1.533723 -1.82 0.069 -5.799136 .2129479
c10 | -2.61048 1.193433 -2.19 0.029 -4.949565 -.2713945
c11 | -.1874524 .683478 -0.27 0.784 -1.527045 1.15214
c12 | -.8298869 1.134931 -0.73 0.465 -3.05431 1.394536
c13 | .030942 .0241904 1.28 0.201 -.0164702 .0783542
c21 | .2389671 .3048742 0.78 0.433 -.3585753 .8365095
c23 | -1.325905 .3962139 -3.35 0.001 -2.102469 -.5493397
c22 | 1.085338 .5149331 2.11 0.035 .0760874 2.094588
c24 | 3.390032 2.078941 1.63 0.103 -.6846185 7.464682
_cons | 15.06209 5.717006 2.63 0.008 3.85696 26.26721
-----+-----
Endogenous variables: c23 c22 c24 c4
Exogenous variables: c9 c10 c11 c12 c13 c21 c26 c27 y m1 m4 m7 m10 f3 f4 f5
c33 c34 m16 f11 c36 m3 c6 c7
-----+-----

.. *****wholesample
. reg3 (c23 c9 c10 c11 c12 c13 c21 c26 c27 y m1 m4 m7 m10 f3 f4 f5) ///
> (c22 c4 c9 c10 c11 c12 c13 c33 c34 m1 m16 f11) ///
> (c24 c9 c10 c11 c12 c13 c36 m1 m3) ///
> (c4 c6 c7 c9 c10 c11 c12 c13 c21 c23 c22 c24) , 3sls

```

Three-stage least-squares regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
c23	186	16	1.619663	0.2159	59.58	0.0000
c22	186	11	1.48176	0.0068	36.20	0.0002
c24	186	8	.3850105	0.1055	22.24	0.0045
c4	186	11	5.082302	-0.3592	50.49	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
c23					
c9	-.051247	.5620498	-0.09	0.927	-1.152844 1.05035
c10	-.0887241	.4384883	-0.20	0.840	-.9481455 .7706973
c11	.135796	.2410665	0.56	0.573	-.3366856 .6082776
c12	-.229163	.4033654	-0.57	0.570	-1.019745 .5614187
c13	-.0177622	.0078044	-2.28	0.023	-.0330585 -.0024659
c21	.0666991	.1157989	0.58	0.565	-.1602625 .2936607
c26	1.023855	.9316465	1.10	0.272	-.802139 2.849848
c27	-.0954118	.0307897	-3.10	0.002	-.1557585 -.0350652
y	-.0883411	.0997121	-0.89	0.376	-.2837733 .1070911
m1	2.29e-06	3.84e-06	0.60	0.551	-5.24e-06 9.82e-06
m4	-.5839802	.2490279	-2.35	0.019	-1.072066 -.0958946
m7	-.5913271	.2552428	-2.32	0.021	-1.091594 -.0910603
m10	.0338218	.0502043	0.67	0.501	-.0645768 .1322204
f3	.1764845	.224072	0.79	0.431	-.2626886 .6156575
f4	.0296386	.022219	1.33	0.182	-.0139098 .073187
f5	-.031138	.0464404	-0.67	0.503	-.1221594 .0598834
_cons	7.632696	1.371235	5.57	0.000	4.945124 10.32027
c22					
c4	.1118039	.0497764	2.25	0.025	.014244 .2093638
c9	.5535105	.4779022	1.16	0.247	-.3831606 1.490181
c10	.688404	.3765803	1.83	0.068	-.0496799 1.426488
c11	-.2714291	.2136521	-1.27	0.204	-.6901795 .1473212
c12	.0076252	.3518493	0.02	0.983	-.6819867 .6972372
c13	.0008715	.0070581	0.12	0.902	-.0129621 .0147051
c33	.2224093	.2494775	0.89	0.373	-.2665576 .7113762
c34	.3643121	.2103955	1.73	0.083	-.0480556 .7766797
m1	9.80e-06	3.21e-06	3.05	0.002	3.50e-06 .0000161
m16	.3116585	.1665971	1.87	0.061	-.0148657 .6381828
f11	-.1252188	.1239191	-1.01	0.312	-.3680957 .1176581
_cons	-2.723906	1.22118	-2.23	0.026	-5.117376 -.330437
c24					
c9	-.0405538	.1311621	-0.31	0.757	-.2976268 .2165193
c10	.0688505	.1007446	0.68	0.494	-.1286053 .2663063
c11	.0110973	.0572136	0.19	0.846	-.1010394 .123234
c12	.0257661	.0960204	0.27	0.788	-.1624305 .2139626
c13	-.0037486	.0018297	-2.05	0.040	-.0073346 -.0001625
c36	-.0240917	.0629068	-0.38	0.702	-.1473867 .0992034
m1	-1.50e-06	9.02e-07	-1.67	0.096	-3.27e-06 2.64e-07
m3	.2364614	.1024231	2.31	0.021	.0357158 .4372071
_cons	1.286299	.2393762	5.37	0.000	.81713 1.755468

```

-----+-----
c4 |
c6 | .1161024 .0545432 2.13 0.033 .0091997 .2230051
c7 | .1374436 .0770653 1.78 0.075 -.0136017 .2884889
c9 | -2.749348 1.530623 -1.80 0.072 -5.749314 .2506186
c10 | -2.58166 1.19202 -2.17 0.030 -4.917976 -.2453439
c11 | -.2297558 .6825448 -0.34 0.736 -1.567519 1.108007
c12 | -.8222381 1.133605 -0.73 0.468 -3.044064 1.399588
c13 | .0258592 .023972 1.08 0.281 -.0211251 .0728435
c21 | .2412815 .3036225 0.79 0.427 -.3538077 .8363706
c23 | -1.517387 .3854998 -3.94 0.000 -2.272952 -.7618208
c22 | 1.02465 .5027026 2.04 0.042 .0393711 2.009929
c24 | 2.981327 2.014534 1.48 0.139 -.9670878 6.929742
_cons | 18.1415 5.451432 3.33 0.001 7.456885 28.82611
-----+-----
Endogenous variables: c23 c22 c24 c4
Exogenous variables: c9 c10 c11 c12 c13 c21 c26 c27 y m1 m4 m7 m10 f3 f4 f5
c33 c34 m16 f11 c36 m3 c6 c7
-----+-----
.
. *****13-15 yrs olds
.
. reg3 (c23 c9 c10 c11 c12 c13 c21 c26 c27 y m1 m4 m7 m10 f3 f4 f5) ///
> (c22 c4 c9 c10 c11 c12 c13 c33 c34 m1 m16 f11) ///
> (c24 c9 c10 c11 c12 c13 c36 m1 m3) ///
> (c4 c6 c7 c9 c10 c11 c12 c13 c21 c23 c22 c24) if c37==1 ,3sls

```

Three-stage least-squares regression

```

-----+-----
Equation   Obs  Parms   RMSE  "R-sq"  chi2    P
-----+-----
c23        93   16  1.857558  0.2156  31.04  0.0133
c22        93   11  1.544267  0.2227  26.74  0.0050
c24        93    8  .4228254  0.1669  18.17  0.0200
c4         93   11  4.338906 -0.0073  21.19  0.0315
-----+-----

```

```

-----+-----
|   Coef.  Std. Err.   z  P>|z|   [95% Conf. Interval]
-----+-----
c23 |
c9 | .0582387 .9718183  0.06  0.952  -1.84649  1.962967
c10 | .113749 .6472019  0.18  0.860  -1.154743  1.382241
c11 | .6546318 .4135154  1.58  0.113  -.1558435  1.465107
c12 | -1.315943 1.409712 -0.93  0.351  -4.078928  1.447042
c13 | -.0065895 .0213291 -0.31  0.757  -.0483937  .0352147
c21 | -.0560778 .1609111 -0.35  0.727  -.3714576  .2593021
c26 | .959095 1.381636  0.69  0.488  -1.748861  3.667051
c27 | -.1339139 .0443332 -3.02  0.003  -2.208053  -.0470225
y | -.1024245 .1395534 -0.73  0.463  -3.759442  .1710952
m1 | 1.55e-06 5.90e-06  0.26  0.793  -.00001  .0000131
m4 | -.7569815 .4850612 -1.56  0.119  -1.707684  .193721
m7 | -.9348986 .4498019 -2.08  0.038  -1.816494  -.0533032
m10 | .0395336 .0883216  0.45  0.654  -.1335734  .2126407
-----+-----

```

```

f3 | -.162459 .3963542 -0.41 0.682 -.939299 .614381
f4 | .0297865 .0425655 0.70 0.484 -.0536404 .1132134
f5 | -.0369105 .0813608 -0.45 0.650 -.1963747 .1225537
_cons | 7.050922 4.070549 1.73 0.083 -.9272073 15.02905
-----+-----
c22 |
c4 | .0177816 .0682615 0.26 0.794 -.1160084 .1515716
c9 | -.2229056 .8032914 -0.28 0.781 -1.797328 1.351517
c10 | .4077536 .5144189 0.79 0.428 -.6004889 1.415996
c11 | -.5754266 .3248675 -1.77 0.077 -1.212155 .0613019
c12 | -.5390275 1.186134 -0.45 0.650 -2.863807 1.785752
c13 | .01279 .0177888 0.72 0.472 -.0220753 .0476553
c33 | .2959564 .4201293 0.70 0.481 -.5274818 1.119395
c34 | .5442465 .3210257 1.70 0.090 -.0849524 1.173445
m1 | .0000145 4.92e-06 2.94 0.003 4.83e-06 .0000241
m16 | .4872282 .2883549 1.69 0.091 -.077937 1.052393
f11 | -.1822082 .2411491 -0.76 0.450 -.6548517 .2904353
_cons | -2.123188 3.113461 -0.68 0.495 -8.22546 3.979084
-----+-----
c24 |
c9 | -.0609397 .2221425 -0.27 0.784 -.496331 .3744517
c10 | .0796433 .1416608 0.56 0.574 -.1980069 .3572934
c11 | -.0070789 .0883678 -0.08 0.936 -.1802766 .1661188
c12 | .7527737 .3163551 2.38 0.017 .132729 1.372818
c13 | .0003827 .0047915 0.08 0.936 -.0090084 .0097738
c36 | -.0435819 .090216 -0.48 0.629 -.2204019 .1332382
m1 | -3.30e-06 1.26e-06 -2.62 0.009 -5.77e-06 -8.30e-07
m3 | .2893436 .1630042 1.78 0.076 -.0301387 .6088259
_cons | -.0772455 .8034205 -0.10 0.923 -1.651921 1.49743
-----+-----
c4 |
c6 | .054193 .0826316 0.66 0.512 -.1077619 .216148
c7 | .2599143 .1212161 2.14 0.032 .0223352 .4974935
c9 | -.54768 2.195982 -0.25 0.803 -4.851725 3.756365
c10 | .609411 1.429741 0.43 0.670 -2.19283 3.411652
c11 | .0845289 .8914277 0.09 0.924 -1.662637 1.831695
c12 | -2.999155 3.446793 -0.87 0.384 -9.754745 3.756436
c13 | .0536672 .0471873 1.14 0.255 -.0388181 .1461526
c21 | -.1569538 .3671479 -0.43 0.669 -.8765504 .5626428
c23 | -1.120823 .3708674 -3.02 0.003 -1.84771 -.3939366
c22 | .1180812 .4508513 0.26 0.793 -.7655712 1.001734
c24 | -1.797665 2.032149 -0.88 0.376 -5.780603 2.185273
_cons | 13.62797 9.397978 1.45 0.147 -4.791733 32.04766
-----+-----

```

Endogenous variables: c23 c22 c24 c4

Exogenous variables: c9 c10 c11 c12 c13 c21 c26 c27 y m1 m4 m7 m10 f3 f4 f5
c33 c34 m16 f11 c36 m3 c6 c7

```

. *****9-11 yrs olds
. reg3(c23 c9 c10 c11 c12 c13 c21 m1 m4 c26 c27 y m10 f3 f4 f5) ///
> (c22 c4 c9 c10 c11 c12 c13 c33 m1 m16) ///
> (c24 c9 c10 c11 c12 c13 c36 m1 m3) ///
> (c4 c6 c7 c9 c10 c11 c12 c13 c21 c23 c22 c24)if c37==0, 3sls

```

Three-stage least-squares regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
c23	97	15	1.164338	0.1835	22.34	0.0991
c22	97	9	1.358227	-0.5470	30.98	0.0003
c24	97	8	.2977994	0.0409	3.95	0.8613
c4	97	11	6.657848	-1.6612	33.93	0.0004

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	

c23						
c9	-.5572209	.6232418	-0.89	0.371	-1.778752	.6643106
c10	-.434748	.5582602	-0.78	0.436	-1.528918	.6594219
c11	-.1074253	.2530393	-0.42	0.671	-.6033732	.3885225
c12	.0323601	.3295198	0.10	0.922	-.6134868	.6782069
c13	-.0111199	.0142957	-0.78	0.437	-.0391389	.0168992
c21	.167738	.1734613	0.97	0.334	-.1722399	.5077159
m1	3.35e-06	4.43e-06	0.76	0.449	-5.32e-06	.000012
m4	-.3293084	.2690052	-1.22	0.221	-.8565488	.1979321
c26	1.729371	1.56873	1.10	0.270	-1.345283	4.804025
c27	-.0201089	.0513939	-0.39	0.696	-.120839	.0806213
y	-.1804538	.1727597	-1.04	0.296	-.5190566	.158149
m10	.0592134	.0656495	0.90	0.367	-.0694572	.1878841
f3	.618222	.2540752	2.43	0.015	.1202438	1.1162
f4	.0160441	.0228898	0.70	0.483	-.028819	.0609072
f5	-.0778672	.0517497	-1.50	0.132	-.1792947	.0235603
_cons	7.08773	2.072008	3.42	0.001	3.026668	11.14879

c22						
c4	.1855815	.0360932	5.14	0.000	.1148401	.256323
c9	1.570697	.5862282	2.68	0.007	.421711	2.719683
c10	1.589229	.5284151	3.01	0.003	.5535548	2.624904
c11	.1053329	.2401002	0.44	0.661	-.3652548	.5759206
c12	.1537058	.3110489	0.49	0.621	-.4559389	.7633505
c13	.0014436	.0134155	0.11	0.914	-.0248502	.0277375
c33	-.0159821	.2095746	-0.08	0.939	-.4267408	.3947765
m1	1.04e-06	2.56e-06	0.41	0.685	-3.99e-06	6.07e-06
m16	.055348	.1249681	0.44	0.658	-.189585	.300281
_cons	-4.775763	1.851723	-2.58	0.010	-8.405074	-1.146453

c24						
c9	-.1534092	.1525548	-1.01	0.315	-.452411	.1455927
c10	-.1024125	.1366168	-0.75	0.453	-.3701764	.1653514
c11	.0293955	.0632009	0.47	0.642	-.094476	.153267
c12	-.0281732	.0828088	-0.34	0.734	-.1904755	.1341292
c13	-.0015328	.0035485	-0.43	0.666	-.0084876	.0054221
c36	-.0259787	.0817842	-0.32	0.751	-.1862727	.1343153
m1	8.98e-07	1.06e-06	0.85	0.395	-1.17e-06	2.97e-06
m3	.1164827	.114872	1.01	0.311	-.1086624	.3416278
_cons	1.156699	.4508061	2.57	0.010	.2731351	2.040263

c4						
c6	.0229901	.0780744	0.29	0.768	-.130033	.1760132
c7	.02299	.0865581	0.27	0.791	-.1466608	.1926408

c9	-8.165978	2.790074	-2.93	0.003	-13.63442	-2.697534
c10	-8.219935	2.444441	-3.36	0.001	-13.01095	-3.428919
c11	-.6838724	1.07898	-0.63	0.526	-2.798633	1.430889
c12	-.8457567	1.421909	-0.59	0.552	-3.632648	1.941134
c13	-.0103622	.060433	-0.17	0.864	-.1288087	.1080844
c21	-.1695022	.7091568	-0.24	0.811	-1.559424	1.22042
c23	-.284202	.5853871	-0.49	0.627	-1.43154	.8631357
c22	4.636181	1.407046	3.29	0.001	1.878421	7.393941
c24	-1.527355	2.642815	-0.58	0.563	-6.707178	3.652468
_cons	28.05207	9.117464	3.08	0.002	10.18217	45.92197

Endogenous variables: c23 c22 c24 c4

Exogenous variables: c9 c10 c11 c12 c13 c21 m1 m4 c26 c27 y m10 f3 f4 f5
c33 m16 c36 m3 c6 c7

. log close

log: c:\data\output8.log

log type: text

closed on: 9 May 2010, 13:57:33

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