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Heather Brown
Jennifer Roberts

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Department of Economics
University of Sheffield
9 Mappin Street
Sheffield
S1 4DT
United Kingdom
www.shef.ac.uk/economics

Born to be wide? Exploring Correlations in Mother and Adolescent Body Mass Index using data from the British Household Panel Survey

Authors:

Heather Brown

Institute of Health and Society, Newcastle University, UK

Jennifer Roberts

Department of Economics, University of Sheffield

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Key words: body mass index, restricted maximum likelihood, intergenerational correlation.

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Abstract:

The channels contributing to the intergenerational correlation in body mass are not well understood. Decomposition analysis is used to estimate the contribution of maternal characteristics, household income, and adolescent behaviours related to eating and physical activity on the intergenerational correlation in BMI. The analysis uses data on mothers and their adolescent children aged 11 to 15 from the British Household Panel Survey (2004 and 2006). The overall intergenerational correlation in BMI is 0.25. Maternal educational attainment and adolescent participation in some form of physical activity on a daily basis are the largest contributing factors to the intergenerational correlation in BMI. Maternal employment and more than four hours a day of television viewing by the adolescent are also important contributing factors. Overall, observable characteristics explain 11.2% of the intergenerational correlation in BMI.

I. Introduction

Worldwide adult obesity rates have doubled since 1980 (World Health Organisation 2011). Obesity rates in children have been following a similar pattern with obesity in children aged 11-15 in the UK increasing by 24% between 1995 and 2010 (NHS Information Centre 2012). It is likely that this rise in obesity is not caused by genetics alone. The channels contributing to correlated body mass index (BMI) outcomes in families are not well understood. As well as shared genetic material, rising obesity rates for these two groups may arise from parents and children reacting to the same changing incentives and environment, or from social influence, where unhealthy behaviours may spread from parents to their children.

There is an extensive literature documenting an intergenerational correlation in BMI. For example, using data from 1698 individuals and 409 families enrolled in the Quebec Family Study the intergenerational correlation in BMI was found to be 0.23 for parents-offspring(Bouchard et al. 1987, Bouchard and Perusse 1994). Tambs et al. (1991) using a large dataset (n=43,586 parent and offspring pairs) from Norway, found the intergenerational correlation in BMI to be 0.20 which varied little by parent or offspring age, suggesting a stable effect of genes and family environment throughout adulthood. Classen (2010) investigates the intergenerational correlation of body mass between parents and their offspring when they were both the same age (between 16 and 24 years old) using data from the US National Longitudinal Study of Youth. He finds a correlation of 0.38 for mothers and their daughters and a correlation of 0.32 for mothers and sons. However, this research has not investigated the possible channels, such as family background and the shared environment, by which intergenerational relationships lead to correlated BMI outcomes.

A general framework for understanding how different possible channels may lead to correlated outcomes was proposed by Manski (1993), who suggested three potential non-mutually exclusive avenues. Correlations are influenced by shared individual characteristics such as propensity to exercise; this may include shared genetic composition leading to correlated outcomes. The shared environment both within and outside the household may contribute to correlated outcomes. For example, the availability of fast-food in the local area and shared diet in the household may lead to correlated BMI outcomes in parents and children. Social influence may also lead to correlated BMI outcomes in parents and children. Parents may influence the diet and exercise behaviour of their children via their own attitudes and behaviours.

The influence of these three channels on the intergenerational correlation in BMI have different policy implications for reducing family obesity. For example, if the shared environment influenced correlated BMI outcomes this would suggest that policy should focus on facilitating healthy choices and a healthy environment. Whereas if the social influence of mothers explained a large portion of the intergenerational correlation in BMI policy should be targeted at mother's behaviours and choices which would have a spillover effect on her children.

There is a growing literature in sociology and economics which has tried to identify the importance of family background on children's weight outcomes. Anderson et al. (2007) examine changes in the relationship between parent and offspring's BMI for children aged between 2 and 11 using data from the National Health and Nutrition Examination Survey from the US over the period 1971 to 2004. They find that correlation between mother and offspring BMI increased between 1971 and 2004 suggesting that shared environmental factors have become more important in influencing correlations in BMI. Martin (2008) uses sibling data from the US National Longitudinal Study of Adolescent Health and estimates a structural equation model incorporating sibling genetic characteristics to investigate the role of family's social characteristics on adolescent weight. Specifically, Martin tests for shared family lifestyle measured by similarities in sibling meal patterns and physical activity, initial development inequalities measured by birth weight, and family socio-economic characteristics measured by parent's education, parent's income, family size, and immigration status. The results indicate that family social characteristics compound biological weight trajectories and that the association between adolescent weight and inactivity is embedded in the family's lifestyle.

Along a similar vein, there have been a number of studies investigating how maternal behaviours such as employment influence their children's weight outcomes (Anderson et al.2003, Ruhm 2008). The findings suggest a positive relationship between maternal employment and their children's body weight for families from an advantaged background. These children may have less opportunities for organised sports or active family activities as well as their mother's having less time to go food shopping and prepare healthy meals. It is unclear whether maternal employment only affects children's' obesity or whether there is also an effect on mothers' weight contributing to the intergenerational correlation in BMI.

Adolescent behaviours related to weight such as eating and exercise behaviour may be learned from parents and thus contribute to the intergenerational correlation in BMI. Alternatively, eating and exercise behaviour may be a mechanism by which children exert their independence from their parents. Thus, these behaviours would not contribute to the intergenerational correlation in BMI. There is evidence that the intake of fruits and vegetables declines whereas the consumption of sugary drinks increases as individuals move from childhood into adolescence. Growing independence, increased number of meals away from home, the need for peer acceptance and busy schedules has an effect on eating patterns and food choices of adolescents (Story et al. 2002).

This is the first paper that attempts to identify some of the channels contributing to the intergenerational correlation in BMI using a novel decomposition method from quantitative genetics (see for example Searle et al. 1992, Demidenko 2004); which has not been widely applied in economics. Gaining a better understanding on how social and economic factors impact on the intergenerational correlation in BMI is important for developing effective policies and interventions to stem the rise in obesity and inequality from family obesity traps. The decomposition analysis is performed using data on mothers and their adolescent offspring (aged 11 to 15) from the British Household Panel Survey (BHPS) waves 14 and 16 (2004 and 2006). We focus on the contribution of maternal behaviours and outcomes such as employment status and educational attainment, household income, and adolescent behaviours such as eating and physical activity.

2. Method

Analysis

The first step of the analysis is to estimate the intergenerational correlation in BMI using the following formula (Goldberg 1989, Solon et al. 1991, Mazumder 2008).

$$BMI_{ijt} = \beta X_{ijt} + \varepsilon_{ijt} \qquad (1)$$

The outcome of interest is BMI where the subscript i denotes individuals, j indexes mothers, and t denotes time. The data is stacked by generation and the adolescent's personal identification number is used to match mothers with their offspring. The standard errors are adjusted using the cluster command in STATA to account for multiple children by a single mother. The vector X_{ijt} contains age and year dummies to account for life cycle effects. These variables are treated as fixed effects and are removed from ε_{ijt}, which is decomposed to calculate the intergenerational correlation in BMI:

$$\varepsilon_{ijt} = a_f + u_{ij} + v_{ijt} \tag{2}$$

The terms on the right hand side of equation (2) are treated as random effects that are independent of each other (Mazumder 2008). Let a_f denote the component in BMI that is common to all members of family, *f*. Let u_{ij} denote the component in BMI that is individual specific and let v_{ijt} be the transitory component that reflects noise either due to temporary shocks to BMI or measurement error. The variance of age-adjusted BMI, ε_{ijt} is then:

$$\sigma_\varepsilon^2 = \sigma_a^2 + \sigma_u^2 + \sigma_v^2 \tag{3}$$

where σ_a^2 shows the variance in BMI outcomes that is due to differences between families, the second term, σ_u^2 shows the variance in BMI outcomes within families, and σ_v^2 is the variance in the transitory term. The first two variance terms are used to calculate the intergenerational correlation in BMI, ρ.

$$\rho = \frac{\sigma_a^2}{\sigma_a^2 + \sigma_u^2} \tag{4}$$

The intergenerational correlation in BMI from equation (4) is equivalent to the fraction of the overall variance in BMI that stems from shared family background and environment.

The variance components are estimated using a restricted maximum likelihood (REML) approach which has a number of advantages to using alternative decomposition techniques such as ANOVA. REML allows for spatial and/or temporal correlations so it can be used for repeated measure data. Additionally, it permits a changing variance structure; the correlation does not need to be constant over time. This approach provides consistent results when using unbalanced data compared with ANOVA which requires balanced data (Searle et al. 1992, Demidenko 2004). Additionally, REML has the advantage over a standard ML by including an adjustment to control for the loss of degrees of freedom from estimation of the fixed effects (Richardson and Welsh 1995).

REML partials out the fixed effects to maximise the likelihood that the residuals contain the random effects variance-covariance structure. It requires the assumption that the data are normally distributed. Sample BMI is graphed and found to be approximately normally distributed. Standard errors are calculated using the bivariate delta method (Searle et al. 1992, Demidenko 2004).

The contribution of the observable characteristics of maternal employment status, maternal educational attainment, household income, family meals, adolescent television viewing, physical activity participation, and dietary habits are calculated, to understand how they affect the intergenerational correlation in BMI. Each variable is separately added to the vector X in equation (1). This is treated as an additional fixed effect which is then removed from the residuals for decomposition of the variance components. It is assumed that the addition of these extra variables should reduce the residual variation in BMI, producing lower estimates of the variance in family BMI (σ_a^{2*}) compared to a model estimated without their inclusion (σ_a^2). The reduction in the variance of the family component (σ_a^2 - σ_a^{2*}) shows the amount of variance in the family component that can be attributed to the contribution of the variable in question. This provides an upper bound estimate of the contribution of the maternal and adolescent characteristics because it includes all omitted variables that are correlated with the included fixed effects. For example, the reduction in σ_a^2 from maternal employment status will also reflect unobserved factors such as motivation which may also contribute to BMI and be correlated with maternal employment status. The change in the variance in the family component from each additional variable divided by the denominator in equation (1) which only includes age and offspring gender shows the fraction of the overall intergenerational correlation in BMI from the variable in question.

3. Data

The BHPS began in 1991, as an annual survey of approximately 5,500 nationally representative private households, where 10,000 individuals aged 16 or older are surveyed. The initial household selection for the survey was determined by using a two-stage stratified systematic sampling procedure designed to give each address an approximately equal probability of selection. The same individuals are re-interviewed in each wave. In Wave 9 (1999), two additional samples of 3000 households were recruited from Scotland and Wales allowing for independent analysis of the countries, and comparison with England. In Wave 11 (2001), an additional sample from Northern Ireland of approximately 2000 households was added to increase the representativeness of the sample across the UK. From wave 4 (1994), a youth questionnaire for household members aged 11-15 was included in the survey.

The adult BHPS questionnaire covers a wide range of topics including employment status, wages and income, health status and education. The youth BHPS questionnaire covers health, health related behaviours, opinions, and aspirations.

The analysis uses data from waves 14 and 16 (2004 and 2006) of the BHPS as these are the only two waves to contain information on weight and height for both mother and offspring. The sample includes adolescents who are between the ages of 11 and 15 and their mothers.

We use an unbalanced panel and all pregnant women are omitted from the analysis. The sample includes observations on 1540 adolescents and 1150 mothers.

Body Mass Index (BMI)

The main outcome measure is BMI for mothers and adolescents calculated using self-reported height and weight. BMI is currently the most commonly used method to measure and grade obesity; it is calculated as weight in kilograms divided by height in metres squared. BMI is an anthropometric measure that indirectly measures body fat. Direct measures of body fat such as computerised tomography, magnetic resonance, underwater weighing, dual energy x-ray absorpiometry, subscapular skinfold measurements, and bioelectrical impedance are not always readily available and are either expensive to measure and/or require highly trained personnel. BMI is found to be strongly correlated with direct measures of body fat, and other indexes based upon height and weight do not appear to be superior for middle age adults (Willet 1998). For children, no additional information was obtained from subscapular skinfold measurement once BMI was accounted for (Mei et al. 2007). Thus, BMI provides a meaningful outcome variable in our analysis.

The validity of self-reported height and weight measures in identifying obesity prevalence rates has been widely discussed in the epidemiology and public health literature. In a Scottish adult population (aged 25-64) it was found that there was minimal reporting error in BMI calculated from self-reported height and weight. It was also shown that the difference between BMI calculated from measured height and weight and BMI from self-reported height and weight was not significantly different by occupational social class, education, housing tenure, smoking habits, adherence to a special diet, or levels of physical activity (Bolton-Smith et al. 2000). Using data from the US, a continuous BMI measure calculated from self-reported height and weight was shown to be a reliable measure for adults less than 60 years old (Kuczmarski et al. 2001).

Covariates

All equations control for maternal age and adolescent age and gender. To test the contribution of maternal employment status, maternal educational attainment, log of household income, adolescent eating and physical activity behaviour on the intergenerational correlation in BMI each variable is added separately to equation (1). A description of the variables can be found in Table 1.

Table 2 shows descriptive statistics for mothers and children. The mean BMI for mothers is 26.9 kg/m^2 which is classified as overweight according to the WHO BMI classification system (World Health Organisation 2011). The mean age of women is 41.3 years old. The majority of mothers in the sample are employed. The mean BMI for adolescents in the sample is 19.9 kg/m^2. The majority of adolescents participate in some healthy activities such as eating fruit and physical activity daily. The majority of adolescents eat with their family at least once a week.

4. Results

The results for the intergenerational correlation in BMI and the contribution of maternal, household, and adolescent characteristics on this correlation are shown in Table 3. The intergenerational correlation in BMI is 0.25. This correlation coefficient is consistent with the findings from other studies investigating the intergenerational correlation in BMI (Bouchard et al. 1987, Tambs et al. 1991, Bouchard and Perusse 1994). Adding maternal educational attainment to equation (1) reduced the variance in the family component by 0.008

explaining 3.1% of the intergenerational correlation in BMI. Maternal employment explains 1.6% of the intergenerational correlation in BMI. Log of household income does not explain any of the intergenerational correlation in BMI. The above two results suggest that it may be time influencing family meal choices and activities rather than the income from maternal employment impacting on the intergenerational correlation in BMI. This hypothesis is consistent with the findings from Anderson et al. (2003) that maternal working hours over the child's lifetime was a significant factor in the likelihood that the child would be overweight. Next, looking at adolescent behaviours related to eating and exercise, having a family meal at least once a week compared to no family meals explains 0.7%, watching more than 4 hours of TV a day explains 1.6%, eating some fruit on a daily basis explains 1.2%, and participating in some form of physical activity on a daily basis explains 3.1% of the intergenerational correlation in BMI. Eating junk food and eating fast food at least once a week do not explain any of the intergenerational correlation in BMI. In total, the observed variables explain approximately 11.2% of the intergenerational correlation in BMI. This suggests there are economic and social factors contributing to the intergenerational correlation in BMI that can be influenced by policy and interventions.

5. Conclusion

This study attempts to uncover the importance of maternal characteristics, household income, and adolescent behaviours related to eating habits and physical activity on the intergenerational correlation in BMI. Decomposition analysis shows that these observable characteristics and behaviours explain 11.2% of the intergenerational correlation in BMI. The largest contributing factors are maternal educational attainment and whether the adolescent participates in some form of physical activity on a daily basis. The results suggest that maternal employment explains some of the intergenerational correlation in BMI which is equivalent to that of the adolescent watching four or more hours of television a day.

It has been suggested that human capital accumulation makes individuals more efficient producers of health and thus there are increasing intergenerational returns in parental human capital (see for example Ben-Porath 1967, Becker et al. 1990, and Rosenzweig and Wolpin 1994). Hence, reducing educational inequalities or improving maternal educational attainment may also help to shrink health inequalities stemming from family obesity traps.

References:

Anderson PM, Butcher FK and Schazenbach DW. (2007) Childhood disadvantage and obesity: Is nurture trumping nature. NBER Working Paper Series.

Anderson PM, Butcher KF and Levine PB. (2003) Maternal employment and overweight children. *Journal of Health Economics* 22: 477-504.

Becker GS, Murphy KM and Tamura R. (1990) Human capital, fertility, and economic growth. *Journal of Political Economy* 98: 512-537.

Ben-Porath Y. (1967) The production of human capital and the lifecycle of earnings. *Journal of Political Economy* 75: 362-365.

Bolton-Smith C, Woodward M, Tunstall-Pedoe H, et al. (2000) Accuracy of the estimated prevalence of obesity from self reported height and weight in an adult Scottish population. *Journal of Epidemiology and Community Health* 54: 143-148.

Bouchard C and Perusse L. (1994) Genetics of obesity. In: Bouchard C (ed) *Family studies.* Boca Raton, FL: CRC Press, 79-92.

Bouchard C, Perusse L, Leblanc C, et al. (1987) Inheritance of the amount and distribution of human body fat. *International Journal of Obesity* 12: 205-215.

Classen TJ. (2010) Measures of the intergenerational transmission of body mass index between mothers and their children in the United States 1981-2004. . *Economics and Human Biology* 8: 30-43.

Demidenko E. (2004) *Mixed models: theory and application,* New York: Wiley.

Goldberg AS. (1989) Economic and mechanical models of intergenerational transmission. . *American Economic Review* 79: 504-513.

Kuczmarski RJ, Fanelli M and Najjar M. (2001) Effects of age on validity of self-reported height, weight, and Body Mass Index: findings from the Third National Health and Nutrition

Examination Survey 1988–1994. *Journal of American Dietetic Association* 101: 28-34.

Manski CF. (1993) Identification of endogenous social effects: the reflection problem. . *Review of Economic Studies* 60: 531-542.

Martin MA. (2008) The intergenerational correlation in weight: How genetic resemblance reveals the social role of families. *American Journal of Sociology* 114: S67-S105.

Mazumder B. (2008) Sibling similarities and economic inequality in the US. *Journal of Population Economics* 21: 685-701.

Mei Z, Grummer-Strawn LM, Wang J, et al. (2007) Do skinfold measurements provide additional information to Body Mass Index in the assessment of body fatness among children and adolescents? . *Pedatrics* 119: 1306-1313.

NHS Information Centre (2012) *Statistics on obesity, physical activity, and diet, England*. Available at: http://www.ic.nhs.uk/pubs/opad11

Richardson AM and Welsh AH. (1995) Robust Restricted Maximum Likelihood in Mixed Linear Models. *Biometrics* 51: 1429-1439.

Rosenzweig MR and Wolpin KI. (1994) Are There Increasing Returns to the Intergenerational Production of Human Capital? Maternal Schooling and Child Intellectual Achievement. *Journal of Human Resources* 2: 670-693.

Ruhm CJ. (2008) Maternal employment and adolescent development. *Labour Economics* 15: 958-983.

Searle SR, Casella G and McCulloch H. (1992) *Variance Components,* New York: Wiley.

Solon G, Corcoran M, Gordon R, et al. (1991) A longitudinal analysis of sibling correlations in economic status. *Journal of Human Resources* 26: 509-534.

Story M, Neumark-Stzainer D and French S. (2002) Individual and environmental influences on adolescent eating behaviors. *Journal of the American Dietary Association* 102: S40-S51.

Tambs K, Mourn T, Eaves L, et al. (1991) Genetic and environmental contributions to the variance of the body mass index in a Norwegian sample of first- and second-degree relatives. *American Journal of Human Biology* 3: 257-267.

Willet W. (1998) *Nutritional Epidemiology. ,* Oxford: Oxford University Press.

World Health Organisation (2011) Overweight and Obesity Fact Sheet.

Table 1: *Variable List and Description*

Variable Name	Description
BMI	Body Mass Index – weight in kilograms/height in metres squared
Mothers	
Education:	0=No qualifications (Base Category)
University	1=Higher or First Degree
Some higher education	1=HND, HNC, teaching, or A-level

High School	1=CSE or O level
Employed	1-Employed/Self-Employed/ 0- Not in the Labour Force or unemployed
Age	Age in years
Log household income	Log of annual household income/household size (GBP)
Adolescents	
Age	Age in years
Eats fruit everyday	1-Everyday/0 - less than once a day
Physical activity everyday	1-Almost Everyday/Everyday/ 0 – less than almost everyday
Eats junk food everyday	1-Everyday/0 - less than once a day
Eat with family (1x week or more)	1 – at least once a week/ 0-less than once a week
Watches TV 4 hrs+ daily	1 – four more hrs per day / 0-less than four hours per day
Eats fast food (1x week or more)	1- at least once a week / 0-less than once a week.

Table2: *Descriptive Statistics*

BMI (kg/ m^2)	
Mothers	26.92 (5.40)
Adolescents	19.92 (4.11)
Age (years)	
Mothers	41.26 (6.00)
Adolescents	13.19 (1.45)
Household Income (£)/household size	9250.03 (6987.14)
Mother Employed (%)	0.76 (0.42)
Education: high school (%)	0.44 (0.50)
some higher edu. (%)	0.24 (0.43)
university (%)	0.12 (0.33)
Adolescent eat fruit everyday (%)	0.64 (0.50)
Adolescent physical activity everyday (%)	0.58 (0.49)
Adolescent eat junk food everyday (%)	0.60 (0.50)
Adolescent eat with family (1x a week or more) (%)	0.89 (0.31)
Adolescent watch four more hours TV daily (%)	0.18 (0.39)
Adolescent eat fast food (1x a week or more) (%)	0.31 (0.46)
Number of observations	
Mothers	1150
Adolescents	1540

Notes: Standard deviations are in parenthesis. Means over years 2004 and 2006 are shown.

Intergeneration correlation in BMI Observations	0.25** (0.06) 3564	
Upper bound estimates of the contribution to intergenerational correlation in BMI from…	Contribution	Percent
Maternal Educational Attainment	0.008	3.1
Mother employed vs. unemployed	0.004	1.6
Log of household income	0	0
Adolescent eat with family (1x a week or more)	0.002	0.7
Adolescent watch four more hours TV daily	0.004	1.6
Adolescent eat fruit everyday	0.003	1.2
Adolescent eat fast food (1x a week or more)	0	0
Adolescent eat junk food everyday	0	0
Adolescent physical activity everyday	0.008	3.1
All characteristics	0.029	11.2

Notes: ** indicates significant at p<0.01. Standard errors are in parenthesis.