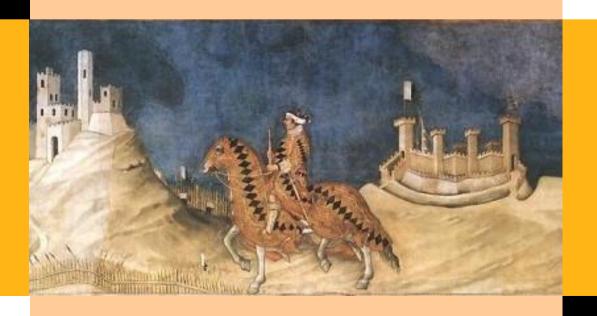


QUADERNI DEL DIPARTIMENTO DI ECONOMIA POLITICA E STATISTICA

Federico Crudu Laura Neri Silvia Tiezzi

Family Ties and Child Obesity in Italy

n. 845 - Ottobre 2020



Family Ties and Child Obesity in Italy*

Federico Crudu[†]

8

9

10

11

12

13

14

15

16

17

Laura Neri[‡]

Silvia Tiezzi[§]

University of Siena and CRENoS

University of Siena

University of Siena

October 2020

Abstract

This paper examines the impact of overweight family members on weight outcomes of Italian children aged 6 to 14 years. We use an original dataset matching the 2012 cross sections of the Italian Multipurpose Household Survey and the Household Budget Survey. Since the identification of within-family peer effects is known to be challenging, we implement our analysis on a partially identified model using inferential procedures recently introduced in the literature and based on standard Bayesian computation methods. We find evidence of a strong, positive effect of both overweight peer children in the family and of overweight adults on children weight outcomes. The impact of overweight peer children in the household is larger than the impact of adults. In particular, the estimated confidence sets associated to the peer children variable is positive with upper bound around one or larger, while the confidence sets for the parameter associated to obese adults often include zero and have upper bound that rarely is larger than one.

8 Keywords: child obesity; confidence sets; partial identification; peer effects within the family.

^{*}We thank three anonymous referees and the Associate Editor Tinna Ásgeirsdóttir, whose comments greatly improved the paper. Comments from Pamela Giustinelli, Giovanni Mellace, Nicole Hair, and participants at the 2018 Workshop on Institutions, Individual Behavior and Economic Outcomes, Alghero, Italy; the IAAE 2019 Conference, Nicosia, Cyprus; the Nordic Health Economic Study Group (NHESG) 2019, Reykjavik, Iceland; and the 2019 Annual Health Econometrics Workshop, Knoxville TN, USA are gratefully acknowledged.

 $^{^\}dagger$ Department of Economics and Statistics, University of Siena, Piazza San Francesco, 7/8 53100 Siena, federico.crudu@unisi.it.

[‡]Department of Economics and Statistics, University of Siena, Piazza San Francesco, 7/8 53100 Siena, laura.neri@unisi.it.

 $[\]S$ Department of Economics and Statistics, University of Siena, Piazza San Francesco, 7/8 53100 Siena, silvia.tiezzi@unisi.it.

₁ 1 Introduction

- 2 In the last decades children overweight and obesity prevalence have risen substantially in
- 3 most countries. According to a new global assessment of child malnutrition by UNICEF
- 4 (UNICEF, 2019) the most profound increase has been in the 5-19 age group, where the
- 5 global rate of overweight increased from 10.3% in 2000 to 18.4% in 2018.
- Identifying the determinants of child obesity is a compelling issue since obesity is not
- only a direct threat for children's health and a cost to society, but also has documented
- s consequences for adult life, such as effects on health (Llewellyn et al., 2016), on self-esteem,
- body image and confidence, and on wages (Schwartz et al., 2011).
- It is recognised that child consumption decisions are affected by those of their peers (Dishion & Tipsord, 2011) and that peer effects are more pronounced in children than in
- adolescents (Nie et al., 2015). While classroom or friends peer effects have been found to
- explain childhood and adolescents obesity (Asirvatham et al., 2014; Gwozdz et al., 2015)
- Nie et al., 2015), the role of within-the-family peers, e.g. interaction with other overweight
- and obese peer children in the family, as a determinant of child overweight and obesity has
- not yet been investigated.
- In fact, within-the-family social interaction could be an important determinant of child
- obesity, because children spend most of their time in the family environment. A likely
- driving mechanism is imitation. Research in experimental psychology (Zmyj, Ascherslebel
- et al., 2012 Zmyj, N. Daum et al., 2012; Zmyj & Seehagen, 2013) postulates that prolonged
- 21 individual experience with peers leads children to imitate peers more than adults. Children
- 22 imitate familiar behaviour for social reasons, such as identification with the role model or
- to communicate likeness. Adults are the natural model on which children rely in unfamiliar
- 24 situations while age is an important indicator of likeness. With prolonged contact with
- peers (i.e. children in the same age group), children are more likely to imitate behaviour

¹An exception is the famous study by Christakis & Fowler (2007) focusing on adults. One of their main findings was that, among pairs of adult siblings, if one sibling became obese, the chance that the other would become obese increased by 40% and that if one spouse became obese, the likelihood that the other spouse would also become obese increased by 37%.

- from them than from adults, because they learn to trust their peers and to refer to them
- for learning also in unfamiliar situations. In this case imitation serves a cognitive function:
- prolonged contact with peers leads children to believe that peers are as competent as
- 4 adults, i.e. a reliable model. Since children plausibly spend extended periods of time with
- 5 family members, such prolonged contact is reflected in increased levels of peers imitation.
- 6 If imitation is the driving mechanism through which within-the-family social interaction
- 7 affects child obesity, then the impact of peer children in the family should be larger than
- 8 the impact of adults.

- The purpose of this paper is to investigate whether the presence of other overweight/obese family members, i.e. children in the same age group and adults, has a positive and significant effect on the probability of a child being overweight/obese. To address this research question we use a unique cross-section of Italian households containing detailed information on families' structure, composition, habits, and weight outcomes. We estimate a binary choice model where the dependent variable is a binary indicator for each child being overweight or obese or not. The main explanatory variables of interest are the share of other overweight or obese children in the same age group in the family, and the share of overweight or obese adults in the family.
- To assess the impact of children in the same age group and family (our peer effect), we use a narrow peer-group definition that includes all children aged 6 to 14 years belonging to the same family whether siblings or not. While assessing the impact of adults does not pose particular challenges, within-the-family peer effects are particularly difficult to identify. Narrow definitions of the peer group, such as ours, have been found to be more endogenous than broad ones, because of shared common traits, habits and environments that may cause simultaneity effects (Black et al., 2017; Trogdon et al., 2008). A shared environment also complicates the problem of controlling for unobserved fixed effects, because the latent heterogeneity that may affect the weight outcome of each child is likely to affect the weight outcome of the other children in the same family and age group.
 - In order to provide some further intuition on the mechanics of our problem and on

the potential causal interpretation of the model, let us consider a simple directed acyclic graph (DAG) (see Figure 1) to represent the relationship among the main variables of our model. Our main problem is to study the relationship of the peer effect variable (Peer) on the obesity score (Obesity) of a given child in the family. We may reasonably conjecture that Obesity would depend on Exogenous and Contextual variables as well as other *Unobserved* characteristics. Identifying peer effects may be complicated for a number of reasons. First, in the context of a group of siblings the assignment to a given family is nonrandom and it would reasonably depend on the characteristics of the parents 2 Second, genetic and behavioral characteristics may be important to determine whether an individual is obese or not. The former set of characteristics more than the latter may be difficult to observe. However, there may exist some suitable proxy variables that may 11 work as mediators between the *Unobserved* variables and *Peer*, these may be physical 12 characteristics such as adults' weight and height (or BMI) and history of chronic diseases. 13 If this is the case, by controlling for the Exogenous effects and the Contextual effects in 14 Figure 1 we may be able to identify the causal relation between *Peer* and *Obesity*. The assumption that *Unobserved* does not affect *Peer* may be difficult to maintain in some 16 applications. In the analysis of peer effects in the classroom context, for example, one would reasonably assume that such unobserved factors may be related to family characteristics 18 and in particular to teacher quality. In this case, i.e. if *Unobserved* affects *Peer*, identifying 19 the causal effect of *Peer* on *Obesity* may be impossible.

²The implicit assumption here is that family members are consanguineous.

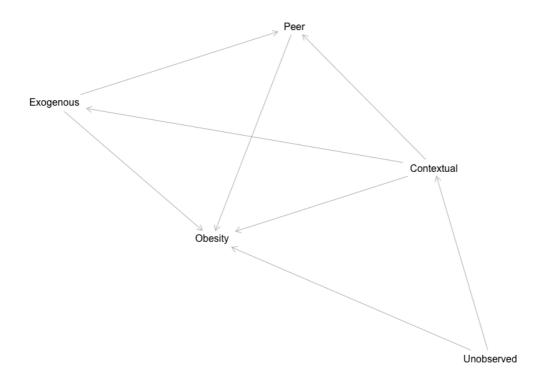


Figure 1: This DAG shows the causal relationship between *Obesity* and the peer effect variable *Peer*. In this model, controlling for *Exogenous* and *Contextual* allows one to identify the causal effect of *Peer* on *Obesity*.

- Due to the narrow peer group and to the structure of the data, however, our identific-
- 2 ation problem remains hard to solve. We resort to a binary choice model and to partial
- identification results for such models (see Section 4 for further details on the identification
- 4 problem and, e.g., Blume et al., 2011; Brock & Durlauf 2001, 2007.
- Inferential procedures for partially identified models are often rather complicated. How-
- ever, the method we use in this paper, introduced by Chen et al. (2018), is computationally
- rather simple and boils down to calculating confidence sets for the parameters of interest
- by means of standard Bayesian computation methods. Consistently with the hypothesised
- 9 driving mechanism, we find evidence of a strong, positive and statistically significant effect
- of overweight and obese peer children and a smaller positive and generally statistically
- significant effect of overweight and obese adults in the family on children's obesity.
- Our contribution to the existing literature is threefold. First, to our knowledge this is
- the only paper studying the causal role of within-family peer effects on obesity as a relevant

- health outcome. If peers in the family have important influences on child weight outcomes,
- 2 policies affecting one child in the family may have beneficial effects on the other children
- 3 as well as a social multiplier effect.
- Second, as stressed by Blume et al. (2011), the literature on partial identification for
- 5 social interaction models has evolved separately from that on the estimation of partially
- 6 identified models via bounds initiated by Tamer (2003) and used in industrial organization.
- 7 This paper is an attempt to integrate these two bodies of literature in a very specific
- 8 context.
- Finally, this is the only study on social interaction and child obesity in Italy. Obesity rates are low in Italy compared to most OECD countries, but the picture is different for children. According to the fifth wave of the Italian Surveillance System Okkio alla Sa-11 lute, in 2016 the prevalence rates of overweight (including obese) and obese primary school 12 children were 30.6% and 9.3%, respectively, with southern regions displaying higher rates than northern regions (Lauria et al., 2019). The Surveillance System Okkio alla Salute 14 (http://www.epicentro.iss.it/okkioallasalute/) monitors overweight and obesity of Italian children in primary schools (6-11 years of age). The System, promoted and financed 16 by the Italian Ministry of Health, was started in 2007 and participates in the World Health Organization (WHO) European Childhood Obesity Surveillance Initiative (COSI). In ad-18 dition, family ties are culturally strong in Italy which makes social interaction within the 19 family a particularly interesting issue to explore.
- The remainder of the paper unfolds as follows. Section 2 summarizes the literature.
- 22 Section 3 describes the data. Section 4 discusses our identification strategy. Section 5
- presents the estimation methods and main results. Section 6 concludes. Finally, the Ap-
- 24 pendix contains a description of statistical matching, results for the full sets of parameters
- 25 and the results of the robustness checks.

¹ 2 Child Obesity and Peer Effects

The main recognized cause of the rise in child obesity is an imbalance between calorie intake and calorie expenditure. There is a vast literature on the factors driving this imbalance. One strand has addressed the relationship between maternal employment and child obesity in many developed countries. Maternal employment is usually associated with higher child weight outcomes, because employed mothers may have less time to pay attention to their children's diet (Cawley & Liu | 2012; Champion et al., 2012; Fertig et al., 2009; Gaina et al. 2009 García et al. 2006 Greve, 2011 Gwozdz et al., 2013 Liu et al., 2009 Morrill 2011 to cite only a few). Overall, these studies find empirical evidence of a positive relationship between maternal employment and childhood obesity. However, there is no evidence of such positive relationship in Italy. In Italy there is a female labor force participation divide and 11 a child obesity divide. The South has a very low female labor force participation compared to the North, but child obesity prevalence is much higher in the South compared to the 13 North (Brilli et al., 2016). 14 A related factor is the increasing use of non-parental child care (informal care by a 15 relative, care by a baby-sitter and centre-based care) which may increase the likelihood of obesity (Herbst & Tekin 2011; Hubbard 2008). The growing use of non-parental care 17 may play a crucial role in shaping children's habits through the quality of the food offered 18 and the level of physical activity. Herbst & Tekin (2011) find that centre-based care is associated with large and stable increases in BMI throughout its distribution, while the 20 impact of other non-parental arrangements appears to be concentrated at the tails of the 21 distribution. 22 A strand of literature, initiated by Christakis & Fowler (2007), has emerged in health 23 economics that addresses the influence of social interaction, particularly of peers, on health status. In their seminal paper Christakis & Fowler (2007) conducted a study to determine 25 whether adult obesity might spread from person to person. Their starting point was that people embedded in social networks are influenced by the behaviours of those around

them such that weight gain in one person might influence weight gain in others. That study focused on social interaction among adults. A follow up study by the same authors (Fowler & Christakis, 2008) produced evidence of person-to-person spread of obesity also in adolescents. Powell et al. (2015) has identified social contagion, i.e. the phenomenon whereby the network in which people are embedded influences their weight over time, as one of the social processes explaining the rise of adult overweight and obesity. The general finding is that weight-related behaviours of adolescents are affected by peer contacts (Fowler & Christakis, 2008; Halliday & Kwak, 2009; Mora & Gil, 2013; Renna et al., 2008 Trogdon et al. 2008. These studies take adolescents as the relevant age group and the classroom or friends as the relevant network. Much less is known about children as the relevant age 11 group and the family as the relevant network. To the best of our knowledge only four studies, besides ours, analyse peer effects among 13 children as the relevant population, and child obesity as the relevant outcome. Asirvatham 14 et al. (2014) study peer effects in elementary schools using measured obesity prevalence 15 for children cohorts within schools and using a panel dataset at grade level from Arkansas public schools. They found that changes in the obesity prevalence at the highest level are associated with changes in obesity prevalence at lower grades and the magnitude of 18 the effect is greater in kindergarten to fourth-grade schools than in kindergarten to sixth-19 grade schools. Nie et al. (2015) analyse peer effects on obesity in a sample of 3 to 18 20 years old children and adolescents in China. Peer effects are found to be stronger in rural areas, among females and among individuals in the upper end of the BMI distribution. Gwozdz et al. (2015) analyse peer effects on childhood obesity using a panel of children 23 aged 2 to 9 from eight European countries. They show that, compared to the other European countries in the sample, peer effects are larger in Spain, Italy and Cyprus. These studies adopt a fairly broad definition of peer effects, either peers at the same grade level

adolescents or adults and uses US data.

Nie et al. (2015) report that most of the empirical literature on peer effects and obesity refers to

- within a school or children in a similar age group within a specific community. Finally,
- Yajuan et al. (2016) estimate peer effects on third grade students' BMI from a childhood
- 3 obesity intervention program targeted at elementary schools students in Texas. Peer effects
- 4 were found for students aged 8-11, with gender differences in the psychological and social
- 5 behavioral motivations.
- None of the above studies focuses on the family as the relevant peer group.
- The literature on the causal role of siblings on children's outcomes is recent and growing.
- 8 This literature has focused on the effects of sibling health status on educational outcomes
- 9 (Black et al., 2017) Fletcher et al., 2012), on the effect of early health shocks on child
- human capital formation (Yi et al., 2015), on the effects of teen motherhood on their
- siblings' short and medium term human capital development (Heissel, 2017, 2019), on the
- effect of siblings on educational choices and early career earnings (Dustan, 2018; Joensen &
- Nielsen, 2018; Nicoletti & Rabe, 2019; Qureshi, 2018), and on the effects of health shocks
- to individuals on their family members consumption of preventive care (Fadlon & Nielsen)
- 15 2019).
- Our study contributes to the latter strand of literature considering children as the
- ⁷ relevant population and obesity as the relevant health outcome. We conjecture that the
- mechanism through which the peer effect plausibly operates is via imitation of good and
- bad behaviours such as eating habits.

$_{\scriptscriptstyle 20}$ 3 Data and Matching

- 21 The choice of the family as the relevant network to analyse peer effects complicates the
- problem of controlling for unobserved fixed effects. Thus, the amount of available inform-
- 23 ation is a crucial issue in our case. Studies of peer effects and childhood obesity usually
- 24 include information on economic characteristics of the household, such as income, in ad-
- dition to personal and socio-demographic information, because low-income individuals are
- more likely to be obese than those with high-income (Trogdon et al. 2008). Moreover, the

relationship between income and weight is reported to vary by gender, race/ethnicity and age. Lacking a single Italian cross section containing individual weight outcomes, detailed family characteristics and socio-economic variables, we used statistical matching (SM) to match two datasets. The first is the 2012 cross section of the Multipurpose Survey on Households: Aspects of Daily Life (MSH) containing detailed information on family characteristics and the weight outcome of each member. The second is the 2012 cross section of The Household Budget Survey (HBS) covering details of current and durable expenditures.

Both surveys are conducted by the Italian National Statistical Institute (ISTAT).

The MSH for the year 2012 is a large nationally representative sample survey covering 19,330 households and 46,463 family members, including children aged 6 to 14 years 5 10 The questionnaire, administered by paper and pencil, contains three blocks of questions: a 11 general questionnaire on individual characteristics of the first six members of the household; 12 a family questionnaire collecting information about household habits and lifestyles; a diary of health and nutritional information for each member of the household. For children and adolescents aged 6-17 a binary indicator for whether the child is overweight or obese is also included. Identification of a child as overweight or obese is based on BMI threshold values 16 for children aged 6 to 17 developed by Cole et al. (2000) and adopted by the International Obesity Task Force (IOTF). The MSH does not contain information on expenditures that 18 could be important covariates in our empirical model. We obtain this information from 19 the 2012 cross section of the HBS which includes monthly consumption expenditures of 22,933 Italian households. ISTAT uses a weekly diary to collect expenditure data on frequently purchased items and a face-to-face interview to collect data on large and durable expenditures. Current expenditures are classified into about 200 elementary goods and services.

The survey also includes detailed information on household structure and socio-demographic

⁴Food Research and Action Center: http://frac.org/obesity-health/relationship-poverty-obesity.

⁵According to both the HBS and the MSH a family or household is defined as the set of cohabiting persons linked by marriage or kinship ties, affinity, adoption, guardianship or affection.

characteristics (such as regional location, household size, gender, age, education and employment condition of each household member). For both surveys, annual samples are drawn independently according to a two-stage design In addition to having a large set of variables in common, the two surveys share many characteristics such as the target population, sampling method, geographic frame and data collection procedure. These common characteristics allow us to use SM as an ideal method for combining information on households' quality of life and child weight outcomes with information on households' consumption expenditures.

The sample under analysis includes 3,906 observations. The unit of analysis is defined as child aged between 6 and 14 years: the barplot in Figure 2 panel (a) displays how children are distributed across households. The 3,906 children involved in the analysis are distributed across 2,954 households. As shown in Figure 2 panel (a), 2,095 children have no siblings in the target age group: 6 to 14 years; 770 households have two children in the same age group, for a total number of children equal to 1,540; 85 households have three children in the same age group, thus the total number of children is 255; finally, 4 households have four children in the target age group, for a total amount of children equal to 16.

For each individual, a rich set of covariates is available. Table I shows summary statistics of the relevant variables in the final SM dataset. We distinguish five sets of variables: individual characteristics of children (panel A), household characteristics (panel B), in some cases related to the household's reference person (RP), behavioural variables (panel C), proxies for genetic characteristics (panel D), regional variables (panel E). More specifically, the individual characteristics are the child overweight/obesity indicator (our dependent variable), gender and age for each child in the household. There are 1,141 overweight/obese children out of 3,906, thus overweight/obese children account for 29% of children aged 6-14

⁶Details on the sampling procedure used to collect data in both surveys can be found in: ISTAT (2012) Indagine Multiscopo sulle Famiglie, aspetti della Vita quotidiana, Anno 2012, for the MSH survey; and in ISTAT (2012) File Standard-Indagine sui Consumi delle Famiglie-Manuale d'uso, anno 2012, for the HBS survey. Downloadable at http://www.istat.it/it/archivio/4021

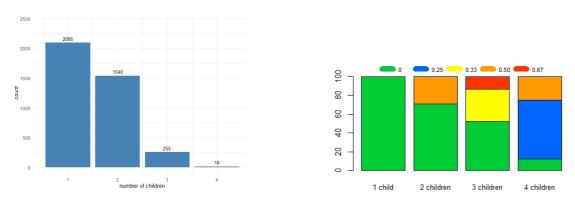
⁷SM of the two data sets is detailed in Appendix A

Table 1: Summary statistics.

	Mean	S.d.	Min.	Max.	Obs.
	Α.	Individu	ıal char	acteristic	es
Child obesity	0.292	0.455	0	1	3,906
Age	9.987	2.595	6	14	3,906
Gender (male)	0.495	0.500	0	1	3,906
	В	Househo	old char	acteristic	
Share of other overweight/obese children	0.072	0.174	0	0.667	3,906
Share of overweight/obese adults	0.420	0.351	0	1	3,906
Household size	4.120	1.018	2	11	,
	-	0.086	0	11	3,906
Children born of previous marriage	0.007		_		3,906
Monthly expenditure (Euro) Employed RP	2,131 0.813	1,346 0.390	237	16,998	3,906
Student or housewife RP		0.390 0.225	0	1 1	3,906
	0.053		_		3,906
Retired or other emp. status RP	0.023	0.150 0.331	0	1 1	3,906
Mother's education (Master) Mother's education (Bachelor)	0.126 0.029	0.331	_		3,906 3,906
,	0.029	0.109 0.476	0	1 1	,
Mother's education (High School) Mother's education (Junior High)		0.470	0	1	3,906
()	0.412 0.068	0.492 0.252	_		3,906
Mother's education (Primary School) Central or northern region	0.008	0.252 0.494	0	1 1	3,906 3,906
Ü					
	C.		ral char	acteristic	es
Siblings (regularly) practising sport	0.176	0.244	0	0.75	3,906
Siblings lunch at home	0.186	0.246	0	0.75	3,906
Siblings walking to school	0.089	0.193	0	0.75	3,906
Siblings TV watching every day	0.810	0.317	0	1	3,906
Parents soda drinks	0.155	0.362	0	1	3,906
Parents smoking	0.372	0.483	0	1	3,906
Children average fruit portions	1.125	0.754	0	5.5	3,906
Adults average fruit portions	1.147	0.778	0	5.5	3,906
	D. Prox	cies for g	genetic	characte	ristics
Mean adult weight (kg)	70.676	9.159	35.5	117.5	3,906
Mean adult height (cm)	168.959	5.694	110	193	3,906
Chronic disease	0.251	0.439	0	1	3,906
Diabetes	0.034	0.181	0	1	3,906
		E. Other	charac	teristics	
CPI (2010=100)	106.022	0.614	104.6	108.1	3,906
% obese adults by region	24.954	5.476	17.7	36.1	3,906
· · · · · · · · · · · · · · · · · · ·					- ,

[†]This table includes summary statistics on individual characteristics of children (panel A), household characteristics (panel B), in some cases related to the household's reference person (RP), behavioural variables (panel C), proxies for genetic characteristics (panel D), regional variables (panel E).

years. The children's mean age is 10 and the percentage of male children is 49.5%.



(a) Distribution of children across families ($6 \le age \le 14$). (b) Conditional distribution of obese/overweight children across families ($6 \le age \le 14$).

Figure 2: Children's distribution and share of obese children

- The peer effect variable is defined as the share of other (overweight and obese) children
- in the family (excluding the child considered). This variable, $m_{g_{-i}}$, is computed as the ratio
- between the number of obese children in family g excluding the reference child i, $n_{g_{-i}}^{O}$, and
- 5 the total number of children in the family, n_g . Hence,

$$m_{g_{-i}} = \frac{n_{g_{-i}}^O}{n_q}$$

- where, in our data set, $1 \le n_g \le 4$, $0 \le n_{g_{-i}}^O \le 3$ and $0 \le m_{g_{-i}} \le \frac{2}{3}$. The minimum
- τ value of the variable corresponds to two different cases. The first case occurs when child i
- 8 has no siblings and the second occurs when child i has no obese siblings. The maximum
- value occurs when there are two out of three obese children in the family.
- Figure 2 (panel b) shows the conditional distribution of the share of other obese/overweight
- children in the family given the number of children in the target age group within the fam-
- 12 ily. Of course, if the reference child has no siblings, the share is zero. As to the children
- having siblings in the age group 6-14, we can observe the following picture: the number
- of children in families with two children in the target age group is 1,540, 71% of them
- has a sibling with normal weight (share = 0) and 21% has an obese/overweight sibling

1 (share = 1/2 = 0.5); the number of children in families with three children in the target 2 age group is 255, 52% the of them has siblings with normal weight (share = 0), 33% of 3 them has one obese/overweight sibling (share = 1/3 = 0.33), and the remaining 13% has 4 two obese/overweight siblings (share = 2/3 = 0.67). Finally, the number of children in 5 families with four children in the target age group is 16, 12.5% of them has normal weight 6 siblings (share = 0), 62.5% has 1 obese/overweight sibling (share = 1/4 = 0.25) and 25% 7 of them has two obese/overweight siblings (share = 2/4 = 0.5).

Further characteristics shown in Table 1 include the share of overweight and obese adult family members (42%), household size (4 on average) and a dummy for children born from 9 a previous marriage, the employment status of the RP (three dummies for whether the 10 household RP is employed, a student or housewife, retired or in other employment positions 11 (e.g. military, unable to work, detained)), dummies for the level of education of the mother 12 (five dummies for whether the mother holds a Master's degree, a Bachelor's degree, has 13 attended High School, Junior High, or only Primary School) and a dummy for whether the 14 household lives in a central or northern Italian region. In addition, we include monthly 15 current expenditure, whose average value is 2,131 Euros. This variable is important as 16 it captures contextual effects and we conjecture that its support (237 - 16,998 Euros) is sufficiently large to ensure that a nonlinear relationship with the share of obese children 18 in the family (the endogenous effect) exists. We also include a set of variables capturing 19 behaviors of siblings in a wider age group (6 to 18 years) compared to the target age group, 20 because older siblings could influence the behaviours of younger ones. Such variables 21 include the share of siblings (excluding the child under consideration) aged between 6 22 and 18 watching TV every day, having lunch at home, practicing physical activities on a 23 regular basis and walking to school, dummies for whether the parents consume soda drinks or smoke. We also include the child's daily average fruit portions and the adults daily 25 average fruit portions. As proxies for the genetic variables we use the mean height and weight of the adult members of the family and two dummy variables for whether the RP 27 or her spouse suffer from a chronic disease or diabetes. Finally, we use two additional

- variables at the regional level: the 2012 consumer price index (CPI) (2010=100) and the
- ² percentage of obese adults by region in 2012.

3 4 Identification

- 4 Our aim is to assess whether the presence of other overweight/obese family members,
- 5 i.e. children in the same age group and adults, has a positive and significant effect on
- 6 the probability of a child being overweight/obese. If imitation behaviour is the driving
- 7 mechanism we also expect that the impact of overweight/obese peer children in the family
- s is larger than the impact of overweight/obese adults. We use a narrow peer-group definition
- 9 that includes all children aged 6 to 14 years belonging to the same family (whether siblings
- or not). Narrow definitions of peer groups have been found to be more endogenous than
- broad ones. In particular Trogdon et al. (2008) report that broader measures of social
- networks (e.g. grade-level peer groups) are more exogenous than narrow ones (e.g. children
- in the same family) as they are likely to be determined by different causal mechanisms.
- While grade-level peer effects may be driven by BMI related social norms and body image
- concerns, family-level peer effects may also operate through additional channels such as
- the influence of diets, habits and physical activities. Christakis & Fowler (2007) showed
- that the influence of the weight of friends, family members and neighbours decreases with
- 18 increasing degrees of separation from the person under investigation. Despite the large
- empirical literature on social interaction in a variety of contexts, identifying such effects
- 20 remains a formidable challenge.
- Let us consider the notation and the definitions in Brock & Durlauf (2007). We assume
- 22 that individual binary weight outcomes are determined by five sets of factors:
- (i) observable individual-specific characteristics known also as the exogenous effects,
- measured by an r-vector X_i ;
- (ii) unobservable individual characteristics summarized by a scalar ε_i ;

- (iii) observable group characteristics, measured by an s-vector Y_g ; these are known as contextual effects and may directly influence individual decisions: for example, peers' characteristics such as parents' income, education or occupation may influence children's weight;
- 5 (iv) unobservable (to the econometrician) group characteristics, measured by a scalar α_g that may affect individual outcomes; these are known as correlated effects: for example, genetic characteristics may affect the weight of all children in the same family;
- (v) the average outcome in the peer group excluding the child under consideration, $m_{g_{-i}}$.

 It is a measure of the share of obese children in the family that could affect each individual outcome (see Section 3 for the definition of $m_{g_{-i}}$).

Thus, our model of social interaction can be described as

19

$$\omega_i = k + c'X_i + d'Y_q + Jm_{q_{-i}} + \varepsilon_i + \alpha_q \tag{1}$$

where ω_i is a binary indicator that takes value one if, according to a BMI score, individual i is overweight/obese and zero otherwise. One important advantage of using a binary choice model is that, under a large support on Y_g , the data reveal a non-linear relationship between $m_{g_{-i}}$ and Y_g . This implies that the so-called reflection problem Manski (1993) does not arise in the binary choice case [8]Identification in binary choice models of social interaction has been thoroughly explored in Brock & Durlauf (2007) (see also Blume et al., 2011, for a survey). In their baseline

and the reflection effect that typically characterizes linear-in-means models is not present.

result, with $\alpha_g = 0$ and random assignment, the model parameters are identified up to scale

The main argument relies on the support of the contextual effects Y_g to be sufficiently

⁸A reflection problem arises when the dependent variable (weight outcome of child i) and the explanatory variable of interest (peer variable $m_{g_{-i}}$) are simultaneously determined, causing an endogeneity issue.

large to establish a nonlinear relationship with $m_{g_{-i}}$. In addition to that, they derive identification results also for the case of non random assignment provided that $\alpha_g = 0$.

With respect to our context, the assumption of random assignment is very difficult to justify. Since individuals within a group are consanguineous with high probability, their assignment to a given group g depends on common genetic traits. Unfortunately, our data set does not contain any explicit information on the genetic factors that determine obesity in the group. However, we may proxy it with mean adult height and weight in the household and by adding two dummy variables for whether the household head or her spouse suffers from a chronic disease or diabetes. We can conjecture that our proxies capture sufficient information from the fixed effect to guarantee identification. However, we cannot be sure that all relevant assumptions are met.

When point identification is not possible, Brock & Durlauf (2007) describe a number 12 of situations where at least partial identification can be achieved. In particular, they 13 prove that under non random assignment, provided that $\alpha_g = 0$ and the support on Y_g is 14 sufficiently large to rule out the reflection problem, J>0 and J is large enough to produce 15 multiple equilibria. This means that group q may coordinate on an equilibrium expected 16 average choice level other than the largest of the possible equilibria associated with it 17 while another group g' may coordinate on an equilibrium other than the lowest possible 18 expected average choice level among those it could have attained. One of the situations 19 where this may happen is the case of assortative matching, where higher group quality 20 is related to higher individual quality. In our context, this may refer to the case where 21 individuals within a specific group share common genetic traits or the same eating habits. 22 It is, though, important to stress that the multiple equilibrium results in Brock & Durlauf 23 (2007) hold for large groups. In particular, Krauth (2006) suggests that multiplicity of equilibria for small groups may happen for lower threshold values of J. 25

We adopt Brock & Durlauf (2007) approach to (partial) identification. In the empirical exercise we need to accommodate the large support assumption on Y_g . More specifically, we consider two cases. In the first case the variable with large support is the log of

expenditures. The second specification includes also average adult weight and average adult height. It is interesting to notice, though, that there seem to be no clear theoretical guidelines on how many variables with large support would be necessary to avoid the reflection effect (see e.g. Blume et al., 2011, p. 907). Dealing with unobservable heterogeneity in the context of social interaction models is generally a very challenging task since, as suggested in Blume et al. (2011), ε_i and α_g are undertheorized. Nonetheless, there are still a number of approaches that can be exploited when sufficient information is available. The most problematic issue in our setting is how to deal with the group fixed effects α_q . The simplest solution here is just to define $\alpha_g = d'Y_g + Jm_{g_{-i}}$ (Blume & Durlauf) 2006). This is, we approximate α_g with observables and change the number of variables in Y_g to assess the stability of the estimates. Our model will include a large number of group characteristics that may reasonably determine 12 obesity and that are either related to genetic factors or to behavioural factors. 10 13 Direct estimation of α_g via group dummies would be impossible in our context due 14 to the large number of families (2,954) compared to the number of individuals (3,906). 15 We could however identify a restricted number of groups by clustering families with com-16 mon characteristics. The resulting number of groups would be considerably smaller than the total number of families. Allocating the families to specific groups may be done via 18 an appropriate clustering algorithm. We give more details on this approach and on the 19 corresponding results in Appendix B (Table B19 and Table B20). 20 Brock & Durlauf (2007) propose a rather clever way to deal with α_q . They suggest 21 specifying α_g as a linear function of Y_g and constructing an auxiliary variable W_i $F_{\varepsilon}^{-1}(P(\omega_i=1|X_i,Y_g,\alpha_g))$ where F_{ε} is the distribution of ε_i . This would correspond to $W_i = k + c'X_i + d'Y_g + Jm_{g_{-i}} + \alpha_g$. The construction of the sample analog for W_i would rely on the existence of suitable information.¹¹ In our case, once again, the limited availabil-⁹Instrumental variables may be a viable option to deal with fixed effects. However, social interaction

⁹Instrumental variables may be a viable option to deal with fixed effects. However, social interaction models do not generally suggest a theoretical justification to exclude variables from the model itself. This feature is known as *openendedness* (Blume et al., 2011).

¹⁰A recent strand of literature stresses that any similarity in weight due to shared household environments is undetectable and ignorable (Cawley & Meyerhoefer 2012; Kinge 2016; Wardle et al., 2008)

¹¹For the problem of social interactions in the classroom example, Brock & Durlauf (2007) suggest using

- 1 ity of data does not allow us to consider this alternative. A further interesting possibility is
- due to Graham (2008), where α_g is interpreted as a random effect. Hence, $Cov[\alpha_g, \varepsilon_i] = 0$,
- 3 for $i \in g$. This approach is justified, at least in Graham's classroom problem, by the
- 4 random assignment of teachers to classrooms.

₅ 5 Estimation and Inference

approaches to partial identification. The latter case involves the identification of bounds and their subsequent estimation by means of appropriate statistical procedures. Instead, Brock & Durlauf's (2007) theory-dependent approach studies how introducing unobserved heterogeneity would affect the properties of the model. Furthermore, they do not establish probability bounds (Blume et al., 2011). Hence, we assume that, given a certain parameter space Θ , there exists a subset of Θ , say Θ_I , such that $F_0 = F_\theta$ for $\theta \in \Theta_I$ where F_0 is the true distribution of the data and F_θ is our parametric model. We refer to Θ_I as the identified set for which an appropriate estimator has to be found. In what follows, we

It is interesting to notice that the results in Brock & Durlauf (2007) differ from the classical

focus our attention on confidence sets for individual parameters. In this regard, we find

the following decomposition useful: $\theta = (\mu', \eta')'$, where μ is the parameter vector we are

interested in and η can be seen as a nuisance parameter. We denote the identified set for

the subvector μ as M_I .

We tackle the estimation problem by using a method introduced in Chen et al. (2018).

The confidence sets produced using this approach are simple to calculate, work well in finite

 $_{21}$ samples and asymptotically achieve frequentist coverage. The estimated confidence sets

 $_{22}$ can be compared to the confidence intervals produced by standard estimation methods

23 for binary choice models under the assumption of point identification. Intuitively, one

24 may argue that (lack of point) identification may not be an issue if confidence sets and

25 confidence intervals are similar.

test scores to recover a sample analogue for W_i .

¹²See, e.g., Manski (2003) and Molinari (in press) for a comprehensive treatment of partial identification.

- In this section we describe how we build valid confidence sets using Procedure 1 and
- 2 Procedure 3 in Chen et al. (2018). They are both simple to compute but the former tends
- 3 to produce conservative confidence sets while the latter can only be applied to scalar sub-
- vectors of the parameter vector of interest. The associated numerical results are collected
- 5 in Table 2 to Table 9. Appendix B contains the robustness check results.

₆ 5.1 Confidence Sets

- 7 The methods proposed in Chen et al. (2018) exploit some classical ideas of Bayesian compu-
- 8 tation. The estimation of the confidence sets is in fact based on sampling from the posterior
- 9 distribution of the parameters. Here we provide a brief description of the three procedures
- introduced in their paper. Considering the discussion in Section 4 on the treatment of the
- ii fixed effect α_g , the model that we estimate is

$$\omega_i = Z_i'\theta + u_i$$

where $Z_i = (1, X_i', Y_g', m_{g_{-i}})$ and $\theta = (k, c', d', J)'$ is a p-dimensional vector where p = 2 + r + s. Let us consider a parametric loglikelihood function that depends on a parameter vector θ that takes values in a set Θ and the data Z_i

$$L_N(\theta) = \frac{1}{N} \sum_{i=1}^{N} \log f(\theta, Z_i).$$

Let us denote the identified set as $\Theta_I = \{\theta \in \Theta : F_0 = F_\theta\}$, where F_θ is our parametric model and F_0 is the true distribution of the data. The posterior distribution, say Π_N , of θ given the data Z is

¹³For ease of notation we drop the group index g.

$$d\Pi_N(\theta, Z) = \frac{\exp(NL_N(\theta)) d\Pi(\theta)}{\int_{\Theta} \exp(NL_N(\theta)) d\Pi(\theta)}$$

- where $\Pi(\theta)$ is a prior distribution. The $100\alpha\%$ confidence set, say $\widehat{\Theta}_{\alpha}$ for Θ_{I} is computed
- 2 in a three step procedure:

3 Procedure 1 (whole parameter vector)

- (a) draw B samples $\{\theta^{(1)}, \dots, \theta^{(B)}\}$ from the posterior distribution Π_N via a Monte Carlo
- Markov chain (MCMC) sampler; ¹⁴
- 6 (b) calculate the $(1-\alpha)$ quantile of $\{L_N(\theta^{(1)}), \ldots, L_N(\theta^{(B)})\}$, say $\zeta_{N,\alpha}$;
- 7 (c) define $\widehat{\Theta}_{\alpha}$ as $\widehat{\Theta}_{\alpha} = \{ \theta \in \Theta : L_N(\theta) \ge \zeta_{N,\alpha} \}.$
- 8 It is possible to adapt procedure 1 to construct confidence sets for the subset vector
- 9 μ . The so-called projection confidence set for M_I is defined as $\widehat{M}_{\alpha}^{proj} = \{\mu : (\mu', \eta')' \in \mathcal{M}_{\alpha}\}$
- $\widehat{\Theta}_{\alpha}$, for some η }. The projection confidence set is known to be conservative in particular
- when the dimension of the subvector μ is smaller in comparison with the dimension of θ .
- Let us now define the set $H_{\mu} = \{ \eta : (\mu', \eta')' \in \Theta \}$ and the profile likelihood for M_I

$$PL_N(M_I) = \inf_{\mu \in M_I} \sup_{\eta \in H_\mu} L_N(\mu, \eta).$$

- Let $\Delta(\theta^b), b = 1, \dots, B$ be an equivalence set, i.e. a set of $\theta \in \Theta$ that produce the same
- likelihood values and let $M(\theta^b) = \{\mu : (\mu', \eta')' \in \Delta(\theta^b), \text{ for some } \eta\}$. Then, the profile
- likelihood for $M(\theta^b)$ is

¹⁴ Chen et al. (2018) suggest using a sequential Monte Carlo sampler as MCMC may be numerically unstable. We do not experience such problems in our application.

$$PL_N(M(\theta^b)) = \inf_{\mu \in M(\theta^b)} \sup_{\eta \in H_\mu} L_N(\mu, \eta).$$

We can now describe the second procedure for a subvector μ of θ :

2 Procedure 2 (subvector)

- 3 (a) draw B samples $\{\theta^{(1)}, \dots, \theta^{(B)}\}$ from the posterior distribution Π_N via a MCMC
- 4 sampler;
- 5 (b) calculate the $(1-\alpha)$ quantile of $\{PL_N(M(\theta^{(1)})), \ldots, PL_N(M(\theta^{(B)}))\}$, say $\zeta_{N,\alpha}$;
- 6 (c) define \widehat{M}_{α} as $\widehat{M}_{\alpha} = \{ \mu \in M : \sup_{\eta \in H_{\mu}} L_N(\mu, \eta) \ge \zeta_{N,\alpha} \}.$
- ⁷ We now describe a simple procedure for scalar subvectors. Let us define the likelihood
- 8 ratio

$$LR_N(\theta) = 2N \left(L_N(\widehat{\theta}) - L_N(\theta) \right)$$

for a maximizer $\widehat{\theta}$. Procedure 3 can be implemented in two simple steps

10 Procedure 3 (scalar subvector)

- (a) calculate a maximizer $\hat{\theta}$;
- (b) define \widehat{M}_{α} as $\widehat{M}_{\alpha} = \{ \mu \in M : \inf_{\eta \in H_{\mu}} LR_{N}(\mu, \eta) \leq q_{\alpha}^{\chi_{1}^{2}} \}$, where $q_{\alpha}^{\chi_{1}^{2}}$ is the α quantile of the χ_{1}^{2} distribution.
- As suggested in Chen et al. (2018), the confidence sets are compared to the confidence
- intervals provided by the standard probit and logit models.

₁ 5.2 Results

Table 2 to Table 9 in this Section contain 95% confidence intervals obtained using the standard logit and probit models as if identification were possible and 95% confidence sets obtained using Procedure 1 and Procedure 3 of the approach described in Section 5.1 and denoted as CCT1 and CCT3 respectively. Table 2 to Table 7 show estimates considering families with at least one child (i.e. all the families). In addition to that, we conduct our analysis in subsets of the data based on age. Two subsets are considered $6 \leq age \leq 11$ (Tables $\boxed{3}$, $\boxed{6}$) and $12 \leq age \leq 14$ (Tables $\boxed{4}$, $\boxed{7}$). Moreover, each model is estimated using four sets of covariates. Table 8 and Table 9 on the other hand, display the estimates of a parsimonious model that includes the number of children as a regressor as well as the average height and weight of adults in the family. Also for these models we consider the age subsets described above. Appendix B shows similar models for families that include 12 either more than one child or only one child. These results serve the purpose of checking 13 the stability of the confidence sets. 14

Our dependent variable is a binary variable for a child being overweight/obese. The explanatory variables of interest are the share of other overweight and obese children in the household (the peer effect) and the share of overweight and obese adults in the household.

The other covariates introduced in the models are described in Section Specifically, these are the individual characteristics of the child (gender, age and age²) and household characteristics, like the share of other overweight and obese children in the household (the key covariate), the share of overweight and obese adults in the household and the household consumption expenditures in logs – the matched variable. As to the effect of

¹⁵Covariates include household, behavioral and regional characteristics as well as proxies for genetic characteristics. Household characteristics include household size, whether the household lives in a Northern or Central Italian region, the employment status of the RP, the level of education of the mother. Regional characteristics includes a general CPI at the regional level and the regional share of obese adults in 2012. Genetic proxies include the mean height and weight of the adult members of the family and two dummy variables for whether the RP or her spouse suffer from a chronic disease or diabetes. Behavioral variables includes the share of siblings (excluding the child under consideration) aged between 6 and 18 watching TV every day, having lunch at home, practicing physical activities on a regular basis and walking to school, dummies for whether the parents consume soda drinks or smoke. The full set of confidence intervals and confidence sets can be found in Tables B1 to B3 and Tables B10 to B12

the key covariate, we observe that the presence of other obese children in the family has a positive effect on the probability that a child be obese. This result is robust to all the specifications of the model we considered. The results obtained with the standard binary choice model, either logit or probit, are very similar to the confidence sets computed via CCT3. This may suggest that if there is no point identification, this has only a mild effect on the confidence intervals. The confidence sets obtained via CCT1 are generally larger than those built with CCT3: this is in line with what is suggested in Chen et al. (2018). Furthermore, we find that the effect of obese adults in the family is generally smaller than that of peer children. We also find that by including the genetic proxies and the behavioural variables the confidence sets tend to move to the left and in some cases they include zero. If we look at the results for the two age subsets we notice some differences. However, they 11 may be caused by the difference in sample size. The model specification in Table 8 and 12 Table 9 shows a sizable shift towards the right of the confidence sets associated to the peer effect variable. This result is observed for all age subsets. The confidence sets tend 14 to get larger when we consider the subset of older children; however, also this effect may be caused by the reduced sample size. The effect of the share of obese adults seems to be more ambiguous as it is smaller in comparison with the other model specifications and, for the subset of older children, it includes zero. This result may also depend on the inclusion 18 of average adult weight and height, as they are related to the share of obese adults in the 19 family. As to the variable gender of the child, its effect is significant in almost all the model specifications, with confidence sets defined in a positive subset of the real line, meaning that the probability of being overweight/obese is larger for males than for females. The child age is insignificant in the quadratic polynomial specification in almost all the model specifications. As to the effect of household consumption expenditures, introduced in the model as a logarithmic transformation, its effect is significant, both for the logit and probit 25 models, either for the standard binary choice model or for the one estimated via CCT3, on the set including all children aged 6-14 years and for the subset of children aged 6-11 years, only when the models do not include other household behavioural variables. In such cases,

the confidence sets are defined in a negative subset of the real line (see columns (1) and (3) in Tables [2, 3, 5, 6] meaning that the probability of being overweight/obese decreases with household consumption expenditures. It thus seems that the impact of consumption expenditures, viewed as a proxy of the economic status of the household, is mediated by the included household and behavioural covariates. One possible interpretation of this result is that those families in better economic conditions can offer better opportunities for a healthy diet and physical activity. On the other hand, resource constraints lead to a lack of opportunities and to a lack of information on the ingredients of a healthy children's diet and on healthy behaviours.

₁₀ 6 Conclusion

This paper contributes to the literature on child obesity by assessing the effect of peers on 11 children's weight outcomes in the context of a narrow peer group. We assessed whether 12 the presence of overweight and obese family members – other children and adults – affects 13 children's weight outcomes. To the best of our knowledge no study has yet analysed the impact of the obesity status of other members of a family on child obesity. We chose to carry out our analysis not presuming point identification for our models. With respect 16 to that aspect, we contribute to the integration, albeit in a rather specific context, of 17 the literature on partial identification for social interaction models and that on partially 18 identified models in industrial organization (Blume et al., 2011; Tamer, 2003). We used a data set on Italian children resulting from statistical matching of the 2012 20 cross sections of two surveys, the Multipurpose Household Survey and the Household 21 Budget Survey, both supplied by ISTAT. To provide valid inference for our partially iden-22 tified models we use the method proposed by Chen et al. (2018). We found evidence of 23 a strong, positive impact of overweight and obese peer children in the family and of overweight and obese adults on child weight outcomes. Interestingly, in all empirical models we 25 find that the impact of overweight and obese peer children in the household is larger than

Table 2: Confidence intervals and confidence sets for the logit model.[†]

				Depen	Dependent variable: child obesity	ld obesity			
	Logit (1)	CCT1 (2)	CCT3	Logit (4)	CCT1 (5)	CCT3 (6)	Logit (7)	CCT1 (8)	CCT3 (9)
Share of other obese children	[0.913,1.695]	[0.568,2.046]	[0.925,1.689]	[0.706,1.526]	[0.301,1.991]	[0.711,1.513]	[0.679,1.530]	[0.328,1.956]	[0.690,1.529]
constant	[-1.744, 1.173]	[-3.060, 2.446]	[-1.744,1.130]	[-3.623,22.087]	[-13.770,19.093]	[-3.292,19.093]	[-3.576, 22.700]	[-11.224, 19.916]	[-3.329, 18.600]
gender	[0.158, 0.448]	[0.028, 0.579]	[0.158, 0.443]	[0.157, 0.453]	[0.011, 0.578]	[0.160,0.452]	[0.150, 0.448]	[0.061, 0.545]	[0.154, 0.447]
age	[-0.121, 0.383]	[-0.310, 0.438]	[-0.113,0.375]	[-0.085, 0.428]	[-0.415, 0.697]	[-0.078,0.428]	[-0.099, 0.420]	[-0.218,0.567]	[-0.092,0.416]
age^2	[-0.025,0.001]	[-0.036,0.012]	[-0.024,0.000]	[-0.028,-0.002]	[-0.043, 0.015]	[-0.028,-0.002]	[-0.028, -0.001]	[-0.035,0.004]	[-0.027, -0.002]
$Share\ of\ obese\ adults$	[0.626, 1.042]	[0.441, 1.228]	[0.628,1.042]	[0.537,0.962]	[0.322, 1.224]	[0.541,0.960]	[-0.031,0.651]	[-0.170,0.797]	[-0.023, 0.651]
$log\ expenditures\ (Euro)$	[-0.284, -0.054]	[-0.387, 0.048]	[-0.283,-0.056]	[-0.136, 0.116]	[-0.294, 0.269]	[-0.135,0.116]	[-0.117,0.139]	[-0.210,0.184]	[-0.115, 0.136]
Households characteristics	ON	ON	ON	YES	YES	YES	YES	YES	YES
$Regional\ characteristics$	ON	ON	ON	YES	YES	YES	YES	YES	YES
Genetic proxies	ON	ON	ON	ON	ON	ON	YES	YES	YES
$Behavioral\ variables$	ON	ON	ON	ON	ON	ON	YES	YES	YES
N, p	3737, 7	3737, 7	3737, 7	3737, 19	3737, 19	3737, 19	3737, 30	3737, 30	3737, 30

†This table provides 95% confidence intervals using the standard logit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using all the families.

Table 3: Confidence intervals and confidence sets for the logit model.[†]

				Dependent va	Dependent variable: child obesity $(6 \le age \le 11)$	$y \ (6 \le age \le 11)$			
	$\begin{array}{c} \text{Logit} \\ (1) \end{array}$	CCT1 (2)	CCT3 (3)	Logit (4)	CCT1 (5)	CCT3 (6)	Logit (7)	CCT1 (8)	CCT3 (9)
$Share\ of\ other\ obese\ children$	[0.949, 1.906]	[0.512, 2.331]	[0.957,1.905]	[0.723, 1.726]	[0.170, 2.203]	[0.724,1.710]	[0.671, 1.705]	[0.439, 2.267]	[0.679, 1.695]
constant	[-1.440, 3.801]	[-3.805, 6.106]	[-1.355,3.768]	[-6.249, 24.249]	$\left[-26.552, 23.021 \right]$	[-26.552,23.021] [-5.521,23.021]	[-6.724, 24.517]	[-6.724,24.517] [-15.053,23.818]	[-6.415, 22.378]
gender	[-0.107, 0.234]	[-0.263, 0.387]	[-0.102,0.233]	[-0.120, 0.229]	[-0.302, 0.370]	[-0.119,0.228]	[-0.126, 0.226]	[-0.259, 0.388]	[-0.122, 0.225]
age	[-0.784, 0.383]	[-1.136, 0.384]	[-0.780,0.360]	[-0.752, 0.441]	[-1.307, 1.015]	[-0.744,0.429]	[-0.776, 0.430]	[-1.061, 1.007]	[-0.768, 0.422]
age^2	[-0.026, 0.042]	[-0.058, 0.073]	[-0.026,0.042]	[-0.030, 0.040]	[-0.062, 0.071]	[-0.030,0.039]	[-0.030, 0.041]	[-0.061, 0.060]	[-0.029, 0.040]
$Share\ of\ obese\ adults$	[0.536, 1.025]	[0.319, 1.251]	[0.541,1.018]	[0.457, 0.959]	[0.265, 1.173]	[0.458,0.953]	[0.061, 0.872]	[-0.268, 1.158]	[0.063, 0.870]
$log\ expenditures\ (Euro)$	[-0.307, -0.036]		[-0.431,0.087] [-0.306,-0.038]	[-0.141, 0.157]	[-0.311, 0.317]	[-0.140,0.152]	[-0.118, 0.185]	[-0.206, 0.269]	[-0.115, 0.183]
$How sehold\ characteristics$	ON	ON	ON	YES	YES	YES	YES	YES	YES
$Regional\ characteristics$	NO	NO	ON	YES	YES	YES	YES	YES	YES
Genetic proxies	NO	NO	ON	NO	NO	ON	YES	YES	YES
$Behavioral\ variables$	NO	NO	ON	ON	ON	ON	YES	YES	YES
N, p	2503, 7	2503, 7	2503, 7	2503, 19	2503, 19	2503, 19	2503, 30	2503, 30	2503, 30

†This table provides 95% confidence intervals using the standard logit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using all the families with children with $6 \le age \le 11$.

Table 4: Confidence intervals and confidence sets for the logit model.[†]

				Dependent var	Dependent variable: child obesity (12 \leq age \leq 14)	$y (12 \le age \le 14)$			
	$\begin{array}{c} \text{Logit} \\ (1) \end{array}$	CCT1 (2)	CCT3 (3)	Logit (4)	CCT1 (5)	CCT3 (6)	Logit (7)	CCT1 (8)	CCT3 (9)
$Share of \ other \ obese \ children$	[0.439,1.848]	[-0.201,2.439]	[0.444,1.825]	[0.264,1.759]	[-0.542,2.511]	[0.291,1.740]	[0.432,2.036]	[-0.449,2.849]	[0.450,2.016]
constant	[-27.662,72.548]	[-60.429, 74.899]	[-26.597,71.677]	[-22.476,89.346]	[-56.280,93.211]	[-13.341,88.440]	[-12.926,102.045]	$\left[-64.176, 106.904 \right]$	[-10.059, 101.666]
gender	[0.659, 1.237]	[0.420, 1.494]	[0.661,1.229]	[0.683, 1.271]	[0.455, 1.663]	[0.687,1.260]	[0.681, 1.282]	[0.401, 1.592]	[0.690, 1.279]
age	[-11.176, 4.290]	[-12.660, -0.408]	[-11.159,-0.408]	[-10.468, 5.271]	$\left[-12.017, 1.488 \right]$	[-10.298,1.488]	[-12.037, 4.041]	[-13.973, 0.461]	[-11.947, 0.208]
age^2	[-0.173, 0.423]	[-0.370, 0.434]	[-0.166,0.414]	[-0.211, 0.395]	[-0.438, 0.436]	[-0.162,0.389]	[-0.164, 0.455]	[-0.311, 0.532]	[-0.164, 0.444]
Share of obese adults	[0.587, 1.390]	[0.249, 1.734]	[0.602,1.380]	[0.469, 1.291]	[0.155, 1.763]	[0.480,1.276]	[-0.700, 0.63]	[-1.340,1.310]	[-0.671, 0.614]
log expenditures (Euro)	[-0.390, 0.054]	[-0.581, 0.240]	[-0.381,0.049]	[-0.287, 0.194]	[-0.584, 0.491]	[-0.280,0.187]	[-0.299, 0.197]	[-0.524, 0.448]	[-0.298, 0.193]
How sehold characteristics	NO	ON	ON	YES	YES	YES	YES	YES	YES
Regional char acteristics	NO	ON	ON	YES	YES	YES	YES	YES	YES
$Genetic\ proxies$	NO	ON	ON	ON	ON	ON	YES	YES	YES
$Behavioral\ variables$	NO	ON	ON	NO	ON	ON	YES	YES	YES
N, p	1234, 7	1234, 7	1234, 7	1234, 19	1234, 19	1234, 19	1234, 30	1234, 30	1234, 30

†This table provides 95% confidence intervals using the standard logit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using all the families with children with $12 \le age \le 14$.

Table 5: Confidence intervals and confidence sets for the probit model.[†]

				Depen	Dependent variable: child obesity	ld obesity			
	Probit (1)	CCT1 (2)	CCT3 (3)	Probit (4)	CCT1 (5)	CCT3 (6)	Probit (7)	CCT1 (8)	CCT3 (9)
$Share\ of\ other\ obese\ children$	[0.560, 1.039]	[0.344, 1.248]	[0.568,1.035]	[0.435, 0.933]	[0.158, 1.282]	[0.442,0.930]	[0.421, 0.934]	[0.067, 1.313]	[0.432, 0.923]
constant	[-1.043, 0.704]	[-1.822, 1.485]	[-1.035,0.698]	[-2.39, 13.116]	[-6.889,14.311]	[-2.137,12.849]	[-2.335,13.520]	[-12.436,17.633]	[-2.055, 13.337]
gender	[0.101, 0.275]	[0.026, 0.351]	[0.105,0.271]	[0.100, 0.276]	[-0.002, 0.389]	[0.101,0.274]	[0.094, 0.272]	[-0.017,0.389]	[0.098, 0.270]
age	[-0.074,0.226]	[-0.190, 0.290]	[-0.072,0.224]	[-0.051, 0.254]	[-0.274, 0.428]	[-0.047,0.251]	[-0.057, 0.251]	[-0.265, 0.438]	[-0.052, 0.246]
age^2	[-0.015, 0.000]	[-0.021,0.007]	[-0.014,0.000]	[-0.016, -0.001]	[-0.026, 0.010]	[-0.016,-0.001]	[-0.016, -0.001]	[-0.025, 0.009]	[-0.016,-0.001]
$Share\ of\ obese\ adults$	[0.381, 0.629]	[0.269, 0.740]	[0.384,0.625]	[0.328, 0.582]	[0.153, 0.746]	[0.333,0.578]	[-0.021, 0.386]	[-0.295, 0.677]	[-0.020, 0.382]
$log\ expenditures\ (Euro)$	[-0.171, -0.033]	[-0.231, 0.029]	[-0.170,-0.036]	[-0.082, 0.068]	[-0.204, 0.159]	[-0.080,0.067]	[-0.069, 0.083]	[-0.179, 0.184]	[-0.069, 0.082]
Household characteristics	ON	ON	ON	YES	YES	YES	YES	YES	YES
$Regional\ characteristics$	ON	ON	ON	YES	YES	YES	YES	YES	YES
Geneticproxies	ON	ON	ON	ON	NO	ON	YES	YES	YES
Behavioral variables	ON	ON	NO	NO	NO	ON	YES	YES	YES
N, p	3737, 7	3737, 7	3737, 7	3737, 19	3737, 19	3737, 19	3737, 30	3737, 30	3737, 30

†This table provides 95% confidence intervals using the standard probit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using all the families.

Table 6: Confidence intervals and confidence sets for the probit model.[†]

				Dependent va	Dependent variable: child obesity ($6 \le age \le 11$)	$y \ (6 \le age \le 11)$			
	Probit (1)	CCT1 (2)	CCT3 (3)	Probit (4)	CCT1 (5)	CCT3 (6)	Probit (7)	CCT1 (8)	CCT3 (9)
$Share\ of\ other\ obese\ children$	[0.588, 1.180]	[0.320, 1.449]	[0.599,1.170]	[0.450, 1.065]	[0.125, 1.464]	[0.450,1.058]	[0.418, 1.047]	[-0.032, 1.478]	[0.426, 1.036]
constant	[-0.868, 2.319]	[-2.253, 3.691]	[-0.807,2.245]	[-3.827,14.833]	[-13.042,17.507]	[-3.441,14.452]	[-4.026,15.072]	[-18.730,21.992]	[-3.631,14.671]
gender	[-0.064, 0.143]	[-0.157, 0.236]	[-0.061, 0.14]	[-0.070,0.139]	[-0.228, 0.292]	[-0.065,0.134]	[-0.074,0.138]	[-0.217,0.279]	[-0.072, 0.133]
age	[-0.479, 0.230]	[-0.731, 0.321]	[-0.731,0.321] [-0.464,0.221]	[-0.457, 0.262]	[-0.896, 0.743]	[-0.449,0.246]	[-0.477,0.248]	[-0.937,0.695]	[-0.476, 0.234]
age^2	[-0.016, 0.026]	[-0.034, 0.044]	[-0.015,0.025]	[-0.018, 0.024]	[-0.047, 0.051]	[-0.017,0.023]	[-0.017, 0.025]	[-0.044, 0.053]	[-0.016, 0.025]
$Share\ of\ obese\ adults$	[0.327, 0.623]	[0.198, 0.758]	[0.330, 0.620]	[0.281, 0.584]	[0.026, 0.833]	[0.287,0.581]	[0.034, 0.523]	[-0.480, 0.855]	[0.046, 0.518]
$log\ expenditures\ (Euro)$	[-0.187, -0.023]	[-0.260, 0.048]	[-0.260,0.048] [-0.184,-0.024]	[-0.086, 0.093]	[-0.201, 0.204]	[-0.082,0.090]	[-0.071,0.111]	[-0.185, 0.257]	[-0.069, 0.110]
Household characteristics	NO	NO	ON	YES	YES	YES	YES	YES	YES
$Regional\ characteristics$	NO	NO	ON	YES	YES	YES	YES	YES	YES
Genetic proxies	NO	NO	ON	ON	ON	ON	YES	YES	YES
$Behavioral\ variables$	ON	ON	ON	ON	ON	ON	YES	YES	YES
N, p	2503, 7	2503, 7	2503, 7	2503, 19	2503, 19	2503, 19	2503, 30	2503, 30	2503, 30

†This table provides 95% confidence intervals using the standard probit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using all the families with children with $6 \le age \le 11$.

Table 7: Confidence intervals and confidence sets for the probit model.[†]

				Dependent variable: child obesity (12 \leq age \leq 14)	:: child obesity (1	$2 \le age \le 14)$			
	Probit (1)	CCT1 (2)	CCT3 (3)	Probit (4)	CCT1 (5)	CCT3 (6)	Probit (7)	CCT1 (8)	CCT3 (9)
$Share\ of\ other\ obese\ children$	[0.278, 1.108]	[-0.097, 1.469]	[0.284, 1.107]	[0.17,1.048]	[-0.507,1.547]	[0.177,1.028]	[0.254, 1.185]	[-0.401, 1.766]	[0.256,1.175]
constant	[-16.104, 41.695]	[-40.983,66.704]	[-15.856,41.577]	[-14.302,50.206]	[-52.12,77.035]	[-12.982,49.638]	[-8.386,57.715]	[-46.524,86.252]	[-7.63, 56.746]
gender	[0.384, 0.712]	[0.243, 0.860]	[0.391, 0.711]	[0.396, 0.729]	[0.208, 0.945]	[0.402,0.722]	[0.390, 0.729]	[0.163, 0.975]	[0.393, 0.729]
age	[-6.418, 2.498]	[-7.634,1.233]	[-6.341, 1.233]	[-5.869,3.167]	[-8.744,3.008]	[-5.711,2.818]	[-6.829,2.387]	[-10.177, 2.533]	[-6.602, 2.335]
age^2	[-0.101, 0.243]	[-0.248, 0.395]	[-0.099, 0.240]	[-0.127,0.221]	[-0.327, 0.394]	[-0.123,0.220]	[-0.097, 0.258]	[-0.327, 0.436]	[-0.096, 0.251]
$Share\ of\ obese\ adults$	[0.350, 0.814]	[0.155, 1.022]	[0.359, 0.808]	[0.280, 0.754]	[-0.025, 1.054]	[0.291,0.749]	[-0.399, 0.367]	[-0.936, 0.803]	[-0.392, 0.364]
log expenditures (Euro)	[-0.229, 0.027]	[-0.344, 0.138]	[-0.225, 0.024]	[-0.171,0.107]	[-0.357, 0.264]	[-0.169,0.101]	[-0.177, 0.109]	[-0.355, 0.311]	[-0.173, 0.102]
Household characteristics	ON	NO	ON	YES	YES	YES	YES	YES	YES
$Regional\ characteristics$	NO	NO	NO	YES	YES	YES	YES	YES	YES
Genetic proxies	NO	NO	NO	NO	NO	NO	YES	YES	YES
Behavioral variables	NO	NO	NO	ON	ON	NO	YES	YES	YES
N, p	1234, 7	1234, 7	1234, 7	1234, 19	1234, 19	1234, 19	1234, 30	1234, 30	1234, 30

†This table provides 95% confidence intervals using the standard logit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using all the families with children with $12 \le age \le 14$.

Table 8: Confidence intervals and confidence sets for the logit model.[†]

				Deper	Dependent variable: child obesity	uld obesity			
		$6 \le age \le 14$			$6 \le age \le 11$			$12 \le age \le 14$	
	Logit (1)	CCT1 (2)	CCT3 (3)	Logit (4)	CCT1 (5)	CCT3 (6)	Logit (7)	CCT1 (8)	CCT3 (9)
Share of other obese children	[1.005, 1.850]	[0.663, 2.272]		[1.020,1.849] [1.013,2.023]	[0.471, 2.569]	[1.022,2.018]	[0.652, 2.299]	[-0.322, 3.169]	[0.666, 2.288]
constant	[0.850, 6.364]	[-2.339, 8.945]	[0.885, 6.297]	[1.206, 8.854]	[-3.184, 13.384]	[1.234,8.782]	[-17.614,84.403]	[-56.297,90.862]	[-17.393,84.096]
gender	[0.156, 0.448]	[-0.010, 0.583]	[0.159, 0.443]	[-0.111, 0.232]	[-0.300, 0.399]	[-0.109,0.230]	[0.663, 1.248]	[0.355, 1.581]	[0.664, 1.246]
age	[-0.114, 0.393]	[-0.404,0.693]	[-0.104,0.381]	[-0.773, 0.397]	[-1.312, 0.935]	[-0.762,0.385]	[-12.333,3.314]	$\left[-13.643, -0.901\right]$	[-12.315,-1.167]
age^2	[-0.026, 0.000]	[-0.041, 0.014]	[-0.025,-0.001]	[-0.027,0.041]	[-0.060, 0.072]	[-0.026,0.040]	[-0.135, 0.467]	[-0.396, 0.494]	[-0.130, 0.463]
Share of obese adults	[0.020,0.687]		[-0.323,1.073] [0.034,0.672]	[0.130, 0.917]	[-0.268, 1.338]	[0.138,0.917]	[-0.691, 0.594]	[-1.394, 1.326]	[-0.673, 0.576]
$log\ expenditures\ (Euro)$	[-0.255, -0.021]	[-0.368, 0.104]	[-0.254,-0.025]	[-0.273, 0.002]	[-0.433, 0.162]	[-0.272,0.001]	[-0.381,0.071]	[-0.559, 0.273]	[-0.374, 0.063]
$number\ of\ children$	[-0.228, -0.024]	[-0.342, 0.092]	[-0.227,-0.028]	[-0.216, 0.019]	[-0.329, 0.154]	[-0.212,0.018]	[-0.420, 0.011]	[-0.693, 0.229]	[-0.414,0.008]
average adult weight	[0.013, 0.042]	[-0.005, 0.059]		[0.013,0.041] [-0.003,0.032]	[-0.024, 0.052]	[-0.002,0.031]	[0.030, 0.085]	[-0.001, 0.118]	[0.031, 0.085]
averageadultheight	[-0.051, -0.016]	[-0.070,0.004]	[-0.051,-0.016]	[-0.050,-0.008]	[-0.074, 0.012]	[-0.049,-0.008]	[-0.078, -0.011]	[-0.118,0.027]	[-0.077,-0.012]
N, p	3737, 10	3737, 10	3737, 10	2503, 10	2503, 10	2503, 10	1234, 10	1234, 10	1234, 10

[†]This table provides 95% confidence intervals using the standard logit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models include the number of children in the family as a regressor.

Table 9: Confidence intervals and confidence sets for the probit model.[†]

				Deper.	Dependent variable: child obesity	hild obesity			
		$6 \le age \le 14$			$6 \le age \le 11$			$12 \le age \le 14$	
	Probit (1)	CCT1 (2)	CCT3 (3)	Probit (4)	CCT1 (5)	CCT3 (6)	Probit (7)	CCT1 (8)	CCT3 (9)
$Share\ of\ other\ obese\ children$	[0.616, 1.129]	[0.316, 1.431]		[0.619,1.128] $[0.629,1.251]$	[0.287, 1.607]	$[0.287, 1.607] \qquad [0.631, 1.249] \big [0.379, 1.328]$	[0.379, 1.328]	[-0.169, 1.878]	[0.393, 1.316]
constant	[0.562, 3.851]	[-1.325, 5.781]	[0.585,3.795]	[0.764, 5.397]	[-1.863, 8.142]		[0.827,5.345] [-10.883,47.714]	[-43.759,75.346]	[-10.606, 47.104]
gender	[0.099, 0.273]	[-0.001, 0.376]		[-0.066,0.141]	[-0.188, 0.261]	[0.100,0.271] [-0.066,0.141] [-0.188,0.261] [-0.065,0.138]	[0.381,0.711]	[0.195, 0.903]	[0.386, 0.705]
age	[-0.070, 0.231]	[-0.244, 0.405]	[-0.065,0.225]	[-0.473,0.236]	[-0.473,0.236] [-0.887,0.648] [-0.467,0.228]	[-0.467,0.228]	[-6.954, 2.038]	[-8.481, 0.929]	[-6.944, 0.929]
age^2	[-0.015, 0.000]	[-0.024, 0.009]	[-0.015,0.000]	[-0.016,0.025]	[-0.016,0.025] [-0.040,0.050]	[-0.016,0.025]	[-0.083,0.263]	[-0.278, 0.441]	[-0.078, 0.263]
$Share\ of\ obese\ adults$	[0.012, 0.411]	[-0.215, 0.642]	[0.020,0.407]	[0.020,0.407] [0.074,0.552]	[-0.206, 0.825]	[-0.206,0.825] [0.084,0.546]	[-0.379, 0.363]	[-0.802,0.777]	[-0.376, 0.351]
$log\ expenditures\ (Euro)$	[-0.153, -0.013]	[-0.232,0.067]	[-0.151, -0.014]	[-0.166,0.001]	[-0.262, 0.099]	[-0.262,0.099] [-0.165,-0.003]	[-0.223,0.037]	[-0.376, 0.183]	[-0.221, 0.035]
$number\ of\ children$	[-0.135, -0.015]		[-0.206,0.055] [-0.133,-0.016] [-0.130,0.011] [-0.213,0.091] [-0.129,0.010]	[-0.130,0.011]	[-0.213, 0.091]	[-0.129,0.010]	[-0.230, 0.008]	[-0.373, 0.145]	[-0.226,0.004]
averageadultweight	[0.008, 0.025]	[-0.002, 0.036]	[0.008,0.025]	[-0.002,0.020]	[-0.014, 0.032]	[0.008,0.025] [-0.002,0.020] [-0.014,0.032] [-0.001,0.020]	[0.017, 0.049]	[0.000,0.067]	[0.017, 0.049]
$average\ adult\ height$	[-0.031, -0.010]	[-0.043, 0.003]	[-0.031,-0.010]	[-0.031,-0.010] [-0.030,-0.005]	[-0.045, 0.009] $[-0.030, -0.005]$	[-0.030,-0.005]	[-0.045, -0.007]	[-0.068, 0.016]	[-0.045, -0.007]
N, p	3737, 10	3737, 10	3737, 10	2503, 10	2503, 10	2503, 10	1234, 10	1234, 10	1234, 10

[†]This table provides 95% confidence intervals using the standard probit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models include the number of children in the family as a regressor.

the impact of adults. We also find that, when genetic proxies and behavioral variables are added, the impact of the presence of overweight and obese adults is driven to zero while the impact of overweight and obese peer children remains positive. Our results are consistent with studies on child imitation behaviour and the role model age (Zmyj, Ascherslebel et al., 2012; Zmyj, N. Daum et al., 2012; Zmyj & Seehagen, 2013), where prolonged contact

6 with peers led children to imitate peers more than adults.

Despite growing rates of child obesity, empirical evidence on the factors affecting Italian child weight outcomes remains poor. Further exploration of causal pathways linking social interaction within the family and child obesity is therefore desirable. We show that the presence overweight/obese parents and/or peer siblings is an important factor affecting child obesity in Italy. In particular, we show that the presence of other overweight and obese 11 children in the family is the most important factor affecting child obesity. Indeed, when 12 the richest model specification is used, i.e. when we include proxies for genetic variables 13 (columns 7, 8, 9 in Tables 2, 4, 5, 7), the share of obese adults is no longer significant, 14 while the peer effect variable is still significant. This result suggests that within-the-family obesity is driven more by peer siblings interaction than by interactions between the parent 16 and the child. In general, it seems that family characteristics and behaviours affect children habits and their probability of being obese. In this context, family-based programmes, 18 based on collaborative approaches, may help preventing child obesity. Particular attention 19 should be paid to households with more than one overweight child where a collaborative 20 approach could have much more impact. Moreover, since siblings relationships are the longest lasting ones, the use of a true family-based approach in taking action against childhood obesity will increase the likelihood that changes in child health behaviours will be sustainable (see, e.g., Berge & Everts, 2011).

25 References

- Asirvatham, J., Nayga, R. M., Jr. & Thomsen, M. R. (2014). Peer-effects in obesity among
- public elementary school children: A grade-level analysis. Applied Economic Perspectives
- and Policy, 36(3), 438-459.
- ⁴ Berge, J. M. & Everts, J. C. (2011). Family-based interventions targeting childhood
- obesity: a meta-analysis. Childhood Obesity, 7(2), 110–121.
- 6 Binkin, N., Fontana, G., Lamberti, A., Cattaneo, C., Baglio, G., Perra, A. & Spinelli, A.
- ⁷ (2010). A national survey of the prevalence of childhood overweight and obesity in Italy.
- 8 Obesity Reviews, 11(1), 2–10.
- 9 Black, S., Breining, S., Figlio, D., Guryan, J., Karbownik, K., Skyt Nielsen, H., ... Si-
- monsen, M. (2017). Sibling spillovers (Working Papers No. 23062). National Bureau of
- Economic Research.
- 12 Blume, L. E., Brock, W. A., Durlauf, S. N. & Ioannides, Y. M. (2011). Identification of
- social interactions. In *Handbook of social economics* (Vol. 1, pp. 853–964).
- Blume, L. E. & Durlauf, S. N. (2006). Identifying social interactions: A review. In J. Oakes
- & S. Kaufmann (Eds.), Methods in social epidemiology (pp. 287–315). Wiley.
- Bracale, R., Milani, L., Ferrara, E., Balzaretti, C., Valerio, A., Russo, V., ... Carruba,
- M. O. (2013). Childhood obesity, overweight and underweight: a study in primary
- schools in milan. Eating and Weight Disorders Studies on Anorexia, Bulimia and
- Obesity, 18(2), 183-191.
- 20 Brilli, Y., Del Boca, D. & Pronzato, C. (2016). Does child care availability play a role
- in maternal employment and children's development? Evidence from Italy. Review of
- Economics of the Household, 14(1), 27-51.
- 23 Brock, W. A. & Durlauf, S. N. (2001). Discrete choice with social interactions. The Review
- of Economic Studies, 68(2), 235-260.

- ²⁵ Brock, W. A. & Durlauf, S. N. (2007). Identification of binary choice models with social
- interactions. Journal of Econometrics, 140(1), 52-75.
- ² Cawley, J. & Liu, F. (2012). Maternal employment and childhood obesity: A search for
- mechanisms in time use data. Economics and Human Biology, 10(4), 352-364.
- 4 Cawley, J. & Meyerhoefer, G. (2012). The medical care costs of obesity: an instrumental
- variables approach. Journal of Health Economics, 31(4), 210-230.
- 6 Champion, S. L., Rumbold, A. R., Steele, E. J., Giles, L. C., Davies, M. J. & Moore, V. M.
- ₇ (2012). Parental work schedules and child overweight and obesity. *International Journal*
- s of Obesity, 36, 573–580.
- 9 Chen, X., Christensen, T. M. & Tamer, E. (2018). Monte carlo confidence sets for identified
- sets. Econometrica, 86(6), 1965-2018.
- 11 Christakis, N. A. & Fowler, J. H. (2007). The spread of obesity in a large social network
- over 32 years. The New England Journal of Medicine, 357, 370–379.
- 13 Cole, T. J., Bellizzi, M. C., Flegal, K. M. & Dietz, W. H. (2000). Establishing a standard
- definition for child overweight and obesity worldwide: international survey. British
- 15 Medical Journal, 320 (7244), 1240.
- 16 Dishion, T. J. & Tipsord, J. M. (2011). Peer contagion in child and adolescent social and
- emotional development. Annual Review of Psychology, 62(1), 189-214.
- Dustan, A. (2018). Family networks and school choice. Journal of Development Economics,
- 19 134, 372-391.
- ²⁰ Fadlon, I. & Nielsen, T. (2019). Family health behaviors. American Economic Review,
- *109*(9), 3162-3191.
- Fertig, A., Glomm, G. & Tchernis, R. (2009). The connection between maternal employ-
- ment and childhood obesity: inspecting the mechanisms. Review of Economics of the
- Household, 7(3), 227-255.

- ²⁵ Fletcher, J., Hair, N. & Wolfe, B. (2012). Am I my brother's keeper? Sibling spillover
- effects: the case of developmental disabilities and externalizing behavior (Working Papers
- No. 18279). National Bureau of Economic Research.
- ³ Fowler, J. & Christakis, N. (2008). Estimating peer effects on health in social networks:
- A response to Cohen-Cole and Fletcher; and Trogdon, Nonnemaker, and Pais. *Journal*
- of Health Economics, 27(5), 1400-1405.
- 6 Gaina, A., Sekine, M., Chandola, T., Marmot, M. & Kagamimori, S. (2009). Mother
- employment status and nutritional patterns in Japanese junior highschool children. *In*-
- ternational Journal of Obesity, 33(7), 753–757.
- 9 García, E., Labeaga, J. M. & Masagué, A. C. O. (2006, July). Maternal Employment and
- 10 Childhood Obesity in Spain (Working Papers No. 2006-17). FEDEA.
- 11 Graham, B. S. (2008). Identifying social interactions through conditional variance restric-
- tions. Econometrica, 76(3), 643-660.
- Greve, J. (2011). New results on the effect of maternal work hours on children's overweight
- status: Does the quality of child care matter? Labour Economics, 18(5), 579-590.
- 15 Gwozdz, W., Sousa-Poza, A., Reisch, L. A., Ahrens, W., Eiben, G., Fernandéz-Alvira,
- J. M., ... others (2013). Maternal employment and childhood obesity—A European
- perspective. Journal of Health Economics, 32(4), 728–742.
- Gwozdz, W., Sousa-Poza, A., Reisch, L. A., Bammann, K., Eiben, G., Kourides, Y., ...
- others (2015). Peer effects on obesity in a sample of European children. Economics \mathcal{E}
- 20 Human Biology, 18, 139–152.
- Halliday, T. & Kwak, S. (2009). Weight gain in adolescents and their peers. *Economics*
- and Human Biology, 7(2), 181-190.
- ²³ Heissel, J. A. (2017). Teenage motherhood and sibling outcomes. American Economic
- Review, 107(5), 633-637.

- ²⁵ Heissel, J. A. (2019). Teen fertility and siblings' outcomes: Evidence of family spillovers
- using matched samples. Journal of Human Resources. (Published ahead of print April
- 2 10, 2019 doi:103368/jhr.56.1.0218-9341R2)
- ³ Herbst, C. M. & Tekin, E. (2011). Child care subsidies and childhood obesity. Review of
- Economics of the Household, 9(3), 349-378.
- 5 Hubbard, M. (2008). The effect of mothers' employment and child care decisions on the
- body mass status of young children. The University of North Carolina at Chapel Hill
- 7 Working Paper.
- 8 Joensen, J. & Nielsen, H. (2018). Spillovers in education choice. Journal of Public Eco-
- 9 nomics, 157, 158-183.
- 10 Kinge, J. (2016). Body mass index and employment status: a new look. Economics and
- 11 Human Biology, 22, 117-125.
- Krauth, B. (2006). Social interactions in small groups. Canadian journal of Economics,
- 13 414–433.
- Lauria, L., Spinelli, A., Buoncristiano, M. & Nardone, P. (2019). Decline of childhood over-
- weight and obesity in italy from 2008 to 2016: results from 5 rounds of the population-
- based surveillance system. BMC Public Health, 19(618), 1–9.
- Liu, E., Hsiao, C., Matsumoto, T. & Chou, S. (2009). Maternal full-time employment
- and overweight children: Parametric, semi-parametric, and non-parametric assessment.
- Journal of Econometrics, 152(1), 61-69.
- Llewellyn, A., Simmonds, M., Owen, C. & Woolacott, N. (2016). Childhood obesity as
- a predictor of morbidity in adulthood: a systematic review and meta-analysis. Obesity
- 22 Reviews, 17, 56-67.

- Lobstein, T., Jackson-Leach, R., Moodie, M. L., Hall, K. D., Gortmaker, S. L., Swinburn,
- B. A., ... McPherson, K. (2015). Child and adolescent obesity: part of a bigger picture.
- ² The Lancet, 385 (9986), 2510–2520.
- ³ Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem.
- The review of economic studies, 60(3), 531-542.
- ⁵ Manski, C. F. (2003). Partial identification of probability distributions. Springer Science
- 6 & Business Media.
- ⁷ Molinari, F. (in press). Econometrics with partial identification. Handbook of economet-
- rics.
- 9 Mora, T. & Gil, J. (2013). Peer effects in adolescent BMI: evidence from Spain. Health
- Economics, 22(5), 501-516.
- Morrill, M. S. (2011). The effects of maternal employment on the health of school-age
- children. Journal of Health Economics, 30(2), 240-257.
- Nicoletti, C. & Rabe, B. (2019). Siblings spillover effects in school achievement. Journal
- of Applied Econometrics, 34, 482-501.
- Nie, P., Sousa-Poza, A. & He, X. (2015). Peer effects on childhood and adolescent obesity
- in China. China Economic Review, 35, 47–69.
- Powell, K., Wilcox, J., Clonan, A., Bissell, P., Preston, L., Peacock, M. & Holdsworth, M.
- 18 (2015). The role of social networks in the development of overweight and obesity among
- adults: a scoping review. BMC Public Health, 15(1), 996.
- ²⁰ Qureshi, J. (2018). Siblings, teachers, and spillovers on academic achievement. Journal of
- 21 Human Resources, 53, 272-297.
- Renna, F., Grafova, I. & Thakur, N. (2008). The effect of friends on adolescent body
- weight. Economics and Human Biology, 6(3), 377-387.

- Schwartz, D. L., Chase, C. C., Oppezzo, M. A. & Chin, D. B. (2011). Practicing versus
- inventing with contrasting cases: The effects of telling first on learning and transfer.
- 2 Journal of Educational Psychology, 103(4), 759.
- ³ Tamer, E. (2003). Incomplete simultaneous discrete response model with multiple equilib-
- ria. The Review of Economic Studies, 70(1), 147-165.
- ⁵ Trogdon, J. G., Nonnemaker, J. & Pais, J. (2008). Peer effects in adolescent overweight.
- 6 Journal of Health Economics, 27(5), 1388–1399.
- ⁷ UNICEF. (2019). The state of the world's children 2019. children, food and nutrition.
- growing well in a changing world.
- 9 Wardle, J., Carnell, S., Hawhort, C. & Plomin, R. (2008). Evidence for a strong ge-
- netic influence on childhood adiposity despite the force of the obesogenic environment.
- 11 American Journal of Clinical Nutrition, 87, 398-404.
- Yajuan, L., Palma, M. A., Towne, S. D., Warren, J. L. & Ory, M. G. (2016). Peer effects
- on childhood obesity from an intervention program. Health Behavior and Policy Review,
- *3*, 323-335.
- Yi, J., Heckman, J., Zhang, J. & Conti, G. (2015). Early health shocks, intra-household
- resource allocation and child outcomes. The Economic Journal, 125, F347-F371.
- ¹⁷ Zmyj, N., Ascherslebel, G., Prinz, W. & Daum, M. (2012). The peer model advantage in
- infants' imitation of familiar gestures performed by differently aged models. Frontiers
- in Psychology, 3, 1-7.
- 20 Zmyj, N., N. Daum, M., Prinz, W., Nielsen, M. & Ascherslebel, G. (2012). Fourteen-
- months-old's imitation of differently aged models. Infant and Child Development, 21,
- 250-266.
- 23 Zmyj, N. & Seehagen, S. (2013). The role of a model's age for the young children's
- imitation: a research review. Infant and Child Development, 22, 622–641.

Appendix for "Family Ties and Child Obesity in Italy"

Federico Crudu* Laura Neri[†] Silvia Tiezzi[‡]
University of Siena and CRENoS University of Siena University of Siena

October 2020

4 Appendix A Statistical Matching

- ⁵ Matching procedures impute the target variables from a donor to a recipient survey. In
- 6 the basic framework SM integrates two data sources \mathcal{A} and \mathcal{B} drawn from the same target
- 7 population (Cohen, 1991; Radner et al., 1980; Rodgers, 1984). A contains vector-valued
- variables (X,Y), whereas \mathcal{B} contains vector-valued variables (X,Z) such that X is shared
- 9 by both sources. The X variables common to both surveys are used as a bridge to create
- records containing (X, Y, Z) which can then be used to investigate the relationship between
- Y and Z (D'Orazio et al., 2006). Our purpose was to integrate households' total current
- consumption expenditure from the HBS (denoted survey A) into the MSH dataset (survey
- 13 B).
- The first step was to identify the vector of matching variables X. Since \mathcal{A} and \mathcal{B}
- are representative samples of the same population, the common variables are expected to
- share the same marginal/joint distribution. This check was performed using the Cramer's
- V association measures. Potentially, all the variables identified and chosen according to this
- check could be used. In actual fact, only the most relevant ones were identified and selected

^{*}Department of Economics and Statistics, University of Siena, Piazza San Francesco, 7/8 53100 Siena, federico.crudu@unisi.it.

[†]Department of Economics and Statistics, University of Siena, Piazza San Francesco, 7/8 53100 Siena, laura.neri@unisi.it.

 $^{^{\}ddagger}$ Department of Economics and Statistics, University of Siena, Piazza San Francesco, 7/8 53100 Siena, silvia.tiezzi@unisi.it.

- according to a linear model for predicting the logarithm of total current consumption
- 2 expenditure, our target variable. Table A1 shows the set of matching variables used to
- predict/impute the target variable. The listed common variables explained 70% of the
- 4 total variability of the target variable. In addition to these, we included a number of
- 5 interaction terms in the specification.

Table A1: Final matching variables.

Northwest	Household living in the North West
Northeast	Household living in the North East
Central	Household living in the Centre
$Single_parent$	Family type: single parent
$Parents_both$	Family type: both parents
Singleton	Family type: Single
$Household\ size$	Household size
$\#_members0_5$	# persons 0-5 years old
$\#_members6_17$	# persons 6-17 years old
$\#_members18_34$	# persons 18-34 years old
$\#_members35_65$	# persons 35-65 years old
$Gender_RP$	Gender of the reference person
$Mstatus_RP$	Marital status of the reference person
$Employment_RP$	Professional position of the reference person
Home	Home ownership
Rooms	# of rooms
$Ec_resource$	Adequacy of economic resources
CPI	Consumer Price Index at the regional level
CPI_food	Food Price Index at the regional level

- The next step was imputation from the donor to the recipient. The chosen imputation
- 7 method was the Sequential Regression Multiple Imputation (Raghunathan et al., 2001)
- 8 implemented through IVEware software that enables imputation of missing data in the
- recipient variables and in the set of matching variables. IVEware has a number of desirable
- properties that make it particularly well suited for imputing missing data in large datasets.
- 11 For example, imputation models can be specified according to the nature of the variable to
- be imputed. The software easily handles arbitrary missing data patterns with categorical
- ¹³ and continuous variables. Finally, a sequential method is used to impute missing values:
- the variable with the least amount of missing data is imputed first and then used in sub-

- 1 sequent imputations; the next variable with the second least amount of missing data is
- 2 then imputed and used in subsequent imputations. The resulting quality of the match-
- 3 ing can be assessed by comparing the marginal distribution of the target variable in the
- 4 observed data (i.e. in the donor dataset) and in the dataset obtained from the matching.
- 5 The distributions of the observed and imputed data were very close (see Figure A1) given
- 6 the high explanatory power of the predictors included in the model of the target variable.
- 7 This closeness increased the reliability of the statistical matching. In addition, it reduced
- ⁸ the problem of conditional independence (CI), a required hypothesis for the validity of SM.

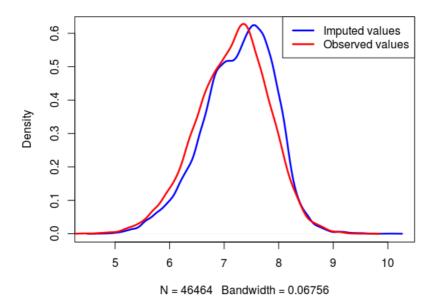


Figure A1: Probability density function of the observed target variable (log expenditure) from the HBS survey (2012) and probability density function of the imputed target variable in the final dataset.

- The CI condition implies that, given three random variables (X, Y, Z) and the model defined by (XY, XZ), any relationship between Y and Z can be explained by the set of matching variables X.
- In our study, the CI condition implied that any existing relationship between Y (household consumption expenditure) and Z (the binary indicator of child obesity) can be explained by the set of matching variables X. In other words, Y and Z may appear to be

related if X is not considered. In order to meet this assumption, a third data set with complete information on (X, Y, Z) is needed. Since this dataset is normally not available, we checked the CI assumption using a variable that expresses a subjective evaluation regarding the household's economic condition (*Ec resource*, introduced in Table A1) as a proxy for the household's total consumption expenditure. This is a binary indicator equal to 1 if the household's economic condition is considered to be "very good" or "adequate" and equal to 0 if it is "scarce" or "absolutely insufficient". The odds ratio of the logit model for obesity given Ec resource indicated a statistically significant relationship (see column 1 in Table A2), implying that good or adequate economic resources at household level reduce the probability of child obesity. In Table A2 column 2 we consider a second model including Ec resource and a subset of our match-11 ing variables as explanatory variables. All covariates were significant, but the variable 12 Ec resource had an odds ratio close to one implying a statistically insignificant effect on 13 obesity. A similar check was conducted considering Ec resource as the dependent variable and the obesity binary indicator as an independent variable, obtaining similar results

17 Appendix B Robustness Checks

We are therefore confident that the CI assumption is not violated.

This Section collects the results for the full set of parameters and the robustness checks as described in Section 5.2 In particular, Tables B1 and B10 show results for the whole sample, while Tables B2 and B11 and Tables B3 and B12 consider families with $6 \le age \le 11$ and $12 \le age \le 14$ respectively. We consider similar subsets of data for families that have more than one child (see Tables B4 and B13 for the age group $6 \le age \le 14$, Tables B5 and B14 for the age group $6 \le age \le 11$ and Tables B6 and B15 for the age group $12 \le age \le 14$). The last subset of data considers families with only one child. The corresponding results are found in Tables B7 and B16 for the age group $6 \le age \le 14$,

¹Available from the authors on request.

Table A2: Check on the CI assumption.

	Depend	lent variable:
	chil	d obesity
	Logit	Logit
	(1)	(2)
constant	0.442***	$1.61e + 07^{**}$
	(0.022)	(1.06e + 08)
$Ec_resource$	0.876*	0.934
	(0.062)	(0.070)
$Central\ or\ Northern\ region$, ,	0.526***
J		(0.040)
age		1.256*
		(0.154)
age2		0.983***
5		(0.006)
CPI		0.847***
		(0.052)
Observations	3,906	3,906
Pseudo R ²	0.001	0.030
Log Likelihood	-2,357.584	-2,288.024
LR Statistic	$3.550^* \text{ (df} = 1)$	$126.220^{***} (df = 5)$

[†]Standard errors in parentheses; *p<0.1; **p<0.05; ***p<0.01.

- Tables $\overline{\mbox{B8}}$ and $\overline{\mbox{B17}}$ for the age group $6 \leq age \leq 11$ and Tables $\overline{\mbox{B9}}$ and $\overline{\mbox{B18}}$ for the age group
- $_{2}$ 12 $\leq age \leq$ 14. If peers imitation increases with prolonged peer contact we should observe,
- as we do, a smaller peer effect for the second sub-group $(12 \le age \le 14)$ as pre-adolescents
- 4 spend more time than their younger counterpart outside the family environment. It is
- 5 worth noticing that some specifications display some issues of multicollinearity. For such
- a reason in some cases we drop one regressor (Tables B6, B7, B8, B15, B16, B17) or two
- 7 regressors (Tables B9 B18).
- In addition, we consider a fixed effect approach where families are clustered in a restric-
- ted number of groups. The number of groups is chosen a priori (10 and 20) and for each
- 10 group we introduce a dummy variable. The clusterisation is based on the characteristics
- of the adults in terms of occupational status, mother's education, presence of diabetes or
- chronic diseases, some characteristics about eating behaviours and the number of individu-

- 1 als in the family. Since most variables involved are binary we cannot use, for example,
- $_2$ standard k-means algorithms. Hence, we resort to apply an approach that works for mixed
- data types based on Huang's k-prototypes algorithm (Szepannek, 2018). The results, re-
- 4 ported in Table B19 and Table B20 match to a large extent the results displayed in the
- 5 main text.

Table B1: Confidence intervals and confidence sets for the logit model.[†]

	Logit (1)	CCT1 (2)	CCT3	Logit (4)	CCT1 (5)	CCT3 (6)	Logit (7)	CCT1 (8)	CCT3 (9)
Share of other obese children	[0.913,1.695]	[0.568,2.046]	[0.925,1.689]	[0.706,1.526]	[0.301,1.991]	[0.711,1.513]	[0.679,1.530]	[0.328,1.956]	[0.690,1.529]
constant	[-1.744,1.173]	[-3.060, 2.446]	[-1.744,1.130]	[-3.623,22.087]	[-13.77,19.093]	[-3.292,19.093]	[-3.576, 22.700]	[-11.224,19.916]	[-3.329, 18.600]
gender	[0.158, 0.448]	[0.028, 0.579]	[0.158,0.443]	[0.157, 0.453]	[0.011, 0.578]	[0.160,0.452]	[0.150, 0.448]	[0.061, 0.545]	[0.154, 0.447]
age	[-0.121, 0.383]	[-0.310, 0.438]	[-0.113,0.375]	[-0.085, 0.428]	[-0.415, 0.697]	[-0.078,0.428]	[-0.099, 0.420]	[-0.218, 0.567]	[-0.092, 0.416]
age^2	[-0.025,0.001]	[-0.036, 0.012]	[-0.024,0.000]	[-0.028, -0.002]	[-0.043, 0.015]	[-0.028,-0.002]	[-0.028, -0.001]	[-0.035,0.004]	[-0.027,-0.002]
$Share\ of\ obese\ adults$	[0.626, 1.042]	[0.441, 1.228]	[0.628,1.042]	[0.537, 0.962]	[0.322, 1.224]	[0.541,0.960]	[-0.031, 0.651]	[-0.170,0.797]	[-0.023, 0.651]
log expenditures (Euro)	[-0.284, -0.054]	[-0.387,0.048]	[-0.283,-0.056]	[-0.136, 0.116]	[-0.294, 0.269]	[-0.135,0.116]	[-0.117,0.139]	[-0.210, 0.184]	[-0.115, 0.136]
Household size				[-0.160, -0.002]	[-0.224, 0.065]	[-0.159,-0.005]	[-0.158, 0.007]	[-0.225, 0.060]	[-0.156,0.005]
Central or Northern region				[-0.317, 0.186]	[-0.557, 0.442]	[-0.315,0.180]	[-0.262, 0.251]	[-0.393, 0.433]	[-0.259, 0.249]
Employed RP				[-0.508, -0.037]	[-0.702, 0.175]	[-0.507,-0.037]	[-0.530, -0.056]	[-0.666, 0.157]	[-0.525, -0.059]
Student or housewife RP				[-0.963, -0.152]	[-1.425, 0.214]	[-0.961,-0.167]	[-1.014,-0.192]	[-1.291,-0.034]	[-1.011,-0.199]
Retired or other emp. status RP				[-0.202, 0.860]	[-0.687, 1.554]	[-0.189,0.852]	[-0.264,0.818]	[-0.539, 1.215]	[-0.256, 0.808]
Mother's education (Master)				[-0.729, 0.440]	[-1.292, 1.048]	[-0.725,0.433]	[-0.742, 0.446]	[-1.253, 0.799]	[-0.735, 0.426]
Mother's education (Bachelor)				[-1.291, 0.194]	[-2.152, 0.822]	[-1.281,0.191]	[-1.406, 0.110]	[-1.889, 0.655]	[-1.401, 0.090]
Mother's education (High School)				[-0.803, 0.315]	[-1.369, 0.960]	[-0.781,0.301]	[-0.864, 0.274]	[-1.444, 0.610]	[-0.863, 0.258]
Mother's education (Junior High)				[-0.623, 0.493]	[-1.212, 1.093]	[-0.607,0.488]	[-0.710,0.427]	[-1.225, 0.772]	[-0.700, 0.409]
Mother's education (Primary School)				[-0.482, 0.749]	[-1.167, 1.405]	[-0.466,0.729]	[-0.554, 0.703]	[-1.018,1.080]	[-0.552, 0.698]
CPI (2010=100)				[-0.226,0.011]	[-0.341, -0.018]	[-0.223,-0.018]	[-0.209,0.029]	[-0.297, 0.010]	[-0.206,-0.007]
% obese adults by region				[0.032, 0.077]	[0.010, 0.113]	[0.032,0.076]	[0.035, 0.080]	[0.017,0.097]	[0.035, 0.080]
Mean adult weight (kg)							[0.008, 0.038]	[-0.004,0.044]	[0.008, 0.038]
Mean adult height (cm)							[-0.043, -0.006]	[-0.053, 0.003]	[-0.042, -0.006]
Diabetes							[-0.304,0.530]	[-0.549, 0.748]	[-0.300, 0.526]
Obese children previous marriage							[1.476, 3.398]	[0.813, 4.446]	[1.510, 3.382]
Chronic disease							[-0.205, 0.155]	[-0.323, 0.282]	[-0.200, 0.154]
Siblings walking to school							[-0.763, 0.041]	[-1.040, 0.272]	[-0.762, 0.034]
Siblings TV watching every day							[0.006, 0.515]	[-0.132,0.697]	[0.011, 0.513]
Parents soda drinks							[-0.139, 0.271]	[-0.316, 0.424]	[-0.137, 0.267]
Parents smoking							[-0.028,0.288]	[-0.162, 0.429]	[-0.025, 0.286]
Children average fruit portions							[-0.534, 0.266]	[-0.780,0.678]	[-0.530, 0.251]
Adults average fruit portions							[-0.229,0.548]	[-0.589,0.793]	[-0.226, 0.542]
N	3737	3737	3737	3737	3737	3737	3737	3737	3737

[†]This table provides 95% confidence intervals using the standard logit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using all the families.

Table B2: Confidence intervals and confidence sets for the logit model.[†]

	$\begin{array}{c} \text{Logit} \\ (1) \end{array}$	CCT1 (2)	CCT3 (3)	Logit (4)	CCT1 (5)	(9)	Logit (7)	CCT1 (8)	CCT3 (9)
$Share\ of\ other\ obese\ children$	[0.949,1.906]	[0.512,2.331]	[0.957,1.905]	[0.723,1.726]	[0.170,2.203]	[0.724, 1.710]	[0.671,1.705]	[0.439, 2.267]	[0.679,1.695]
constant	[-1.440, 3.801]	[-3.805, 6.106]	[-1.355,3.768]	[-6.249, 24.249]	$\left[-26.552, 23.021 \right]$	[-5.521, 23.021]	[-6.724, 24.517]	[-15.053, 23.818]	[-6.415,22.378]
gender	[-0.107, 0.234]	[-0.263, 0.387]	[-0.102,0.233]	[-0.120, 0.229]	[-0.302,0.370]	[-0.119, 0.228]	[-0.126, 0.226]	[-0.259, 0.388]	[-0.122, 0.225]
age	[-0.784, 0.383]	[-1.136,0.384]	[-0.78,0.360]	[-0.752, 0.441]	[-1.307,1.015]	[-0.744,0.429]	[-0.776,0.430]	[-1.061,1.007]	[-0.768, 0.422]
age^2	[-0.026,0.042]	[-0.058,0.073]	[-0.026,0.042]	[-0.030, 0.040]	[-0.062,0.071]	[-0.030,0.039]	[-0.030,0.041]	[-0.061, 0.060]	[-0.029, 0.040]
$Share\ of\ obese\ adults$	[0.536, 1.025]	[0.319, 1.251]	[0.541,1.018]	[0.457, 0.959]	[0.265, 1.173]	[0.458, 0.953]	[0.061, 0.872]	[-0.268, 1.158]	[0.063, 0.870]
$log\ expenditures\ (Euro)$	[-0.307, -0.036]	[-0.431, 0.087]	[-0.306,-0.038]	[-0.141, 0.157]	[-0.311,0.317]	[-0.140,0.152]	[-0.118,0.185]	[-0.206,0.269]	[-0.115, 0.183]
Household size				[-0.176,0.011]	[-0.248,0.126]	[-0.172,0.009]	[-0.173,0.022]	[-0.305, 0.061]	[-0.172,0.021]
Central or Northern region				[-0.405, 0.178]	[-0.664,0.457]	[-0.403, 0.174]	[-0.339,0.256]	[-0.634, 0.459]	[-0.336, 0.249]
Employed RP				[-0.599,-0.02]	[-0.888,0.199]	[-0.592,-0.021]	[-0.616, -0.034]	[-0.838,0.217]	[-0.614, -0.039]
Student or housewife RP				[-1.141, -0.175]	[-1.774,0.230]	[-1.126,-0.175]	[-1.209,-0.227]	[-1.530, 0.131]	[-1.194,-0.238]
Retired or other emp. status RP				[-0.670, 0.678]	[-1.208, 1.522]	[-0.656,0.667]	[-0.711, 0.666]	[-1.265,1.300]	[-0.695, 0.652]
Mother's education (Master)				[-1.091, 0.372]	[-1.665, 1.043]	[-1.091, 0.359]	[-1.150, 0.344]	[-1.423, 0.929]	[-1.138, 0.335]
Mother's education (Bachelor)				[-1.763, 0.049]	[-2.674, 0.722]	[-1.748,0.036]	[-1.880,-0.030]	[-2.645, 0.950]	[-1.846, -0.030]
Mother's education (High School)				[-1.155, 0.261]	[-1.838,1.132]	[-1.148,0.232]	[-1.253,0.197]	[-1.666,0.773]	[-1.247,0.182]
Mother's education (Junior High)				[-1.027, 0.390]	[-1.547,1.107]	[-1.011, 0.383]	[-1.159, 0.296]	[-1.640, 0.926]	[-1.148, 0.278]
Mother's education (Primary School)				[-0.860, 0.712]	[-1.505, 1.562]	[-0.854, 0.695]	[-0.979, 0.636]	[-1.443,1.270]	[-0.977,0.612]
CPI (2010=100)				[-0.230, 0.048]	[-0.392,0.058]	[-0.225, 0.046]	[-0.209, 0.071]	[-0.269,0.083]	[-0.208, 0.062]
% obese adults by region				[0.031, 0.084]	[0.006, 0.109]	[0.032, 0.084]	[0.036, 0.089]	[0.012, 0.118]	[0.037,0.089]
Mean adult weight (kg)							[-0.007,0.030]	[-0.015, 0.043]	[-0.007, 0.029]
Mean adult height (cm)							[-0.042, 0.002]	[-0.055, 0.013]	[-0.041,0.002]
Diabetes							[-0.284,0.732]	[-0.454,1.088]	[-0.282, 0.730]
Obese children previous marriage							[1.864, 5.025]	[1.301, 8.052]	[1.915, 4.984]
Chronic disease							[-0.311, 0.125]	[-0.489, 0.320]	[-0.309, 0.124]
Siblings walking to school							[-0.627, 0.330]	[-1.125, 0.693]	[-0.611, 0.326]
Siblings TV watching every day							[-0.103, 0.471]	[-0.308, 0.771]	[-0.101, 0.466]
Parents soda drinks							[-0.188, 0.285]	[-0.362, 0.438]	[-0.184, 0.284]
Parents smoking							[-0.041, 0.333]	[-0.146,0.449]	[-0.038, 0.328]
Children average fruit portions							[-0.943, 0.16]	[-1.282, 0.436]	[-0.935, 0.158]
Adults average fruit portions							[-0.148, 0.93]	[-0.436, 1.264]	[-0.144, 0.921]
N	2503	2503	2503	2503	2503	2503	2503	2503	2503

†This table provides 95% confidence intervals using the standard logit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using all the families with children with $6 \le age \le 11$.

Table B3: Confidence intervals and confidence sets for the logit model.[†]

	$\begin{array}{c} \text{Logit} \\ (1) \end{array}$	CCT1 (2)	CCT3	Logit (4)	CCT1 (5)	CCT3	Logit (7)	CCT1 (8)	CCT3 (9)
Share of other obese children	[0.439,1.848]	[-0.201,2.439]	[0.444,1.825]	[0.264,1.759]	[-0.542,2.511]	[0.291,1.74]	[0.432,2.036]	[-0.449,2.849]	[0.450,2.016]
constant	[-27.662,72.548]	[-60.429,74.899]	[-26.597,71.677]	[-22.476,89.346]	[-56.28,93.211]	[-13.341,88.44]	[-12.926,102.045]	[-64.176,106.904]	[-10.059, 101.666]
gender	[0.659, 1.237]	[0.420, 1.494]	[0.661, 1.229]	[0.683, 1.271]	[0.455, 1.663]	[0.687,1.260]	[0.681, 1.282]	[0.401, 1.592]	[0.690, 1.279]
age	[-11.176, 4.290]	[-12.660, -0.408]	[-11.159,-0.408]	[-10.468, 5.271]	[-12.017,1.488]	[-10.298,1.488]	[-12.037,4.041]	[-13.973,0.461]	[-11.947,0.208]
age^2	[-0.173,0.423]	[-0.370, 0.434]	[-0.166,0.414]	[-0.211, 0.395]	[-0.438, 0.436]	[-0.162,0.389]	[-0.164, 0.455]	[-0.311, 0.532]	[-0.164, 0.444]
$Share\ of\ obese\ adults$	[0.587, 1.390]	[0.249, 1.734]	[0.602,1.380]	[0.469, 1.291]	[0.155, 1.763]	[0.480,1.276]	[-0.700,0.630]	[-1.340, 1.310]	[-0.671, 0.614]
log expenditures (Euro)	[-0.390, 0.054]	[-0.581, 0.240]	[-0.381,0.049]	[-0.287,0.194]	[-0.584, 0.491]	[-0.280,0.187]	[-0.299,0.197]	[-0.524, 0.448]	[-0.298, 0.193]
Household size				[-0.209,0.093]	[-0.362, 0.234]	[-0.205,0.090]	[-0.202, 0.115]	[-0.405, 0.267]	[-0.195, 0.111]
Central or Northern region				[-0.401,0.610]	[-0.938, 1.202]	[-0.376,0.597]	[-0.376, 0.652]	[-0.830, 1.134]	[-0.354, 0.638]
Employed RP				[-0.675, 0.164]	[-1.083, 0.678]	[-0.674,0.162]	[-0.735,0.126]	[-1.222,0.620]	[-0.719,0.118]
Student or housewife RP				[-1.176,0.371]	[-2.523,1.163]	[-1.146,0.344]	[-1.211, 0.358]	[-2.425, 1.325]	[-1.175, 0.340]
Retired or other emp. status RP				[-0.024,1.734]	[-1.423, 2.433]	[0.018,1.693]	[-0.274, 1.538]	[-1.429, 2.736]	[-0.251, 1.516]
Mother's education (Master)				[-0.828,1.315]	[-1.914, 2.852]	[-0.807,1.263]	[-0.737, 1.468]	[-1.945, 2.658]	[-0.689, 1.403]
Mother's education (Bachelor)				[-1.324,1.447]	[-3.441, 2.782]	[-1.304,1.399]	[-1.560, 1.352]	[-3.202,2.845]	[-1.553,1.318]
Mother's education (High School)				[-0.868,1.108]	[-1.665, 2.272]	[-0.830,1.079]	[-0.920, 1.112]	[-1.632,2.348]	[-0.909, 1.102]
Mother's education (Junior High)				[-0.544, 1.411]	[-1.322, 3.039]	[-0.530,1.365]	[-0.581, 1.429]	[-1.328, 2.657]	[-0.564, 1.409]
Mother's education (Primary School)				[-0.477, 1.636]	[-1.326, 2.930]	[-0.466,1.598]	[-0.506, 1.666]	[-1.523, 3.027]	[-0.466, 1.602]
CPI (2010=100)				[-0.411, 0.060]	[-0.627, 0.271]	[-0.409,0.054]	[-0.415, 0.061]	[-0.578, 0.322]	[-0.415, 0.058]
% obese adults by region				[0.006, 0.093]	[-0.035, 0.129]	[0.007,0.093]	[0.003, 0.092]	[-0.035, 0.145]	[0.004, 0.091]
Mean adult weight (kg)							[0.021, 0.079]	[-0.006,0.111]	[0.022,0.078]
Mean adult height (cm)							[-0.069, 0.002]	[-0.108,0.041]	[-0.068,0.001]
Diabetes							[-0.818, 0.724]	[-1.905, 1.451]	[-0.786,0.705]
Obese children previous marriage							[-0.236, 2.715]	[-1.696, 4.366]	[-0.227, 2.712]
Chronic disease							[-0.226, 0.437]	[-0.681, 0.754]	[-0.217, 0.435]
Siblings walking to school							[-1.754, -0.172]	[-3.000, 0.554]	[-1.744, -0.200]
Siblings TV watching every day							[-0.034, 1.147]	[-0.681, 1.818]	[-0.025, 1.136]
Parents soda drinks							[-0.401, 0.466]	[-0.893, 0.862]	[-0.397, 0.454]
Parents smoking							[-0.181, 0.436]	[-0.509,0.748]	[-0.179, 0.431]
Children average fruit portions							[-0.426, 0.800]	[-1.071, 1.389]	[-0.400, 0.793]
Adults average fruit portions							[-0.655, 0.524]	[-1.180, 1.134]	[-0.642, 0.503]
N	1234	1234	1234	1234	1234	1234	1234	1234	1234

[†]This table provides 95% confidence intervals using the standard logit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using all the families with children with $12 \le age \le 14$.

Table B4: Confidence intervals and confidence sets for the logit model.[†]

	Logit (1)	CCT1 (2)	CCT3 (3)	Logit (4)	CCT1 (5)	CCT3 (6)	Logit (7)	CCT1 (8)	CCT3 (9)
Share of other obese children	[1.103,1.953]	[0.713,2.345]	[1.112,1.946]	[0.794,1.670]	[0.385,2.008]	[0.795,1.663]	[0.716,1.612]	[0.507,1.977]	[0.729,1.606]
constant	[-1.660, 2.054]	[-3.345,3.745]	[-1.593,1.993]	[-8.226,23.641]	[-25.045,18.736]	[-8.158,18.736]	[-8.456, 24.196]	[-17.171,21.069]	[-8.304,18.853]
gender	[0.089, 0.457]	[-0.078, 0.626]	[0.090,0.450]	[0.076, 0.452]	[-0.123, 0.594]	[0.080,0.449]	[0.069, 0.449]	[-0.029, 0.581]	[0.070, 0.445]
age	[-0.253, 0.391]	[-0.537, 0.473]	[-0.242,0.388]	[-0.212, 0.444]	[-0.550, 0.902]	[-0.198,0.433]	[-0.220, 0.445]	[-0.398,0.733]	[-0.215, 0.436]
age^2	[-0.026,0.007]	[-0.041, 0.021]	[-0.026,0.006]	[-0.030,0.004]	[-0.052, 0.022]	[-0.029,0.003]	[-0.029, 0.004]	[-0.045, 0.012]	[-0.029,0.004]
$Share\ of\ obese\ adults$	[0.566, 1.094]	[0.333, 1.329]	[0.573,1.089]	[0.456, 0.999]	[0.207, 1.258]	[0.462,0.993]	[-0.015, 0.840]	[-0.263,1.377]	[-0.014, 0.831]
$log\ expenditures\ (Euro)$	[-0.344,-0.049]	[-0.476,0.083]	[-0.343,-0.050]	[-0.190, 0.133]	[-0.359, 0.318]	[-0.188,0.127]	[-0.188, 0.141]	[-0.315, 0.242]	[-0.186, 0.135]
Household size				[-0.140, 0.083]	[-0.271,0.162]	[-0.135,0.079]	[-0.130, 0.099]	[-0.194, 0.182]	[-0.129, 0.098]
Central or Northern region				[-0.404, 0.255]	[-0.707,0.657]	[-0.404,0.244]	[-0.355, 0.319]	[-0.649, 0.569]	[-0.354, 0.310]
Employed RP				[-0.569, 0.021]	[-0.877,0.306]	[-0.566,0.019]	[-0.592, 0.004]	[-0.906, 0.196]	[-0.583,-0.005]
Student or housewife RP				[-1.291, -0.242]	[-1.762,0.381]	[-1.286,-0.247]	[-1.335,-0.273]	[-1.697,0.000]	[-1.320, -0.274]
Retired or other emp. status RP				[-1.403, 0.589]	[-2.489,1.504]	[-1.400,0.576]	[-1.448,0.568]	[-2.144,1.335]	[-1.441,0.562]
Mother's education (Master)				[-1.263, 0.693]	[-2.142,2.147]	[-1.232,0.674]	[-1.372,0.631]	[-1.857,1.321]	[-1.344,0.614]
Mother's education (Bachelor)				[-1.668, 0.577]	[-2.750, 1.886]	[-1.627,0.574]	[-1.831, 0.470]	[-2.643, 1.046]	[-1.823, 0.450]
Mother's education (High School)				[-1.256, 0.659]	[-2.012,2.489]	[-1.239,0.625]	[-1.415,0.548]	[-1.853,1.023]	[-1.389,0.529]
Mother's education (Junior High)				[-1.068, 0.849]	[-1.872, 2.556]	[-1.067,0.812]	[-1.239,0.728]	[-1.713,1.26]	[-1.232, 0.720]
Mother's education (Primary School)				[-0.979, 1.060]	[-1.972,2.707]	[-0.932,1.053]	[-1.119,0.977]	[-1.912,1.691]	[-1.111,0.963]
$^{ m CPI} (2010 = 100)$				[-0.237, 0.055]	[-0.362,0.028]	[-0.232,0.028]	[-0.221, 0.072]	[-0.300, 0.054]	[-0.221, 0.032]
% obese adults by region				[0.031, 0.089]	[0.008, 0.115]	[0.031,0.088]	[0.035, 0.094]	[0.003, 0.116]	[0.035, 0.093]
Mean adult weight (kg)							[-0.001,0.037]	[-0.013, 0.050]	[0.000,0.037]
Mean adult height (cm)							[-0.044,0.003]	[-0.062,0.018]	[-0.043,0.003]
Diabetes							[-0.664, 0.420]	[-1.044,0.751]	[-0.645,0.407]
Obese children previous marriage							[1.224, 3.658]	[0.220, 4.908]	[1.262, 3.629]
Chronic disease							[-0.328, 0.144]	[-0.438, 0.342]	[-0.328,0.137]
Siblings walking to school							[-0.768,0.078]	[-1.020,0.288]	[-0.756,0.076]
Siblings TV watching every day							[-0.064, 0.581]	[-0.300, 0.869]	[-0.052, 0.574]
Parents soda drinks							[-0.169, 0.358]	[-0.319, 0.536]	[-0.164, 0.355]
Parents smoking							[-0.127, 0.282]	[-0.259, 0.461]	[-0.121, 0.279]
Children average fruit portions							[-0.115,1.089]	[-0.472, 1.579]	[-0.099, 1.082]
Adults average fruit portions							[-1.054, 0.126]	[-1.549, 0.445]	[-1.046,0.123]
N	2319	2319	2319	2319	2319	2319	2319	2319	2319

[†]This table provides 95% confidence intervals using the standard logit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using families with more than one child.

Table B5: Confidence intervals and confidence sets for the logit model.[†]

				Dependent	Dependent variable: child obesity $6 \le age \le 11$	sity $6 \le age \le 11$			
	Logit (1)	CCT1 (2)	CCT3 (3)	Logit (4)	CCT1 (5)	CCT3 (6)	Logit (7)	CCT1 (8)	CCT3 (9)
Share of other obese children	[1.090,2.101]	[0.640, 2.567]	[1.099,2.085]	[0.794, 1.840]	[0.224, 2.411]	[0.798,1.837]	[0.715,1.789]	[0.519,2.140]	[0.715,1.780]
constant	[-1.080, 5.432]	[-3.989,8.418]	[-0.995,5.423]	[-12.764,23.615]	[-31.300,24.304]	[-11.993,21.987]	[-11.813, 25.514]	[-20.675, 25.353]	[-11.360,22.613]
gender	[-0.127, 0.292]	[-0.315, 0.477]	[-0.126,0.289]	[-0.161, 0.268]	[-0.331, 0.472]	[-0.161,0.261]	[-0.175, 0.260]	[-0.315, 0.371]	[-0.169, 0.254]
age	[-1.083, 0.358]	[-1.595, 0.318]	[-1.067,0.318]	[-1.119,0.360]	[-1.665, 1.172]	[-1.092,0.341]	[-1.183,0.313]	[-1.599, 0.594]	[-1.178, 0.306]
age^2	[-0.026, 0.059]	[-0.065,0.098]	[-0.024,0.058]	[-0.026, 0.061]	[-0.075,0.096]	[-0.025,0.060]	[-0.023, 0.065]	[-0.040,0.088]	[-0.022, 0.065]
$Share\ of\ obese\ adults$	[0.492,1.09]	[0.223, 1.358]	[0.497,1.085]	[0.372, 0.991]	[0.147, 1.255]	[0.382,0.987]	[0.057, 1.042]	[-0.221, 1.346]	[0.064, 1.029]
$log\ expenditures\ (Euro)$	[-0.389, -0.054]	[-0.539, 0.099]	[-0.383,-0.057]	[-0.202, 0.167]	[-0.383,0.367]	[-0.201,0.162]	[-0.185, 0.191]	[-0.310, 0.280]	[-0.179, 0.190]
Household size				[-0.172,0.084]	[-0.285,0.188]	[-0.170,0.083]	[-0.157, 0.106]	[-0.317,0.198]	[-0.156, 0.104]
Central or Northern region				[-0.503, 0.234]	[-0.787,0.728]	[-0.496,0.223]	[-0.430, 0.325]	[-0.743,0.440]	[-0.420, 0.321]
Employed RP				[-0.742, -0.048]	[-1.079, 0.325]	[-0.739,-0.058]	[-0.760,-0.059]	[-0.961, 0.237]	[-0.756, -0.066]
Student or housewife RP				[-1.567, -0.343]	[-2.149, 0.180]	[-1.561,-0.361]	[-1.615, -0.375]	[-2.173, -0.110]	[-1.611, -0.381]
Retired or other emp. status RP				[-1.742, 0.408]	[-2.846, 1.328]	[-1.708,0.4]	[-1.789, 0.396]	[-2.799, 1.104]	[-1.774, 0.355]
Mother's education (Master)				[-1.860,0.291]	[-3.223,1.211]	[-1.835,0.271]	[-2.015, 0.192]	[-2.770, 0.806]	[-2.011, 0.192]
Mother's education (Bachelor)				[-2.066, 0.370]	[-3.334, 1.703]	[-2.062,0.330]	[-2.245, 0.253]	[-3.448,1.148]	[-2.241, 0.220]
Mother's education (High School)				[-1.752, 0.349]	[-2.900, 1.400]	[-1.727,0.315]	[-1.962, 0.197]	[-2.628, 0.902]	[-1.950, 0.189]
Mother's education (Junior High)				[-1.595, 0.510]	[-2.876, 1.455]	[-1.564,0.492]	[-1.817, 0.349]	[-2.576, 1.098]	[-1.797, 0.319]
Mother's education (Primary School)				[-1.442,0.812]	[-2.860, 1.716]	[-1.427,0.792]	[-1.632, 0.692]	[-2.580, 1.419]	[-1.610, 0.652]
$ ext{CPI} (2010 = 100)$				[-0.210, 0.119]	[-0.390,0.112]	[-0.204,0.112]	[-0.196, 0.136]	[-0.298, 0.143]	[-0.191, 0.120]
% obese adults by region				[0.027, 0.093]	[-0.001, 0.127]	[0.027,0.092]	[0.032, 0.099]	[0.006, 0.124]	[0.033,0.099]
Mean adult weight (kg)							[-0.014, 0.029]	[-0.022, 0.041]	[-0.014, 0.029]
Mean adult height (cm)							[-0.049, 0.004]	[-0.067, 0.014]	[-0.048,0.004]
Diabetes							[-0.799,0.479]	[-1.149,0.867]	[-0.783, 0.460]
Obese children previous marriage							[1.86, 6.522]	[1.153, 10.009]	[1.868, 6.520]
Chronic disease							[-0.357, 0.189]	[-0.479,0.337]	[-0.355, 0.189]
Siblings walking to school							[-0.663, 0.334]	[-0.960, 0.585]	[-0.648, 0.320]
Siblings TV watching every day							[-0.146, 0.568]	[-0.252, 0.825]	[-0.144, 0.564]
Parents soda drinks							[-0.190, 0.404]	[-0.430,0.586]	[-0.184, 0.402]
Parents smoking							[-0.112, 0.357]	[-0.279, 0.561]	[-0.109, 0.349]
Children average fruit portions							[-0.271, 1.407]	[-0.854, 2.028]	[-0.243, 1.388]
Adults average fruit portions							[-1.367, 0.284]	[-1.971, 0.748]	[-1.367, 0.281]
N	1694	1694	1694	1694	1694	1694	1694	1694	1694

†This table provides 95% confidence intervals using the standard logit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using families with more than one child $6 \le age \le 11$.

Table B6: Confidence intervals and confidence sets for the logit model. †

	Logit (1)	CCT1 (2)	CCT3 (3)	Logit (4)	CCT1 (5)	CCT3 (6)	Logit (7)	CCT1 (8)	CCT3 (9)
$Share\ of\ other\ obese\ children$	[0.679,2.309]	[-0.018,2.987]	[0.694,2.276]	[0.793,1.669]	[0.411,2.095]	[0.803,1.653]	[0.714,1.609]	[0.325,2.102]	[0.720,1.600]
constant	[-49.534,93.726]	[-94.087,86.266]	[-49.529,86.266]	[-8.615, 23.148]	[-18.642, 19.116]	[-8.289,19.116]	[-9.136, 23.345]	[-25.313,22.703]	[-8.869,22.046]
gender	[0.536, 1.345]	[0.237, 1.700]	[0.549,1.342]	[0.076, 0.452]	[-0.115,0.601]	[0.080,0.449]	[0.069,0.449]	[-0.086, 0.634]	[0.074, 0.445]
age	[-14.560, 7.564]	[-14.277, 0.684]	[-14.277,0.684]	[-0.210, 0.446]	[-0.468, 0.695]	[-0.210,0.436]	[-0.217, 0.447]	[-0.589, 0.806]	[-0.208, 0.440]
age^2	[-0.298, 0.554]	[-0.554, 0.519]	[-0.292,0.519]	[-0.030,0.004]	[-0.042,0.017]	[-0.030,0.004]	[-0.030,0.004]	[-0.049,0.022]	[-0.029,0.004]
$Share\ of\ obesee adults$	[0.334, 1.479]	[-0.151,1.988]	[0.346,1.465]	[0.460, 1.003]	[0.143,1.315]	[0.462,0.995]	[-0.004, 0.850]	[-0.433, 1.411]	[0.014, 0.834]
$log\ expenditures\ (Euro)$	[-0.431, 0.202]	[-0.705, 0.467]	[-0.419,0.195]	[-0.188,0.134]	[-0.422, 0.312]	[-0.185,0.134]	[-0.185, 0.143]	[-0.365, 0.314]	[-0.180, 0.143]
Household size				[-0.143,0.079]	[-0.285, 0.190]	[-0.141,0.075]	[-0.135,0.093]	[-0.308, 0.241]	[-0.131,0.091]
Central or Northern region				[-0.399,0.260]	[-0.737,0.577]	[-0.392,0.259]	[-0.351, 0.323]	[-0.706,0.691]	[-0.339, 0.310]
Employed RP				[-0.57, 0.020]	[-0.884, 0.318]	[-0.568,0.014]	[-0.594,0.002]	[-0.925, 0.312]	[-0.588,0.000]
Student or housewife RP				[-1.293,-0.244]	[-2.008, 0.124]	[-1.276,-0.264]	[-1.337,-0.276]	[-2.020, 0.291]	[-1.319,-0.292]
Retired or other emp. status RP				[-1.367,0.619]	[-2.563,1.551]	[-1.358,0.596]	[-1.390,0.616]	[-2.526, 1.791]	[-1.349, 0.613]
Mother's education (Master)				[-0.302,0.308]	[-0.700, 0.559]	[-0.293,0.305]	[-0.260, 0.358]	[-0.611, 0.741]	[-0.256, 0.345]
Mother's education (Bachelor)				[-0.899,0.368]	[-1.759, 0.989]	[-0.899,0.351]	[-0.920, 0.378]	[-1.888,1.087]	[-0.896, 0.366]
Mother's education (Junior High)				[-0.037,0.399]	[-0.229, 0.606]	[-0.035,0.395]	[-0.057,0.391]	[-0.297, 0.609]	[-0.050, 0.390]
Mother's education (Primary School)				[-0.081,0.749]	[-0.424, 1.244]	[-0.070,0.739]	[-0.067,0.780]	[-0.674, 1.209]	[-0.065, 0.771]
CPI (2010=100)				[-0.236, 0.055]	[-0.379,0.007]	[-0.234,0.007]	[-0.220,0.073]	[-0.408, 0.085]	[-0.219, 0.059]
% obese adults by region				[0.031, 0.089]	[0.006,0.108]	[0.032,0.088]	[0.035,0.094]	[0.009, 0.129]	[0.035, 0.094]
Mean adult weight (kg)							[-0.001,0.037]	[-0.020,0.058]	[0.000,0.036]
Mean adult height (cm)							[-0.042,0.004]	[-0.067, 0.03]	[-0.041, 0.004]
Diabetes							[-0.660, 0.424]	[-1.215, 0.859]	[-0.650, 0.419]
Obese children previous marriage							[1.217, 3.649]	[0.055, 5.994]	[1.255, 3.594]
Chronic disease							[-0.335, 0.137]	[-0.589, 0.379]	[-0.325, 0.135]
Siblings walking to school							[-0.765,0.081]	[-1.152, 0.566]	[-0.753,0.080]
Siblings TV watching every day							[-0.071, 0.572]	[-0.417, 0.894]	[-0.060, 0.563]
Parents soda drinks							[-0.170, 0.357]	[-0.440, 0.723]	[-0.169, 0.347]
Parents smoking							[-0.123, 0.286]	[-0.301, 0.486]	[-0.118, 0.279]
Children average fruit portions							[-0.119, 1.092]	[-0.781, 1.721]	[-0.099, 1.089]
Adults average fruit portions							[-1.060, 0.126]	[-1.696, 0.735]	[-1.057, 0.121]
N	625	625	625	625	625	625	625	625	625

†This table provides 95% confidence intervals using the standard logit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using families with more than one child and $12 \le age \le 14$.

Table B7: Confidence intervals for the logit model. †

	Depend	lent variable: chi	ld obesity
	Logit (1)	Logit (2)	Logit (3)
constant	[-3.946,0.878]	[-9.973,34.586]	[-7.155,39.029]
gender	[0.111,0.588]	[0.124, 0.609]	[0.105, 0.597]
age	[-0.149,0.682]	[-0.137,0.71]	[-0.183, 0.677]
age^2	[-0.039,0.002]	[-0.041,0.001]	[-0.040,0.003]
Share of obese adults	[0.520, 1.197]	[0.443,1.138]	[-0.457,0.711]
log expenditures (Euro)	[-0.264,0.112]	[-0.161,0.251]	[-0.144,0.277]
Household size		[-0.180,0.105]	[-0.227, 0.069]
Central or Northern region		[-0.456,0.332]	[-0.449,0.356]
Employed RP		[-0.651,0.139]	[-0.678,0.121]
Student or housewife RP		[-0.897, 0.416]	[-0.948,0.389]
Retired or other emp. status RP		[-0.199,1.180]	[-0.286,1.137]
Mother's education (Master)		[-0.709,0.825]	[-0.648,0.920]
Mother's education (Bachelor)		[-1.879,0.398]	[-1.985,0.347]
Mother's education (High School)		[-0.938,0.481]	[-0.916,0.534]
Mother's education (Junior High)		[-0.797,0.613]	[-0.843, 0.602]
Mother's education (Primary)		[-0.629,1.001]	[-0.627,1.050]
CPI (2010=100)		[-0.351,0.062]	[-0.357,0.063]
% obese a dults by region		[0.006, 0.079]	[0.002, 0.076]
Mean adults weight (kg)			[0.007, 0.060]
Mean adults height (cm)			[-0.064,-0.002]
Diabetes			[-0.140,1.24]
Obese children previous marriage			[1.182,4.561]
Chronic disease			[-0.190,0.380]
Siblings watching TV every day			[-0.110,0.746]
Parents soda drinks			[-0.279,0.388]
Parents smoking			[-0.070,0.441]
Children average fruit portions			[-1.140,-0.067]
Adults average fruit portions			[0.133, 1.157]
N	1418	1418	1418

 $^{^{\}dagger}$ This table provides 95% confidence intervals using the standard logit model as if it were identified. The models are estimated using families with one child.

Table B8: Confidence intervals for the logit model.

	Dependent var	riable: child obesi	$ty \ (6 \le age \le 11)$
	Logit (1)	Logit (2)	Logit (3)
constant	[-5.800,3.224]	[-8.079,50.447]	[-10.416,50.707]
gender	[-0.274,0.322]	[-0.287, 0.324]	[-0.325,0.298]
age	[-0.838,1.180]	[-0.816,1.271]	[-0.753,1.378]
age^2	[-0.072,0.045]	[-0.078, 0.044]	[-0.086,0.038]
Shareofobeseadults	[0.330, 1.185]	[0.322, 1.205]	[-0.416,1.092]
log expenditures (Euro)	[-0.260,0.212]	[-0.186, 0.343]	[-0.183, 0.359]
Household size		[-0.198, 0.172]	[-0.266, 0.125]
Central or Northern region		[-0.600, 0.372]	[-0.598, 0.401]
Employed RP		[-0.648, 0.428]	[-0.685, 0.399]
Student or housewife RP		[-0.989,0.66]	[-1.083,0.603]
Retired or other emp. status RP		[-0.542,1.377]	[-0.737,1.295]
Mother's education (Master)		[-0.861,1.208]	[-0.775,1.368]
Mother's education (Bachelor)		[-3.762,-0.098]	[-3.694,0.051]
Mother's education (High School)		[-1.286,0.689]	[-1.206,0.851]
Mother's education (Junionr High)		[-1.264,0.714]	[-1.273,0.800]
Mother's education (Primary)		[-1.167,1.178]	[-1.09,1.373]
CPI (2010=100)		[-0.497,0.039]	[-0.477,0.069]
% obese a dults by region		[0.005, 0.096]	[0.003, 0.097]
Mean adults weight (kg)			[-0.016,0.053]
Mean adults height (cm)			[-0.059, 0.022]
Diabetes			[0.124, 2.052]
Obese children previous marriage			[0.882, 5.666]
Chronic disease			[-0.484,0.269]
Siblings watching tv every day			[-0.298, 0.705]
Parents soda drinks			[-0.408, 0.410]
Parents smoking			[-0.203, 0.445]
Children average fruit portions			[-2.023,-0.356]
Adults average fruit portions			[0.353, 1.972]
N	1694	1694	1694

[†]This table provides 95% confidence intervals using the standard logit model as if it were identified. The models are estimated using families with one child and $6 \le age \le 11$.

Table B9: Confidence intervals for the logit model.

	Dependent var	iable: child obesity	$(12 \le age \le 14)$
	Logit (1)	Logit (2)	Logit (3)
constant	[-44.303,96.891]	[-56.468,104.276]	[-49.543,117.459]
gender	[0.540, 1.376]	[0.547, 1.406]	[0.524, 1.406]
age	[-14.882,6.902]	[-14.413,7.953]	[-14.962,8.133]
age^2	[-0.274, 0.564]	[-0.314,0.547]	[-0.322, 0.567]
$Share\ of\ obese\ adults$	[0.515, 1.656]	[0.381, 1.558]	[-1.084,0.899]
log expenditures (Euro)	[-0.498, 0.134]	[-0.410,0.274]	[-0.413, 0.304]
Household size		[-0.302,0.161]	[-0.351,0.132]
Central or Northern region		[-0.624, 0.764]	[-0.582, 0.840]
Employed RP		[-0.994, 0.207]	[-1.048,0.198]
Student or housewife RP		[-1.331,1.011]	[-1.323,1.068]
Retired or other emp. status RP		[-0.313,1.661]	[-0.516,1.534]
Mother's education (Master)		[-1.554,0.531]	[-1.456,0.670]
Mother's education (High School)		[-0.908,1.606]	[-1.215,1.528]
Mother's education (Junior high)		[-0.183, 0.746]	[-0.227, 0.735]
Mother's education (Primary)		[-0.175,1.348]	[-0.237,1.361]
CPI (2010=100)		[-0.378, 0.297]	[-0.423, 0.267]
% obese a dults by region		[-0.028, 0.095]	[-0.032,0.095]
Mean adults weight (kg)			[0.011, 0.098]
Mean adults height (cm)			[-0.106,-0.002]
Diabetes			[-1.157,1.076]
Obese children previous marriage			[0.013, 5.400]
Chronic disease			[-0.061, 0.860]
Siblings watching TV every day			[-0.234,1.519]
Parents soda drinks			[-0.292, 0.945]
Parents smoking			[-0.190, 0.686]
Children average fruit portions			[-0.811,0.829]
Adults average fruit portions			[-0.610,0.940]
N	625	625	625

[†]This table provides 95% confidence intervals using the standard logit model as if it were identified. The models are estimated using families with one child and $12 \le age \le 14$.

Table B10: Confidence intervals and confidence sets for the probit model.[†]

	Probit (1)	CCT1 (2)	CCT3 (3)	Probit (4)	CCT1 (5)	CCT3 (6)	Probit (7)	CCT1 (8)	CCT3 (9)
Share of other obese children	[0.560,1.039]	[0.344,1.248]	[0.568,1.035]	[0.435,0.933]	[0.158, 1.282]	[0.442,0.930]	[0.421,0.934]	[0.067,1.313]	[0.432,0.923]
constant	[-1.043, 0.704]	[-1.822, 1.485]	[-1.035,0.698]	[-2.390,13.116]	[-6.889,14.311]	[-2.137,12.849]	[-2.335, 13.520]	[-12.436,17.633]	[-2.055, 13.337]
gender	[0.101, 0.275]	[0.026, 0.351]	[0.105,0.271]	[0.100, 0.276]	[-0.002, 0.389]	[0.101,0.274]	[0.094, 0.272]	[-0.017, 0.389]	[0.098, 0.270]
age	[-0.074, 0.226]	[-0.190, 0.290]	[-0.072,0.224]	[-0.051, 0.254]	[-0.274, 0.428]	[-0.047,0.251]	[-0.057, 0.251]	[-0.265, 0.438]	[-0.052, 0.246]
age^2	[-0.015,0.000]	[-0.021,0.007]	[-0.014,0.000]	[-0.016, -0.001]	[-0.026, 0.010]	[-0.016,-0.001]	[-0.016, -0.001]	[-0.025,0.009]	[-0.016, -0.001]
$Share\ of\ obese\ adults$	[0.381, 0.629]	[0.269, 0.740]	[0.384,0.625]	[0.328, 0.582]	[0.153, 0.746]	[0.333,0.578]	[-0.021, 0.386]	[-0.295, 0.677]	[-0.020, 0.382]
logexpenditures(Euro)	[-0.171, -0.033]	[-0.231, 0.029]	[-0.170,-0.036]	[-0.082, 0.068]	[-0.204, 0.159]	[-0.080,0.067]	[-0.069, 0.083]	[-0.179, 0.184]	[-0.069,0.082]
Household size				[-0.096, -0.003]	[-0.160, 0.052]	[-0.094,-0.004]	[-0.094, 0.003]	[-0.159,0.070]	[-0.092,0.001]
Central or Northern region				[-0.186, 0.115]	[-0.383, 0.316]	[-0.185,0.111]	[-0.153, 0.153]	[-0.362, 0.332]	[-0.152, 0.150]
Employed RP				[-0.308, -0.022]	[-0.502, 0.171]	[-0.305,-0.026]	[-0.322, -0.035]	[-0.511, 0.129]	[-0.317, -0.039]
Student or housewife RP				[-0.562, -0.085]	[-0.847, 0.295]	[-0.559,-0.086]	[-0.593, -0.111]	[-1.000,0.185]	[-0.581, -0.114]
Retired or other emp. status RP				[-0.115, 0.530]	[-0.488, 0.911]	[-0.106,0.530]	[-0.153, 0.505]	[-0.600, 0.952]	[-0.145, 0.497]
Mother's education (Master)				[-0.442, 0.258]	[-0.856, 0.746]	[-0.435,0.244]	[-0.448, 0.26]	[-0.885, 0.713]	[-0.433, 0.245]
Mother's education (Bachelor)				[-0.766, 0.105]	[-1.329, 0.617]	[-0.759,0.086]	[-0.840,0.047]	[-1.382, 0.583]	[-0.826,0.027]
Mother's education (High School)				[-0.486, 0.184]	[-0.848, 0.698]	[-0.473,0.183]	[-0.522, 0.155]	[-0.920, 0.591]	[-0.508, 0.148]
Mother's education (Junior High)				[-0.382, 0.287]	[-0.761, 0.776]	[-0.373,0.279]	[-0.436, 0.242]	[-0.842, 0.686]	[-0.426, 0.238]
Mother's education (Primary School)				[-0.296, 0.444]	[-0.815, 0.988]	[-0.287,0.442]	[-0.340, 0.411]	[-0.798,0.887]	[-0.338, 0.411]
CPI (2010=100)				[-0.134,0.008]	[-0.190, 0.021]	[-0.132,0.007]	[-0.124, 0.020]	[-0.207, 0.070]	[-0.121, 0.018]
% obese adults by region				[0.019, 0.046]	[0.001, 0.064]	[0.020,0.046]	[0.021, 0.048]	[0.003, 0.065]	[0.021, 0.048]
Mean adult weight (kg)							[0.005, 0.023]	[-0.008,0.038]	[0.006, 0.023]
Mean adult height (cm)							[-0.026, -0.004]	[-0.039,0.010]	[-0.026, -0.005]
Diabetes							[-0.183, 0.318]	[-0.539, 0.610]	[-0.179, 0.308]
Obese children previous marriage							[0.890, 1.964]	[0.320, 2.855]	[0.909, 1.959]
Chronic disease							[-0.122,0.091]	[-0.275, 0.239]	[-0.119,0.088]
Siblings walking to school							[-0.454, 0.022]	[-0.813, 0.324]	[-0.445,0.014]
Siblings TV watching every day							[0.007, 0.305]	[-0.172, 0.532]	[0.013, 0.304]
Parents soda drinks							[-0.082, 0.162]	[-0.250, 0.316]	[-0.078,0.161]
Parents smoking							[-0.018,0.170]	[-0.146, 0.285]	[-0.015, 0.167]
Children average fruit portions							[-0.296, 0.165]	[-0.593, 0.481]	[-0.289, 0.156]
Adults average fruit portions							[-0.145, 0.302]	[-0.467, 0.575]	[-0.141, 0.301]
N	3737	3737	3737	3737	3737	3737	3737	3737	3737

[†]This table provides 95% confidence intervals using the standard probit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using all the families.

Table B11: Confidence intervals and confidence sets for the probit model.[†]

	Probit (1)	CCT1 (2)	CCT3 (3)	Probit (4)	CCT1 (5)	CCT3 (6)	Probit (7)	CCT1 (8)	CCT3 (9)
$Share\ of\ other\ obese\ children$	[0.588, 1.180]	[0.320, 1.449]	[0.599,1.17]	[0.450, 1.065]	[0.125, 1.464]	[0.450,1.058]	[0.418, 1.047]	[-0.032, 1.478]	[0.426, 1.036]
constant	[-0.868, 2.319]	$\left[-2.253, 3.691 \right]$	[-0.807,2.245]	[-3.827,14.833]	[-13.042,17.507]	[-3.441,14.452]	[-4.026,15.072]	[-18.730,21.992]	[-3.631,14.671]
gender	[-0.064, 0.143]	[-0.157, 0.236]	[-0.061,0.140]	[-0.070, 0.139]	[-0.228, 0.292]	[-0.065,0.134]	[-0.074,0.138]	[-0.217, 0.279]	[-0.072, 0.133]
age	[-0.479, 0.23]	[-0.731, 0.321]	[-0.464,0.221]	[-0.457, 0.262]	[-0.896,0.743]	[-0.449,0.246]	[-0.477,0.248]	[-0.937, 0.695]	[-0.476, 0.234]
age^2	[-0.016, 0.026]	[-0.034, 0.044]	[-0.015,0.025]	[-0.018, 0.024]	[-0.047,0.051]	[-0.017,0.023]	[-0.017,0.025]	[-0.044, 0.053]	[-0.016,0.025]
$Share\ of\ obese\ adults$	[0.327, 0.623]	[0.198, 0.758]	[0.330,0.620]	[0.281, 0.584]	[0.026, 0.833]	[0.287,0.581]	[0.034, 0.523]	[-0.480, 0.855]	[0.046, 0.518]
$log\ expenditures\ (Euro)$	[-0.187, -0.023]	[-0.260, 0.048]	[-0.184,-0.024]	[-0.086, 0.093]	[-0.201, 0.204]	[-0.082,0.090]	[-0.071,0.111]	[-0.185, 0.257]	[-0.069, 0.110]
Household size				[-0.106, 0.006]	[-0.174, 0.073]	[-0.104,0.003]	[-0.105, 0.011]	[-0.183, 0.079]	[-0.104,0.010]
Central or Northern region				[-0.244, 0.109]	[-0.496, 0.335]	[-0.244,0.100]	[-0.206, 0.154]	[-0.405, 0.399]	[-0.202, 0.147]
Employed RP				[-0.365, -0.010]	[-0.586, 0.241]	[-0.360,-0.018]	[-0.376, -0.020]	[-0.583, 0.209]	[-0.375,-0.023]
Student or housewife RP				[-0.673,-0.099]	[-1.126,0.237]	[-0.672,-0.107]	[-0.711,-0.131]	[-1.077, 0.216]	[-0.699,-0.137]
Retired or other emp. status RP				[-0.405, 0.423]	[-1.020, 0.928]	[-0.391,0.416]	[-0.437,0.413]	[-0.982,0.937]	[-0.420, 0.394]
Mother's education (Master)				[-0.664, 0.229]	[-1.274, 0.883]	[-0.664,0.208]	[-0.699,0.205]	[-1.232,0.76]	[-0.689,0.197]
Mother's education (Bachelor)				[-1.071, 0.016]	[-1.726,0.687]	[-1.068,0.004]	[-1.148,-0.042]	[-1.878,0.717]	[-1.144,-0.043]
Mother's education (High School)				[-0.702, 0.162]	[-1.184,0.738]	[-0.699,0.155]	[-0.761, 0.116]	[-1.275, 0.663]	[-0.747,0.115]
Mother's education (Junior High)				[-0.630, 0.236]	[-1.236, 0.883]	[-0.615,0.219]	[-0.709,0.172]	[-1.226, 0.721]	[-0.695, 0.171]
Mother's education (Primary School)				[-0.527, 0.432]	[-1.109,1.161]	[-0.513,0.427]	[-0.599, 0.379]	[-1.223,1.039]	[-0.583,0.377]
CPI (2010=100)				[-0.141, 0.029]	[-0.239,0.066]	[-0.138,0.028]	[-0.128,0.043]	[-0.226, 0.123]	[-0.127,0.042]
% obese adults by region				[0.019, 0.052]	[0,0.075]	[0.020,0.052]	[0.022, 0.054]	[0.004, 0.081]	[0.022, 0.054]
Mean adult weight (kg)							[-0.004,0.018]	[-0.018, 0.035]	[-0.003,0.018]
Mean adult height (cm)							[-0.025, 0.001]	[-0.041, 0.02]	[-0.025,0.001]
Diabetes							[-0.166,0.448]	[-0.591, 0.851]	[-0.154, 0.443]
Obese children previous marriage							[1.136, 2.735]	[0.303, 4.555]	[1.162,2.708]
Chronic disease							[-0.184, 0.076]	[-0.347, 0.262]	[-0.181,0.071]
Siblings walking to school							[-0.374, 0.201]	[-0.722, 0.594]	[-0.363, 0.195]
Siblings TV watching every day							[-0.06, 0.281]	[-0.244, 0.498]	[-0.056, 0.273]
Parents soda drinks							[-0.113, 0.172]	[-0.313, 0.345]	[-0.107, 0.165]
Parents smoking							[-0.027,0.199]	[-0.185, 0.371]	[-0.022,0.197]
Children average fruit portions							[-0.563, 0.093]	[-1.050, 0.521]	[-0.558, 0.093]
Adults average fruit portions							[-0.086, 0.555]	[-0.461, 1.023]	[-0.071, 0.544]
N	2503	2503	2503	2503	2503	2503	2503	2503	2503

†This table provides 95% confidence intervals using the standard probit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using all the families with children with $6 \le age \le 11$.

Table B12: Confidence intervals and confidence sets for the probit model.[†]

				Dependent varial	Dependent variable: child obesity (12 \leq age \leq 14)	$12 \le age \le 14)$			
	Probit (1)	CCT1 (2)	CCT3	Probit (4)	CCT1 (5)	CCT3	Probit (7)	CCT1 (8)	CCT3 (9)
Shareof other obese children	[0.278,1.108]	[-0.097,1.469]	[0.284,1.107]	[0.17,1.048]	[-0.507,1.547]	[0.177,1.028]	[0.254,1.185]	[-0.401,1.766]	[0.256,1.175]
constant	[-16.104,41.695]	[-40.983,66.704]	[-15.856,41.577]	[-14.302, 50.206]	[-52.120, 77.035]	[-12.982,49.638]	[-8.386,57.715]	[-46.524,86.252]	[-7.630, 56.746]
gender	[0.384, 0.712]	[0.243, 0.860]	[0.391,0.711]	[0.396, 0.729]	[0.208, 0.945]	[0.402, 0.722]	[0.390, 0.729]	[0.163, 0.975]	[0.393, 0.729]
age	[-6.418, 2.498]	[-7.634,1.233]	[-6.341,1.233]	[-5.869, 3.167]	[-8.744,3.008]	[-5.711,2.818]	[-6.829,2.387]	[-10.177,2.533]	[-6.602, 2.335]
age^2	[-0.101, 0.243]	[-0.248, 0.395]	[-0.099,0.240]	[-0.127, 0.221]	[-0.327, 0.394]	[-0.123,0.220]	[-0.097, 0.258]	[-0.327, 0.436]	[-0.096, 0.251]
Share of obese adults	[0.350, 0.814]	[0.155, 1.022]	[0.359,0.808]	[0.280, 0.754]	[-0.025, 1.054]	[0.291,0.749]	[-0.399,0.367]	[-0.936, 0.803]	[-0.392, 0.364]
logexpenditures(Euro)	[-0.229,0.027]	[-0.344,0.138]	[-0.225,0.024]	[-0.171, 0.107]	[-0.357, 0.264]	[-0.169,0.101]	[-0.177, 0.109]	[-0.355, 0.311]	[-0.173, 0.102]
Household size				[-0.122, 0.051]	[-0.247, 0.168]	[-0.121,0.05]	[-0.116, 0.065]	[-0.255, 0.166]	[-0.115, 0.064]
Central or Northern region				[-0.228, 0.361]	[-0.670, 0.726]	[-0.219,0.360]	[-0.206, 0.392]	[-0.520, 0.853]	[-0.201, 0.382]
Employed RP				[-0.397,0.098]	[-0.732, 0.501]	[-0.396,0.090]	[-0.430,0.074]	[-0.814, 0.454]	[-0.417, 0.070]
Student or housewife RP				[-0.657, 0.222]	[-1.241, 0.732]	[-0.643,0.214]	[-0.694, 0.204]	[-1.285, 0.833]	[-0.686, 0.191]
Retired or other emp. status RP				[-0.014, 1.044]	[-0.637, 1.796]	[0.002,1.034]	[-0.158, 0.926]	[-0.863, 1.659]	[-0.150, 0.920]
Mother's education (Master)				[-0.470, 0.737]	[-1.145, 1.494]	[-0.452, 0.721]	[-0.405, 0.842]	[-1.133,1.609]	[-0.385, 0.806]
Mother's education (Bachelor)				[-0.726, 0.814]	[-1.936, 1.652]	[-0.704,0.782]	[-0.819, 0.783]	[-1.858, 1.797]	[-0.788,0.763]
Mother's education (High School)				[-0.504, 0.608]	[-1.176, 1.544]	[-0.489,0.583]	[-0.525, 0.623]	[-1.264, 1.439]	[-0.499, 0.593]
Mother's education (Junior High)				[-0.327, 0.775]	[-0.955, 1.759]	[-0.324,0.745]	[-0.346, 0.792]	[-0.953, 1.522]	[-0.328, 0.772]
Mother's education (Primary School)				[-0.283, 0.920]	[-1.118, 1.977]	[-0.274,0.883]	[-0.297, 0.946]	[-0.964, 1.696]	[-0.265, 0.917]
CPI (2010=100)				[-0.233, 0.039]	[-0.402, 0.204]	[-0.230,0.033]	[-0.233,0.041]	[-0.395, 0.216]	[-0.228,0.037]
% obese adults by region				[0.004, 0.055]	[-0.039,0.091]	[0.004,0.054]	[0.003, 0.055]	[-0.028, 0.091]	[0.003, 0.054]
Mean adult weight (kg)							[0.013, 0.046]	[-0.007,0.070]	[0.013, 0.046]
Mean adult height (cm)							[-0.040, 0.000]	[-0.071, 0.026]	[-0.040, -0.001]
Diabetes							[-0.499, 0.413]	[-1.185, 0.912]	[-0.486, 0.403]
Obese children previous marriage							[-0.098, 1.562]	[-1.195, 2.798]	[-0.065, 1.548]
Chronic disease							$\left[-0.131, 0.251 \right]$	[-0.349, 0.515]	[-0.122, 0.244]
Siblings walking to school							[-0.968, -0.076]	[-1.627, 0.502]	[-0.961, -0.079]
Siblings TV watching every day							[-0.018, 0.629]	[-0.395, 1.116]	[-0.013, 0.613]
Parents soda drinks							[-0.232, 0.269]	[-0.559, 0.594]	[-0.221, 0.268]
Parents smoking							[-0.097, 0.26]	[-0.322, 0.469]	[-0.091, 0.253]
Children average fruit portions							[-0.212, 0.481]	[-0.669, 0.851]	[-0.209, 0.467]
Adults average fruit portions							[-0.403, 0.262]	[-0.8,0.673]	[-0.398, 0.257]
N	1234	1234	1234	1234	1234	1234	1234	1234	1234

†This table provides 95% confidence intervals using the standard logit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using all the families with children with $12 \le age \le 14$.

18

Table B13: Confidence intervals and confidence sets for the probit model.[†]

	Probit (1)	CCT1 (2)	CCT3 (3)	Probit (4)	CCT1 (5)	CCT3 (6)	Probit (7)	CCT1 (8)	CCT3 (9)
Share of other obese children	[0.676,1.192]	[0.448,1.424]	[0.679,1.18]	[0.489,1.018]	[0.107,1.391]	[0.496,1.015]	[0.444,0.982]	[0.112,1.332]	[0.445,0.974]
constant	[-0.951, 1.271]	[-1.937, 2.254]	[-0.929,1.246]	[-5.057,14.259]	$\left[-11.986, 15.823 \right]$	[-4.916,13.938]	[-5.132,14.663]	[-16.074,18.245]	[-5.074,14.285]
gender	[0.059, 0.279]	[-0.038, 0.380]	[0.061,0.275]	[0.052, 0.276]	[-0.117, 0.420]	[0.057,0.274]	[0.047, 0.273]	[-0.094, 0.405]	[0.047,0.269]
age	[-0.160, 0.223]	[-0.327,0.328]	[-0.155,0.216]	[-0.135, 0.254]	[-0.448,0.510]	[-0.128,0.249]	[-0.138,0.255]	[-0.350, 0.514]	[-0.132, 0.252]
age^2	[-0.015,0.004]	[-0.024, 0.013]	[-0.015,0.004]	[-0.017,0.003]	[-0.030,0.017]	[-0.017,0.003]	[-0.017,0.003]	[-0.031, 0.014]	[-0.017,0.003]
$Share\ of\ obese\ adults$	[0.349, 0.664]	[0.208, 0.809]	[0.350,0.659]	[0.278, 0.602]	[0.063, 0.826]	[0.279,0.595]	[-0.008, 0.501]	[-0.393, 0.874]	[0.004, 0.490]
$log\ expenditures\ (Euro)$	[-0.208,-0.031]	[-0.286,0.048]	[-0.208,-0.034]	[-0.115,0.077]	[-0.236,0.212]	[-0.114,0.076]	[-0.111,0.084]	[-0.256, 0.231]	[-0.108, 0.084]
Household size				[-0.082, 0.050]	[-0.170,0.146]	[-0.081,0.047]	[-0.076,0.059]	[-0.155, 0.140]	[-0.074,0.057]
Central or Northern region				[-0.237, 0.157]	[-0.494, 0.450]	[-0.236,0.154]	[-0.207,0.194]	[-0.476, 0.427]	[-0.203, 0.190]
Employed RP				[-0.343, 0.017]	[-0.569,0.245]	[-0.339,0.015]	[-0.358, 0.005]	[-0.603, 0.244]	[-0.355,0.004]
Student or housewife RP				[-0.735, -0.129]	[-1.123,0.267]	[-0.730,-0.140]	[-0.766, -0.153]	[-1.194,0.219]	[-0.766,-0.166]
Retired or other emp. status RP				[-0.814, 0.374]	[-1.630,1.091]	[-0.805,0.349]	[-0.848, 0.361]	[-1.545, 1.238]	[-0.842,0.338]
Mother's education (Master)				[-0.761, 0.411]	[-1.542,1.186]	[-0.743,0.387]	[-0.827, 0.363]	[-1.512, 1.203]	[-0.826, 0.353]
Mother's education (Bachelor)				[-1.011, 0.326]	[-1.800,1.310]	[-0.983,0.305]	[-1.118, 0.241]	[-2.078, 1.19]	[-1.088,0.233]
Mother's education (High School)				[-0.756, 0.392]	[-1.544,1.134]	[-0.733,0.377]	[-0.856, 0.310]	[-1.540, 1.132]	[-0.838,0.296]
Mother's education (Junior High)				[-0.649, 0.500]	[-1.405, 1.261]	[-0.624,0.480]	[-0.757, 0.412]	[-1.448, 1.216]	[-0.748,0.409]
Mother's education (Primary School)				[-0.594, 0.629]	[-1.384,1.409]	[-0.594,0.619]	[-0.687, 0.561]	[-1.420, 1.616]	[-0.684, 0.543]
CPI (2010=100)				[-0.143, 0.034]	[-0.231, 0.046]	[-0.143,0.033]	[-0.133, 0.045]	[-0.248, 0.085]	[-0.133,0.041]
% obese adults by region				[0.019, 0.054]	[-0.002,0.077]	[0.020,0.053]	[0.021, 0.057]	[-0.002,0.076]	[0.022, 0.056]
Mean adult weight (kg)							[0.000, 0.023]	[-0.016,0.037]	[0.000,0.022]
Mean adult height (cm)							[-0.027, 0.001]	[-0.043,0.017]	[-0.026,0.001]
Diabetes							[-0.389, 0.252]	[-0.831, 0.643]	[-0.384,0.241]
Obese children previous marriage							[0.743, 2.119]	[-0.053, 3.149]	[0.756, 2.114]
Chronic disease							[-0.197, 0.082]	[-0.413, 0.268]	[-0.193,0.082]
Siblings walking to school							[-0.453, 0.047]	[-0.765, 0.359]	[-0.447,0.041]
Siblings TV watching every day							[-0.029, 0.348]	[-0.240, 0.610]	[-0.025, 0.344]
Parents soda drinks							[-0.097,0.217]	[-0.290, 0.424]	[-0.095, 0.215]
Parents smoking							[-0.081, 0.163]	[-0.227, 0.322]	[-0.078,0.161]
Children average fruit portions							[-0.045, 0.655]	[-0.475, 1.108]	[-0.043, 0.645]
Adults average fruit portions							[-0.638,0.048]	[-1.163, 0.490]	[-0.629, 0.039]
N	2319	2319	2319	2319	2319	2319	2319	2319	2319

[†]This table provides 95% confidence intervals using the standard probit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using families with more than one child.

Table B14: Confidence intervals and confidence sets for the probit model.[†]

	Probit (1)	CCT1 (2)	CCT3	Probit (4)	CCT1 (5)	CCT3	Probit (7)	CCT1 (8)	CCT3 (9)
Share of other obese children	[0.675, 1.297]	[0.394, 1.581]	[0.683,1.292]	[0.493,1.132]	[0.104, 1.605]	[0.498,1.120]	[0.441, 1.092]	[-0.062,1.560]	[0.446,1.085]
constant	[-0.625, 3.312]	[-2.356, 5.082]	[-0.611,3.246]	[-7.838,14.443]	$\left[-19.410,18.235\right]$	[-7.709,14.166]	[-7.235,15.607]	[-20.379,24.328]	[-7.018, 15.592]
gender	[-0.075, 0.178]	[-0.187, 0.290]	[-0.070,0.174]	[-0.093,0.164]	[-0.268, 0.323]	[-0.089,0.162]	[-0.102, 0.158]	[-0.286, 0.323]	[-0.102, 0.157]
age	[-0.660, 0.211]	[-0.936, 0.321]	[-0.657,0.202]	[-0.676,0.210]	[-1.275, 0.752]	[-0.661,0.199]	[-0.715,0.179]	[-1.301, 0.679]	[-0.701, 0.179]
age^2	[-0.015, 0.036]	[-0.038, 0.058]	[-0.015,0.036]	[-0.015,0.037]	[-0.046, 0.072]	[-0.015,0.037]	[-0.013, 0.039]	[-0.043, 0.075]	[-0.012, 0.039]
$Share\ of\ obese\ adults$	[0.303, 0.665]	[0.142, 0.826]	[0.309,0.659]	[0.229,0.600]	[-0.021, 0.864]	[0.229,0.596]	[0.033, 0.624]	[-0.330, 0.984]	[0.042, 0.612]
$log\ expenditures\ (Euro)$	[-0.237, -0.035]	[-0.328, 0.053]	[-0.235,-0.035]	[-0.124,0.097]	[-0.281, 0.253]	[-0.119,0.097]	[-0.110,0.115]	[-0.251, 0.262]	[-0.106, 0.112]
Household size				[-0.103,0.050]	[-0.191, 0.145]	[-0.099,0.050]	[-0.095, 0.062]	[-0.200, 0.169]	[-0.092, 0.061]
Central or Northern region				[-0.299, 0.145]	[-0.556, 0.466]	[-0.298,0.136]	[-0.254, 0.200]	[-0.564, 0.470]	[-0.251, 0.199]
Employed RP				[-0.451,-0.024]	[-0.698, 0.251]	[-0.449,-0.027]	[-0.463, -0.032]	[-0.721,0.238]	[-0.460, -0.033]
Student or housewife RP				[-0.916,-0.200]	[-1.449, 0.249]	[-0.900,-0.214]	[-0.947, -0.222]	[-1.510, 0.240]	[-0.945, -0.238]
Retired or other emp. status RP				[-1.038,0.260]	[-1.882, 1.049]	[-1.023,0.250]	[-1.067, 0.255]	[-1.948,1.113]	[-1.051, 0.248]
Mother's education (Master)				[-1.134,0.173]	[-1.945, 0.983]	[-1.117,0.155]	[-1.218, 0.104]	[-1.993,1.002]	[-1.206,0.094]
Mother's education (Bachelor)				[-1.269,0.206]	[-2.162, 1.092]	[-1.242,0.205]	[-1.378,0.119]	[-2.430,1.012]	[-1.353,0.108]
Mother's education (High School)				[-1.067,0.210]	[-1.863,1.021]	[-1.047,0.206]	[-1.187,0.106]	[-1.919, 0.966]	[-1.161,0.092]
Mother's education (Junior High)				[-0.978,0.302]	[-1.754,1.013]	[-0.971,0.286]	[-1.104, 0.194]	[-1.885, 1.11]	[-1.099, 0.172]
Mother's education (Primary School)				[-0.887,0.483]	[-1.776, 1.342]	[-0.862,0.460]	[-0.997,0.398]	[-1.929, 1.304]	[-0.982, 0.390]
CPI (2010=100)				[-0.129,0.073]	[-0.245, 0.126]	[-0.126,0.071]	[-0.120, 0.083]	[-0.247, 0.171]	[-0.119,0.081]
% obese adults by region				[0.017,0.057]	[-0.009, 0.085]	[0.018,0.057]	[0.020, 0.061]	[-0.001, 0.086]	[0.021, 0.061]
Mean adult weight (kg)							[-0.008,0.018]	[-0.024,0.037]	[-0.008,0.018]
Mean adult height (cm)							[-0.030, 0.002]	[-0.053, 0.021]	[-0.030,0.002]
Diabetes							[-0.461, 0.296]	[-0.972, 0.820]	[-0.447, 0.295]
Obese children previous marriage							[1.115, 3.297]	[0.182, 5.388]	[1.128, 3.284]
Chronic disease							[-0.212, 0.113]	[-0.423, 0.318]	[-0.206, 0.108]
Siblings walking to school							[-0.389,0.207]	[-0.816, 0.606]	[-0.385, 0.204]
Siblings TV watching every day							[-0.081, 0.342]	[-0.317, 0.634]	[-0.077, 0.336]
Parents soda drinks							[-0.113,0.243]	[-0.381,0.481]	[-0.111, 0.237]
Parents smoking							[-0.072, 0.210]	[-0.338, 0.377]	[-0.070, 0.204]
Children average fruit portions							[-0.158, 0.83]	[-0.790, 1.614]	[-0.135, 0.812]
Adults average fruit portions							[-0.810, 0.162]	[-1.588, 0.853]	[-0.799,0.138]
N	1694	1694	1694	1694	1694	1694	1694	1694	1694

†This table provides 95% confidence intervals using the standard probit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using families with more than one child and $6 \le age \le 11$.

Table B15: Confidence intervals and confidence sets for the probit model.[†]

	Probit (1)	CCT1 (2)	CCT3 (3)	Probit (4)	CCT1 (5)	CCT3 (6)	Probit (7)	CCT1 (8)	CCT3 (9)
Share of other obese children	[0.419,1.368]	[0.005,1.766]	[0.428,1.364]	[0.208,1.195]	[-0.405,1.847]	[0.209,1.187]	[0.220,1.241]	[-0.383,1.917]	[0.244,1.220]
constant	[-28.499,53.912]	[-62.739,83.057]	[-27.065,53.588]	[-21.970,70.565]	[-69.871,102.298]	[-21.176,69.256]	$\left[-21.549, 73.364 \right]$	[-78.215,105.578]	[-20.663,72.161]
gender	[0.312, 0.772]	[0.115, 0.977]	[0.314, 0.767]	[0.310, 0.780]	[0.0270, 1.049]	[0.316,0.770]	[0.309, 0.794]	[0.012, 1.121]	[0.315, 0.785]
age	[-8.377,4.348]	[-8.973,2.514]	[-8.255,2.514]	[-7.673,5.315]	[-10.838, 5.246]	[-7.519,4.990]	[-8.102,5.240]	[-12.189,5.320]	[-7.945, 4.790]
age^2	[-0.171,0.319]	[-0.377,0.498]	[-0.165,0.314]	[-0.209, 0.291]	[-0.514, 0.457]	[-0.200,0.290]	[-0.205,0.308]	[-0.483, 0.533]	[-0.196, 0.297]
Share of obese adults	[0.212, 0.869]	[-0.071,1.151]	[0.227,0.868]	[0.117, 0.795]	[-0.384, 1.209]	[0.131,0.791]	[-0.554, 0.512]	[-1.229, 1.215]	[-0.538, 0.499]
$log\ expenditures\ (Euro)$	[-0.257, 0.111]	[-0.414, 0.272]	[-0.251,0.109]	[-0.224, 0.181]	[-0.482, 0.415]	[-0.219,0.180]	[-0.257, 0.159]	[-0.569, 0.416]	[-0.251, 0.157]
Household size				[-0.111, 0.158]	[-0.275, 0.335]	[-0.109,0.156]	[-0.104, 0.172]	[-0.310, 0.346]	[-0.098, 0.167]
Central or Northern region				[-0.373, 0.506]	[-0.921, 1.074]	[-0.357,0.489]	[-0.448,0.453]	[-1.002, 1.192]	[-0.426, 0.439]
Employed RP				[-0.381, 0.331]	[-0.806, 0.804]	[-0.367,0.316]	[-0.413, 0.316]	[-0.844, 0.828]	[-0.405, 0.304]
Student or housewife RP				[-0.829, 0.364]	[-1.654, 1.218]	[-0.813,0.347]	[-0.907,0.328]	[-1.917,1.258]	[-0.891, 0.296]
Retired or other emp. status RP				[-1.492, 1.705]	[-4.675, 3.344]	[-1.435,1.643]	[-1.654, 1.655]	[-4.642, 4.423]	[-1.621, 1.584]
Mother's education (Master)				[-0.170, 0.633]	[-0.879, 1.189]	[-0.169,0.625]	[-0.071,0.753]	[-0.678, 1.290]	[-0.062, 0.733]
Mother's education (Bachelor)				[-1.822, 0.494]	[-4.082, 1.428]	[-1.800,0.482]	[-1.777,0.514]	[-4.220, 1.508]	[-1.732, 0.467]
Mother's education (Junior High)				[-0.096, 0.449]	[-0.486, 0.815]	[-0.092,0.447]	[-0.074,0.497]	[-0.383, 0.888]	[-0.062, 0.490]
Mother's education (Primary School)				[-0.322, 0.665]	[-1.119, 1.267]	[-0.300,0.640]	[-0.271, 0.752]	[-1.164, 1.393]	[-0.260, 0.747]
CPI (2010=100)				[-0.371, 0.020]	[-0.637, 0.284]	[-0.367,0.014]	[-0.371,0.028]	[-0.623, 0.291]	[-0.365, 0.024]
% obese adults by region				[-0.001, 0.073]	[-0.052, 0.126]	[0.000,0.072]	[-0.009,0.068]	[-0.055, 0.126]	[-0.007,0.066]
Mean adult weight (kg)							[0.005, 0.052]	[-0.022, 0.083]	[0.006, 0.051]
Mean adult height (cm)							[-0.041,0.017]	[-0.080, 0.055]	[-0.040, 0.016]
Diabetes							[-0.673,0.633]	[-1.627, 1.483]	[-0.653, 0.604]
Obese children previous marriage							[-0.661,1.684]	[-2.541, 3.413]	[-0.617, 1.669]
Chronic disease							[-0.367, 0.205]	[-0.714,0.601]	[-0.356, 0.202]
Siblings walking to school							[-0.983,-0.017]	[-1.665, 0.622]	[-0.972,-0.025]
Siblings TV watching every day							[-0.157, 0.742]	[-0.709, 1.372]	[-0.142, 0.720]
Parents soda drinks							[-0.448,0.281]	[-0.948, 0.686]	[-0.436, 0.273]
Parents smoking							[-0.275,0.249]	[-0.602, 0.631]	[-0.265, 0.245]
Children average fruit portions							[-0.213, 0.825]	[-0.861, 1.510]	[-0.190, 0.816]
Adults average fruit portions							[-0.785,0.216]	[-1.530, 0.950]	[-0.779,0.199]
N	625	625	625	625	625	625	625	625	625

†This table provides 95% confidence intervals using the standard probit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. The models are estimated using families with more than one child and $12 \le age \le 14$.

Table B16: Confidence intervals for the probit model.

		Depend	ent variable: chi	ld obesity
		Probit (1)	Probit (2)	Probit (3)
constant		[-2.397,0.491]	[-6.614,19.885]	[-5.026,22.394]
gender		[0.076, 0.360]	[0.081, 0.369]	[0.067, 0.358]
age		[-0.085,0.412]	[-0.072, 0.433]	[-0.095, 0.417]
age^2		[-0.024,0.001]	[-0.025, 0.000]	[-0.024,0.001]
Share of obese adults		[0.313, 0.718]	[0.272, 0.685]	[-0.278,0.417]
log expenditures (Euro)		[-0.157,0.066]	[-0.098, 0.146]	[-0.085, 0.163]
Household size			[-0.108,0.060]	[-0.136,0.038]
Central or Northern region			[-0.269,0.203]	[-0.262,0.219]
Employed RP			[-0.394,0.080]	[-0.410,0.067]
Student or housewife RP			[-0.535,0.251]	[-0.567,0.230]
Retired or other emp. status RP			[-0.115,0.723]	[-0.167,0.695]
Mother's education (Master)			[-0.436,0.482]	[-0.398,0.534]
Mother's education (Bachelor)			[-1.045,0.243]	[-1.111,0.212]
Mother's education (High School)			[-0.571,0.275]	[-0.552,0.308]
Mother's education (Junior High)			[-0.491,0.351]	[-0.515,0.343]
Mother's education (Primary School)			[-0.389,0.590]	[-0.384,0.620]
CPI (2010=100)			[-0.203,0.043]	[-0.205,0.044]
% obese adults by region			[0.004, 0.048]	[0.002, 0.046]
Mean adult weight (kg)				[0.005, 0.036]
Mean adult height (cm)				[-0.039,-0.002]
Diabetes				[-0.086,0.750]
Obese children previous marriage				[0.721,2.535]
Chronic disease				[-0.113,0.225]
Siblings TV watching every day				[-0.069, 0.427]
Parents soda drinks				[-0.166,0.230]
Parents smoking				[-0.036,0.267]
Children average fruit portions				[-0.663,-0.028]
Adults average fruit portions				[0.066, 0.674]
N	N	1418	1418	1418

 $^{^{\}dagger}$ This table provides 95% confidence intervals using the standard probit model as if it were identified. The models are estimated using families with one child.

Table B17: Confidence intervals for the probit model. †

		Dependent var	riable: child obesi	$ty \ (6 \le age \le 11)$
		Probit (1)	Probit (2)	Probit (3)
constant		[-3.572,1.956]	[-4.800,30.691]	[-6.167,30.890]
gender		[-0.164,0.198]	[-0.175, 0.195]	[-0.194,0.181]
age		[-0.511,0.722]	[-0.495, 0.773]	[-0.471,0.818]
age^2		[-0.044,0.028]	[-0.047, 0.026]	[-0.051,0.024]
Share of obese adults		[0.199,0.718]	[0.201, 0.736]	[-0.254, 0.662]
log expenditures (Euro)		[-0.157,0.130]	[-0.113, 0.205]	[-0.111,0.214]
Household size			[-0.121,0.101]	[-0.157,0.074]
Central or Northern region			[-0.366, 0.222]	[-0.358,0.245]
Employed RP			[-0.397, 0.256]	[-0.420,0.236]
Student or housewife RP			[-0.582,0.408]	[-0.632,0.374]
Retired or other emp. status RP			[-0.331,0.849]	[-0.463,0.785]
Mother's education (Master)			[-0.527, 0.736]	[-0.486,0.805]
Mother's education (Bachelor)			[-2.090,-0.080]	[-2.102,-0.015]
Mother's education (High School)			[-0.783, 0.418]	[-0.739,0.496]
Mother's education (Junior High)			[-0.776, 0.429]	[-0.787, 0.458]
Mother's education (Primary School))		[-0.711,0.720]	[-0.670,0.815]
CPI (2010=100)			[-0.302,0.023]	[-0.290,0.041]
% obese a dults by region			[0.003, 0.058]	[0.002, 0.059]
Mean adult weight (kg)				[-0.010,0.032]
Mean adult height (cm)				[-0.035,0.013]
Diabetes				[0.071, 1.227]
Obese children previous marriage				[0.549, 3.038]
Chronic disease				[-0.288, 0.163]
Siblings TV watching every day				[-0.180, 0.414]
Parents soda drinks				[-0.247, 0.245]
Parents smoking				[-0.118, 0.273]
Children average fruit portions				[-1.178,-0.202]
Adults average fruit portions				[0.201, 1.154]
N	N	1694	1694	1694

[†]This table provides 95% confidence intervals using the standard probit model as if it were identified. The models are estimated using families with one child and $6 \le age \le 11$.

Table B18: Confidence intervals for the probit model.

	Dependent varie	able: child obesity	$(12 \le age \le 14)$
	Probit (1)	Probit (2)	Probit (3)
constant	[-26.257,55.215]	[-35.447,56.664]	[-30.197,65.458]
gender	[0.316, 0.788]	[0.313, 0.795]	[0.298, 0.790]
age	[-8.467,4.092]	[-7.973,4.870]	[-8.467,4.783]
age^2	[-0.163, 0.321]	[-0.193, 0.302]	[-0.189,0.321]
Share of obese adults	[0.304, 0.964]	[0.221, 0.897]	[-0.610, 0.528]
log expenditures (Euro)	[-0.287, 0.075]	[-0.239, 0.154]	[-0.237,0.173]
Household size		[-0.174,0.094]	[-0.203,0.077]
Central or Northern region		[-0.352,0.459]	[-0.324,0.509]
Employed RP		[-0.588, 0.122]	[-0.618,0.105]
Student or housewife RP		[-0.761,0.604]	[-0.765,0.631]
Retired or other emp. status RP		[-0.181,1.006]	[-0.302,0.917]
Mother's education (Master)		[-0.727,0.340]	[-0.693, 0.412]
Mother's education (Bachelor)		[-0.479,0.962]	[-0.610,0.931]
Mother's education (Junior High)		[-0.106, 0.427]	[-0.129,0.421]
Mother's education (Primary School)		[-0.123, 0.789]	[-0.160,0.790]
CPI (2010=100)		[-0.205, 0.184]	[-0.232,0.163]
% obese adults by region		[-0.015,0.057]	[-0.017,0.057]
Mean adult weight (kg)			[0.006, 0.056]
Mean adult height (cm)			[-0.060,-0.001]
Diabetes			[-0.682,0.628]
Obese children previous marriage			[0.020,2.806]
Chronic disease			[-0.045, 0.490]
Siblings TV watching every day			[-0.114,0.849]
Parents soda drinks			[-0.173,0.541]
Parents smoking			[-0.094,0.412]
Children average fruit portions			[-0.472,0.489]
Adults average fruit portions			[-0.367,0.541]
N	625	625	625

[†]This table provides 95% confidence intervals using the standard probit model as if it were identified. The models are estimated using families with one child and $12 \le age \le 14$.

Table B19: Confidence intervals and confidence sets for the logit model with group dummies. †

			Dependent varia	ble: child obesity	,	
	Logit (1)	CCT1 (2)	CCT3 (3)	Logit (4)	CCT1 (5)	CCT3 (6)
Share of other obese children	[0.467,0.952]	[0.163,1.261]	[0.474,0.951]	[0.487,0.973]	[0.224,1.267]	[0.488,0.972]
gender	[0.107, 0.282]	[0.004, 0.403]	[0.109, 0.278]	[0.106,0.281]	[0.009, 0.389]	[0.109, 0.281]
age	[-0.076, 0.226]	[-0.299,0.410]	[-0.070,0.224]	[-0.076,0.227]	[-0.261,0.432]	[-0.072,0.222]
age^2	[-0.015,0.000]	[-0.024,0.012]	[-0.015,0.000]	[-0.015,0.000]	[-0.026, 0.010]	[-0.015,0.000]
$Share\ of\ obese\ adults$	[0.020, 0.421]	[-0.236,0.705]	[0.021, 0.420]	[0.012,0.414]	[-0.234,0.715]	[0.015, 0.408]
log expenditures (Euro)	[-0.126, 0.020]	[-0.22,0.126]	[-0.126, 0.017]	[-0.137,0.008]	[-0.225,0.096]	[-0.134,0.005]
$average\ adult\ weight$	[0.007, 0.024]	[-0.004,0.037]	[0.007, 0.024]	[0.007,0.024]	[-0.008,0.037]	[0.007, 0.024]
$average\ adult\ height$	[-0.029,-0.008]	[-0.042,0.007]	[-0.029,-0.008]	[-0.029,-0.008]	[-0.042,0.006]	[-0.029,-0.008]
group 1	[-0.157,3.202]	[-2.009,5.206]	[-0.114,3.165]	[0.222,3.602]	[-2.15,5.641]	[0.29,3.595]
group 2	[-0.065,3.290]	[-1.850,5.345]	[-0.033,3.238]	[0.109,3.504]	[-2.532,5.584]	[0.173,3.452]
group 3	[-0.178, 3.217]	[-2.196,5.315]	[-0.148,3.191]	[0.327,3.680]	[-2.160,5.866]	[0.353,3.677]
group4	[-0.036,3.347]	[-1.855,5.369]	[-0.030,3.326]	[-0.246,3.190]	[-2.753,5.395]	[-0.202,3.173]
group 5	[0.032,3.377]	[-1.821,5.333]	[0.058, 3.310]	[0.127,3.541]	[-2.519,5.660]	[0.207, 3.512]
group 6	[0.234,3.559]	[-1.675,5.573]	[0.302, 3.523]	[-0.078,3.312]	[-2.519,5.380]	[-0.076,3.263]
group 7	[-0.138,3.209]	[-2.046,5.163]	[-0.080,3.197]	[-0.042,3.348]	[-2.729,5.438]	[-0.007,3.293]
group 8	[0.162,3.494]	[-1.841,5.672]	[0.208, 3.471]	[-0.171,3.261]	[-2.948,5.413]	[-0.161,3.218]
group 9	[0.026,3.38]	[-1.837,5.419]	[0.069, 3.367]	[-0.136,3.271]	[-2.558,5.500]	[-0.116,3.221]
group~10	[-0.024,3.337]	[-1.837,5.436]	[0.000, 3.305]	[0.190,3.585]	[-2.411,5.679]	[0.204, 3.554]
group 11				[0.023,3.406]	[-2.490,5.477]	[0.085,3.385]
$group\ 12$				[0.078,3.490]	[-2.617,5.790]	[0.101,3.412]
group~13				[-0.213,3.288]	[-2.986,5.667]	[-0.189,3.220]
group 14				[-0.002,3.384]	[-2.175,5.595]	[0.022,3.319]
group~15				[-0.030,3.343]	[-2.633,5.385]	[-0.015,3.340]
group16				[0.092,3.460]	[-1.787,5.625]	[0.107, 3.402]
group 17				[-0.275,3.200]	[-3.005,5.305]	[-0.235,3.123]
group 18				[0.015,3.422]	[-2.528,5.575]	[0.035,3.342]
group 19				[-0.040,3.350]	[-2.582,5.468]	[0.020,3.272]
$group\ 20$				[0.395,3.842]	[-2.071,6.180]	[0.429,3.763]
N	3737	3737	3737	3737	3737	3737

[†]This table provides 95% confidence intervals using the standard logit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. Each family is assigned to a group via a k-prototypes algorithm, for each group we include a dummy variable.

Table B20: Confidence intervals and confidence sets for the probit model with group dummies. †

			Dependent varie	uble: child obesity	y	
	Probit (1)	CCT1 (2)	CCT3 (3)	Probit (4)	CCT1 (5)	CCT3 (6)
Share of other obese children	[0.756,1.552]	[0.237,1.953]	[0.757,1.537]	[0.793,1.592]	[0.485,1.844]	[0.801,1.583]
gender	[0.169, 0.462]	[0.054, 0.621]	[0.174, 0.460]	[0.167, 0.461]	[0.082, 0.583]	[0.168, 0.456]
age	[-0.131,0.376]	[-0.364,0.605]	[-0.129, 0.370]	[-0.124,0.385]	[-0.288, 0.571]	[-0.115,0.379]
age^2	[-0.025,0.001]	[-0.036,0.012]	[-0.025, 0.001]	[-0.025,0.000]	[-0.038,0.009]	[-0.025, 0.000]
Share of obese adults	[0.041, 0.711]	[-0.278,1.019]	[0.050, 0.705]	[0.023, 0.695]	[-0.193, 0.910]	[0.030, 0.687]
log expenditures (Euro)	[-0.210,0.033]	[-0.331,0.148]	[-0.210,0.032]	[-0.229,0.013]	[-0.287, 0.084]	[-0.227, 0.009]
$average\ adult\ weight$	[0.010, 0.040]	[-0.003,0.052]	[0.011, 0.039]	[0.010,0.040]	[0.004, 0.054]	[0.011, 0.040]
$average\ adult\ height$	[-0.048,-0.012]	[-0.065,0.000]	[-0.048,-0.013]	[-0.048,-0.012]	[-0.057,-0.002]	[-0.048,-0.012]
group 1	[-0.316,5.327]	[-3.352,7.938]	[-0.273,5.315]	[0.274,5.950]	[-1.893,7.583]	[0.309, 5.860]
group 2	[-0.156,5.482]	[-3.178,8.151]	[-0.088,5.405]	[0.114,5.817]	[-2.436,7.313]	[0.125,5.738]
group 3	[-0.343,5.361]	[-3.168,7.947]	[-0.249,5.253]	[0.480,6.114]	[-2.144,7.964]	[0.511,6.024]
group 4	[-0.110,5.576]	[-3.265,7.969]	[-0.088,5.473]	[-0.468,5.308]	[-2.889,7.083]	[-0.370,5.270]
group 5	[0.001, 5.621]	[-3.021,8.157]	[0.027, 5.560]	[0.150,5.884]	[-2.379,7.396]	[0.188, 5.816]
group 6	[0.336,5.923]	[-2.550,8.450]	[0.339, 5.895]	[-0.196,5.498]	[-2.712,7.028]	[-0.154,5.454]
group 7	[-0.276,5.347]	[-3.067,7.818]	[-0.208,5.289]	[-0.127,5.571]	[-2.767,7.214]	[-0.045,5.500]
group 8	[0.207, 5.804]	[-2.807,8.426]	[0.257,5.703]	[-0.346,5.419]	[-3.036,7.181]	[-0.250,5.323]
group 9	[-0.006,5.629]	[-2.784,8.013]	[0.052, 5.614]	[-0.292,5.430]	[-2.775,6.868]	[-0.242,5.407]
group 10	[-0.095,5.553]	[-3.141,8.177]	[-0.054,5.548]	[0.249,5.954]	[-2.240,7.834]	[0.304,5.900]
group 11				[-0.021,5.665]	[-2.925,7.195]	[0.039,5.662]
group 12				[0.073,5.811]	[-2.443,7.652]	[0.107, 5.715]
group 13				[-0.426,5.467]	[-2.566,7.094]	[-0.419,5.435]
group 14				[-0.067,5.623]	[-2.686,7.286]	[0.034,5.573]
group 15				[-0.106,5.56]	[-2.494,7.140]	[-0.061,5.486]
group 16				[0.084,5.742]	[-2.441,7.309]	[0.120,5.734]
group 17				[-0.522,5.330]	[-2.963,7.085]	[-0.426,5.258]
group 18				[-0.038,5.687]	[-2.500,7.262]	[-0.035,5.684]
group 19				[-0.129,5.567]	[-2.953,7.140]	[-0.098,5.508]
group 20				[0.587,6.366]	[-1.911,8.061]	[0.607,6.349]
N	3737	3737	3737	3737	3737	3737

[†]This table provides 95% confidence intervals using the standard probit model as if it were identified and 95% confidence sets using the approach described in Chen et al. (2018). CCT1 and CCT3 denote Procedure 1 and Procedure 3 respectively. Each family is assigned to a group via a k-prototypes algorithm, for each group we include a dummy variable.

1 References

- ² Chen, X., Christensen, T. & Tamer, E. (2018). Monte Carlo confidence sets for identified
- sets. Econometrica.
- 4 Cohen, M. L. (1991). Statistical matching and microsimulation models. In C. F. Citro &
- E. A. Hanushek (Eds.), Improving information for social policy decisions the uses of

- *microsimulation modeling: Volume II, technical papers* (pp. 62–88). National Academy
- ² Press.
- ³ D'Orazio, M., Zio, M. D. & Scanu, M. (2006). Statistical Matching: Theory and Practice
- 4 (Wiley Series in Survey Methodology). John Wiley & Sons.
- ⁵ Radner, D., Allen, R., Gonzalez, M., Jabine, T. & Muller, H. (1980). Report on exact and
- statistical matching techniques. Statistical Policy Working Paper 5. U.S. Department of
- of Commerce, Office of Federal Statistical Policy and Standards.
- 8 Raghunathan, T. E., Lepkowski, J. M., Van Hoewyk, J. & Solenberger, P. (2001). A mul-
- tivariate technique for multiply imputing missing values using a sequence of regression
- models. Survey Methodology, 27(1), 85–96.
- 11 Rodgers, W. L. (1984). An evaluation of statistical matching. Journal of Business &
- Economic Statistics, 2(1), 91-102.
- Szepannek, G. (2018). clustMixType: User-Friendly Clustering of Mixed-Type Data in R.
- 14 The R Journal, 10(2), 200-208. Retrieved from https://doi.org/10.32614/RJ-2018
- -048 doi: 10.32614/RJ-2018-048