Working paper No.: 1/2023

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Abstract

The increasing trends in obesity and high body mass index (BMI) create a burden for health services and economic productivity worldwide. However, long-term trends of obesity prevalence and high-BMI prevalence by socio-economic status remain largely under-researched, in part due to limitations in data availability by educational level. In this document we describe the creation of a database on obesity prevalence (OP) and high-BMI prevalence (HBP) by educational level and sex for adjacent calendar years and uniform ages for England, Finland, and Italy. Using interpolation across years and smoothing across age, we consolidated the data from available national health surveys from the 1970s onwards, into data without missing years and with similar age groups across time. Subsequently, we applied the two-dimensional Rizzi et al. (2019) smoothing algorithm to obtain prevalence data by educational level (low, middle, high), sex, five-year age groups (25-95+) and single calendar years. The resulting smooth prevalence surfaces across age and time for the low, middle, and highly educated in England, Finland and Italy match the treated data reasonably well, and are consistent with previous evidence regarding obesity and high BMI prevalence by educational level. With our procedure, we managed to deal –in a systematic manner– with the different types of missing and inconsistent information in the obesity and high-BMI prevalence data by educational level, thereby making full advantage of the available data and using recent methodological improvements in smoothing algorithms. Our database facilitates the detailed analysis of long-term trends of obesity prevalence and high-BMI prevalence by socio-economic status and are the basis of further analysis regarding obesity attributable mortality and high-BMI attributable mortality.

Keywords: obesity; high BMI; prevalence; education; socio-economic status; databases

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1. Introduction

The increasing trends of high body mass index (BMI) and obesity worldwide (Lobstein and Jackson-Leach 2006) translate to a rising burden on health services and economic productivity (Wang et al. 2011). Obesity, particularly, is a chronic metabolic disease that has been related to diabetes mellitus (Leitner et al. 2017), cardiovascular diseases (Hamjane et al. 2020), and certain types of cancer (Redinger 2007), among other diseases.

Identifying trends of obesity prevalence (OP) and high-BMI prevalence (HBP) by socio-economic status guide the formulation of focalized, cost-effective policies aimed to deal with obesity and high-BMI in specific demographic groups (Lhachimi et al. 2013). Trends in OP and HBP by socio-economic status remain however under-researched (see Kagenaar et al. 2022 for an overview) and generally include only a limited age range (e.g. Hoffmann et al. 2017) and no age-specific outcomes (Hoffmann et al. 2017; Kagenaar et al. 2022). Hence, in this document we describe the creation of a database on obesity and high BMI prevalence by educational level and sex for adjacent calendar years and uniform ages (25+) for England, Finland, and Italy.

In the next section (**Section 2**) we describe the data we used and the methods we applied to obtain OP and HBP for Finland, England, and Italy. In **Section 3** we show the results of obesity prevalence and high-BMI prevalence in these countries. We offer concluding remarks in **Section 4**. The Appendix at the document briefly describes the use of the MatLab and R scripts and functions that were used to estimate OP and HBP for Finland, England, and Italy.

2. Data and methods

2.1. Survey data

Table 1 shows a summary of the surveys that we used to calculate obesity prevalence and high-BMI (overweight+obesity) prevalence, by educational level, in Finland, Italy, and England. Table 2 provides more details about the information available in these surveys. In the surveys, obesity is defined as BMI >= 30 kg/m2, and high BMI as BMI >= 25 kg/m2.

For Finland, aggregate obesity, overweight, and survey counts by educational level, sex, and age—based on self-reported height and weight—are available for adjacent years from 1978 to 2020. However, there is only information for the ages 15-55+ (every 5 years) in the years 1978 up to 1992, and in 1994, 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, and 2014. Due to this missing information for older adults, linear regression for each age-group was used to extrapolate the information for the age groups 65-75+ between the years 1978 to 1992, on the basis of the observed information available 1993 to 2013, and interpolation with an average between years for the age groups 65-75+ in the years 1994, 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, and 2014. This extrapolation and interpolation were performed before the 1D and the 2D smoothing.

The database of Finland contains information of the following variables: the measure (obesity, overweight, and overweight+obesity), year, education level, age group, sex, the counts of obesity, overweight, and overweight+obesity, the percentage of overweight, and overweight+obesity, the survey counts, the weights, the standard error, the lower confidence interval, and the upper confidence interval of the mean estimations. The data stem from the Health Behavior and Health of Adult Population (AVTK) for the years 1978 to 2014, the Health behavior and Health among Finnish Elderly (EVTK) surveys for every two years between 1993 and 2011), the Adult Health, Welfare and Service Research (ATH) for the years 2013 to 2017, and the FinSote national survey of health for the years 2018 to 2020. Weighted data was only available for 2013-2017. We obtained the data grouped in 10-year age intervals, but the data of ATH starts at age 20 and ends at age 90+, the data of AVTK-EVTK starts at age 15 and ends at 75+, and the data of FinSote starts at age 10 and ends at age 90+.

Table 1. Data sources*

	Window of analysis	Surveys	Age range	Age interval	Data received	Weights
Finland	1978-2020	AVTK (1978-2014) EVTK (1993-2011 every two years) ATH (2013-2017) FinSote (2018-2020)	15-64 (1978-1992, and every 2 years from 1994-2012) 15-84 (every 2 years from 1993-2011)* 20-90+ (2013-2017) 10-90+ (2018-2020)	10 years	Aggregated data based on self-reported height and weight	Weighted data was only available from 2013 to 2017
England	1991-2018	HSE (1991-2018)	15-80+	5 years (1991-2013, 2015-2018) 10 years (2014)	Individual level data on measured height and weight	Weights were only available from 2003 onwards
Italy	1990-2018	NMSS (1990/1) HCHS (1994, 1999/2000, 2004/05, 2013) AVQ (2001-2018)	18-80+ (1990/1) 18-75+ (2001-2018) 15-85+ (1994, 1999/2000, 2004/05, 2013)	5 years (1990/1, 1994, 1999/2000, 2004/05, 2001-2012) 10 years (2013-2018)	Aggregated data (1990/1); individual level data (remaining years); Self-reported height and weight	Weighted data (1990/1) or weights were available throughout

(*) Combining information from the AVTK and the EVTK surveys, see Table 2 for details. The data for Finland were obtained from the Finnish Institute for Health and Welfare (THL). The data for England were obtained from the National Health Service (NHS) UK Dataservice. The data for Italy were obtained from the Italian National Institute of Statistics (ISTAT).

In England, individual level data on measured height and weight for ages 15-85+, for adjacent years from 1991 to 2018, was obtained from the Health Survey for England (HSE). The age of the individuals was provided in five-year age groups for the years 1991-2013 and 2015-2018, and in 10-year age groups for the year 2014. Weights were only available from 2003 onwards. No interpolation or extrapolation was applied to the data of England, and only the information of the year 2014 receive a treatment with the 1D Rizzi et al. algorithm: with the purpose of obtaining uniform age groups, we disaggregated the information of the year 2014 into single-year age groups and later we aggregated this data into five-year age groups similar to those of the years 1991-2013 and 2015-2018.

Table 2. Data sources (detailed)*

Finland

year	survey	age group	age interval
1978	AVTK	15-64	10
1979	AVTK	15-64	10
1980	AVTK	15-64	10
1981	AVTK	15-64	10
1982	AVTK	15-64	10
1983	AVTK	15-64	10
1984	AVTK	15-64	10
1985	AVTK	15-64	10
1986	AVTK	15-64	10
1987	AVTK	15-64	10
1988	AVTK	15-64	10
1989	AVTK	15-64	10
1990	AVTK	15-64	10
1991	AVTK	15-64	10
1992	AVTK	15-64	10
1993	AVTK + EVTK	15-84	10
1994	AVTK	15-64	10
1995	AVTK + EVTK	15-84	10
1996	AVTK	15-64	10
1997	AVTK + EVTK	15-84	10
1998	AVTK	15-64	10
1999	AVTK + EVTK	15-84	10
2000	AVTK	15-64	10
2001	AVTK + EVTK	15-84	10
2002	AVTK	15-64	10
2003	AVTK + EVTK	15-84	10
2004	AVTK	15-64	10
2005	AVTK + EVTK	15-84	10
2006	AVTK	15-64	10
2007	AVTK + EVTK	15-84	10
2008	AVTK	15-64	10
2009	AVTK + EVTK	15-84	10
2010	AVTK	15-64	10
2011	AVTK + EVTK	15-84	10
2012	AVTK	15-64	10
2013	AVTK + EVTK	15-84	10
2013	ATH	20-90+	10
2014	ATH	20-90+	10
2014	AVTK + EVTK	15-84	10
2015	ATH	20-90+	10
2016	ATH	20-90+	10
2017	ATH	20-90+	10
2018	FINSOTE	10-90+	10
2019	FINSOTE	10-90+	10

England

year	survey	age group	age interval
1991	HSE	25-85+	5
1992	HSE	25-85+	5
1993	HSE	25-85+	5
1994	HSE	25-85+	5
1995	HSE	25-85+	5
1996	HSE	25-85+	5
1997	HSE	25-85+	5
1998	HSE	25-85+	5
1999	HSE	25-85+	5
2000	HSE	25-85+	5
2001	HSE	25-85+	5
2002	HSE	25-85+	5
2003	HSE	25-85+	5
2004	HSE	25-85+	5
2005	HSE	25-85+	5
2006	HSE	25-85+	5
2007	HSE	25-85+	5
2008	HSE	25-85+	5
2009	HSE	25-85+	5
2010	HSE	25-85+	5
2011	HSE	25-85+	5
2012	HSE	25-85+	5
2013	HSE	25-85+	5
2014	HSE	25-34, 35-44, 45-54, 55-64, 65-69, 70-74, 75-79, 80-84, 85+	10
2015	HSE	25-85+	5
2016	HSE	25-85+	5
2017	HSE	25-85+	5
2018	HSE	25-85+	5

Italy

year	survey	age group	age interval
1990/1991	NMS	18-80+	5
1994	HHCU	15-85+	5
1999/2000	HHCU	15-85+	5
2001	ADL	18-75+	5
2002	ADL	18-75+	5
2003	ADL	18-75+	5
2004/2005	HHCU	15-85+	5
2005	ADL	18-75+	5
2006	ADL	18-75+	5
2007	ADL	18-75+	5
2008	ADL	18-75+	5
2009	ADL	18-75+	5
2010	ADL	18-75+	5
2011	ADL	18-75+	5
2012	ADL	18-75+	5
2013	HHCU	15-85+	5
2013	ADL	18-75+	10
2014	ADL	18-75+	10
2015	ADL	18-75+	10
2016	ADL	18-75+	10
2017	ADL	18-75+	10
2018	ADL	18-75+	10

(*) The data for Finland were obtained from the Finnish Institute for Health and Welfare (THL). The data for England were obtained from the National Health Service (NHS) UK Dataservice. The data for Italy were obtained from the Italian National Institute of Statistics (ISTAT).

Italy has self-reported height and weight information for the years 1990, 1994, 1999/2000 (that was assigned to the year 1999) and for the years 2001 to 2018. The data from the first two sources were received grouped by five-year age groups, data from the last source was provided by five-year age groups from 2001 up to 2012 and by 10-year age groups from 2013 up to 2018. For all years, weights were available. The missing information of the years 1991-1993, 1995-1998, and the information 2000, were interpolated with an average for each age group. Additionally, 1D smoothing was applied to the information between the years 2013 to 2018 to obtain uniform age-groups, because the age groups between the years 2013 up to 2018 (20-24, 25-34, 35-44, 45-54, 55-59, 60-64, 65-74, 75+) are different compared to the age-groups of the years 1990 to 2012 (20-85+, 5-year age intervals). The sources of the data are the National Multipurpose Social Survey (NMSS) for the year 1990 (aggregate count data), the Health Conditions and use of Health Services (HCHS) for the years 1994, 1999/2000, 2004/2005, 2013 (individual level data), and the Aspects of Daily Life (Aspetti della vita quotidiana, AVQ) for the years 2001 to 2018 (individual level data).

In all databases, the level of education was measured based on the highest level of education completed or highest degree obtained, except for Finland where the level of education was based on years of schooling. The level of education was categorised into low educated (levels 0-2: no, primary or lower secondary education), middle educated (levels 3-4: upper secondary and post-secondary non-tertiary education), and high educated (levels 5-6: tertiary education) using the International Standard Classification of Education (ISCED) 1997. Details about the conversion of the country-specific educational classification to the ISCED 1997 classification can be found in the Supplementary File II of Kagenaar et al. (2022). As in Kagenaar et al. (2022), we use a lower age limit of 25 years to ensure the validity of educational attainment as a measure of socio-economic status.

2.2. Methods

We calculated obesity and high BMI prevalence simultaneously across age and across time, by sex and educational level (low, middle, high), applying the two-dimensional smoothing algorithm of Rizzi et al. (2019). The estimation of obesity and high BMI prevalence by educational level requires a database of obesity and high BMI by adjacent years, sex, educational level (low, middle, high) and uniform age groups. The obstacles to build the database were that the original (raw) data of the surveys have different sources (different types of surveys with different formats) and are grouped in dissimilar age groups, with missing data for some age groups (particularly for the older age groups), and missing data for some years, plus that there were occasional strata with missing data for the years and age groups, because of low cell counts.

Our approach to deal with these obstacles was to interpolate and extrapolate missing values and apply one-dimensional and two-dimensional smoothing using the Rizzi et al. (2015) and the Rizzi et al. (2019) algorithms available in the R package “ungroup” (Pascariu et al., 2018). The Rizzi et al. (2019) algorithm is based on a bivariate Poisson stochastic process, in line with obesity and high BMI having a bivariate distribution of counts by age and calendar years. The Rizzi et al. (2019) algorithm maximizes a penalized likelihood of B-splines applied to the bivariate distributions of obesity and high BMI by age and calendar years. Through this maximization, the Rizzi et al. (2019) algorithm produces detailed smooth surfaces of prevalence, but it needs data of adjacent calendar years and age groups without missing strata for a proper estimation. Hence, before applying two-dimensional (2D) bivariate smoothing, interpolation was applied first to estimate obesity and high-BMI counts for calendar years and age groups with missing information. Later, one-dimensional (1D) smoothing with the Rizzi et al. (2015) algorithm was applied to obtain data for similar age groups across time. In the 2D smoothing algorithm, the optimization is based on the minimization of the Bayesian Information Criterion (BIC), as BIC was suggested as a proper statistic to compare competing models of bivariate densities based on B-splines (Lambert, 2011).

Table 3. Parameters used in the 1D Rizzi et al. algorithm

Rizzi algorithm	Country	Stratum	Last age interval	Knots	Polynomial degree
1D Rizzi	England	All	25	7	3
	Finland	All	25	7	3
	Italy	All	25	7	3

The input of the 1D smoothing algorithm are counts aggregated in age groups (as the Rizzi et al. 1D algorithm is based also on a Poisson stochastic process), and the output produced by the algorithm are counts disaggregated by single years. The inputs of the 2D smoothing algorithm are (1) aggregated counts as the numerator of a ratio, and (2) counts for the denominator of a ratio. The output of the 2D algorithm is not however disaggregated counts, but rather disaggregated rates (in this case, prevalence). Table 3 below shows the values of the parameters we used in the 1D and 2D smoothing algorithms for each country. For Italy, due to a lack of consecutive information by calendar years, it was necessary to use different parameters to calibrate the 2D algorithm by sex and educational level, changing the endpoint of the final age interval, the number of knots or the degree of the polynomial, in order to avoid the presence of the Runge phenomenon (this is, explosive trends at the end of the estimated surface). For the 1D algorithm for Finland, we selected the open-ended age interval to be equal to 25 years for the surveys that go up to 75 years. In England, the final age group is 80 years, and hence in the 1D algorithm we selected the extrapolation to be 20 years. In Italy, the final age group is 75 years, and hence in the 1D algorithm we chose the extrapolation to be 25 years. Thus, for all countries, we chose the last grouped interval to last until 100 years old for extrapolation in the 1D algorithm. We opted for the upper limit of 100 years for the 1D algorithm because when applying the 2D algorithm values above 100 years were discarded as were not considered reliable.

In the case of Italy, we applied an additional fine tuning of the hyper-parameters of the 2D Rizzi et al. (2019) algorithm to avoid the bias in the smoothed trends by educational level. Table 4 shows the results of the fit the smoothed trends, before and after the fine-tuning of the hyper-parameters of the Rizzi et al. algorithm. In all cases, the fit, measured by the R-square (R^2), is equal or higher after fine tuning the parameters of the Rizzi et al. algorithm for each stratum of sex and educational level in Italy. In the case of England and Finland, the same parameters were used for all strata (Table 4).

Table 4. Hyper-parameters of the 2D Rizzi et al. filter used for smoothing each stratum of sex and educational level in Italy, England & Wales, and Finland							
Parameters of the Rizzi filter		**Male**			**Female**		
		Low educated	**Middle educated**	**High educated**	**Low educated**	**Middle educated**	**High educated**
Obesity							
Italy	Knots of the spline	10	10	7	10	6	10
	Polynomial degree	4	4	3	4	3	8
	Last interval (years)	35	35	35	30	35	35
England & Wales	Knots of the spline	8	8	8	8	8	8
	Polynomial degree	6	6	6	6	6	6
	Last interval (years)	25	25	25	25	25	25
Finland	Knots of the spline	8	8	8	8	8	8
	Polynomial degree	6	6	6	6	6	6
	Last interval (years)	20	20	20	20	20	20
High BMI							
Italy	Knots of the spline	10	10	10	10	7	10
	Polynomial degree	5	5	5	4	5	8
	Last interval (years)	30	30	30	30	35	35
England & Wales	Knots of the spline	8	8	8	8	8	8
	Polynomial degree	6	6	6	6	6	6
	Last interval (years)	25	25	25	25	25	25
Finland	Knots of the spline	8	8	8	8	8	8
	Polynomial degree	6	6	6	6	6	6
	Last interval (years)	20	20	20	20	20	20

We followed five steps to derive the database of OP and HBP. A short description can be found below, followed by a more detailed description on the subsequent pages.

1. **Pre-processing:** For Italy and England, aggregate OB and OBOP prevalence data were compiled based on the individual level data on height and weight. Unweighted data was used to calculate OBP and HBP trends in England and Finland, respectively, as in these two countries the unweighted data provides consistent and comparable series of obesity and overweight counts across calendar years. For Italy, we used the weighted data throughout.
2. **Treatment of calendar years and age groups without data:** these missing values were estimated through interpolation (Italy) and extrapolation (Finland).
3. **Treatment of dissimilar age groups over time:** we applied 1D smoothing (Rizzi et al. 2015) to deal with dissimilar age groups (size, start of open-ended age interval) over time for obesity counts, high-BMI counts, and respondents/population counts. The results were count data by single ages.
4. **Aggregation and consolidation:** In this step, we built country-level datasets with counts of adjacent calendar years and uniform five-year age groups. The data that already had uniform five-year age groups was combined with the smoothed data by single age, after their aggregation into the same age groups.
5. **2D smoothing:** we applied 2D smoothing to the consolidated data with uniform age-groups for the different countries to obtain the database of obesity and high BMI prevalence by educational level and sex for adjacent calendar years and uniform ages, for Finland, Italy, and England.

The pre-processing stage was done as part of the data handling in Kagenaar et al. (2022). For Italy and England, aggregate data was compiled based on the individual level data on height and weight, thereby applying the weights for Italy, but not for England, as weights for England were only available from 2003 onwards. So, whereas for Italy we used the weighted data to estimate obesity and high-BMI prevalence, for England –and also for Finland– we used unweighted data because only the unweighted consistent and comparable time series could be obtained. In the case of Italy, there exist surveys for the years 1990/1991, 1999/2000, 2004/2005. For these surveys, it was assumed that the information represents the situation in the years 1990, 1999 and 2004, respectively. In Italy there is also two separate surveys for the year 2013, one is the HHCU survey and the other the ADL survey. The information of the HHCU for the year 2013 was not used in the estimation but rather the information of the ADL survey, in order to keep a consistent time trend, as in Kagenaar et al. (2022). In Finland, there is also information from two separate surveys for the year 2014, one from the ATH survey and the other from the AVTK+EVTK survey. In this case, the information of the AVTK+EVTK survey was used instead of the ATH, in order to keep a consistent time series, as in Kagenaar et al. (2022).

During the treatment of missing values, we distinguished three different types of missing values: (i) missing strata within the available data, (ii) age groups with no data for part of the survey years, (iii) calendar years with no data. That is, to address missing strata within the available data and calendar years with no data, we applied interpolation of the counts of the respective strata by averaging the information of the previous and subsequent survey years. To complete the missing information of older age groups (those aged 65 and over) for Finland in the years 1978 up to 1992, we applied extrapolation with linear regression. The linear regressions were estimated with the observed data of older age groups available for the years 1993, 1995, 1997, 1999, 2001, 2003, 2005, 2007, 2009, 2011 and 2013, while interpolation with an average between years was applied for the age groups 65-75+ in the years 1994, 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, and 2014. Figure 1 shows that the interpolation captures the descending trends of counts of respondents and high BMI for the low educated strata and reflects the historical trends of obesity separately by stratum in the older age groups. Figures 2.1, 2.2 and 2.3 show the age patterns of the observed and the interpolated data of Finland, for all age groups. The linear interpolation captures the observed age patterns of respondents, obesity and high-BMI counts in the age groups of 65-74 and 75+ years, for the different strata: low educated men (s11), middle educated men (s12), highly educated men (s13), low educated women (s21), middle educated women (s22), highly educated women (s23).

Regarding the calendar years with no data for Italy (1991, 1992, 1993, 1995, 1996, 1997, 1998, and 2000), we interpolated both the obesity and obesity/overweight counts, and the population counts on the basis of the available information for adjacent years. Specifically, the counts in 1990 and 1994 were interpolated to obtain an estimate of the counts from 1991 up to 1993; the counts in 1994 and 1999 were interpolated to obtain estimates of the counts from 1995 up to 1998, and the counts in 1999 and 2001 were interpolated to obtain an estimate of the counts in the year 2000. Since the information of the year 1990 of Italy only have information up to 80+ years, the interpolation for the years 1991, 1992 and 1993 only goes up to 80+ years, while the interpolation for the years 1995 to 1998 goes up to 85+ years.

The treatment of dissimilar age groups over time was necessary because the data came with dissimilar age groups over time. That is, the data was provided either in 5- or 10-year age groups, the data in 10-year age groups starts at different ages over time, and also the start of the open-ended age interval differs over time. Figure 3.1 shows that discontinuities in the smoothed surfaces of prevalence are obtained when the 2D Rizzi et al. algorithm is applied separately to surveys with dissimilar age groups. Specifically, Figure 3.1 illustrates as an example the discontinuity produced when applying the smoothing algorithm to the AVTK+EVTK and ATH/FinSote surveys of Finland separately. Figure 3.2 in contrast shows that no discontinuities in the prevalence surface exist when the 2D Rizzi et al. algorithm is applied to a single data frame of consolidated data, this is, to a single database that includes both the AVTK+EVTK and the ATH/FinSote surveys with similar age groups that were uniformized with the 1D algorithm. We therefore first treated the issue of dissimilar age groups over time by performing one-dimensional (1D) smoothing over age through the efficient estimation of smooth distributions by Rizzi et al. (2015). The 1D smoothing technique by Rizzi et al. ensures that the total count across age is closer to the aggregated counts before and after smoothing. Our results show that pre-smoothing the data with the 1D algorithm and subsequently applying the 2D algorithm produces a smooth surface without breaks (Figure 3.2), which also has a good fit to the observed data.

For Finland, we have data by 10-year age groups throughout but the data for the years 1978-2014 started at age 15, compared to 20 or 10 in the other years. Moreover, the data for the years 1978-2012 either only covered the adult ages (15-64) or purely those aged 15-84, whereas the data for the years 2013-2020 included 95+ as the open-ended age interval. We therefore applied 1D smoothing to the data from 1978 to 2012 resulting in data by single years of age from age 15 up to 99 years old which we grouped in the next step. For England, the only issue was that in the year 2014 the individual data from HSE (covering age 15-80+) was grouped in a ten-year age group, whereas in the other years the individual data from HSE was grouped in five-year age groups. We therefore applied 1D smoothing to the data in 2014 resulting in data by single years of age from 15 up to 99 years old, which we grouped in the next step. For Italy, we applied 1D smoothing to the counts for 2014 up to 2018, as in these years the data was available in 10-year age groups instead of 5-year age groups in the other years, and also had a lower starting age of the open-ended age interval (75). The 1D smoothing resulted in data by single years from age 18 up to age 99, which we grouped in the next step.

In the step of aggregation and consolidation, we aggregated the smoothed counts by single ages for the years with less ideal age groupings into uniform age groups across years by country. In Finland, the smoothed counts by single ages (15-99) for the years 1978 up to 2012 were aggregated in ten-year age groups starting at age 20, with an open-ended age group of 90+, in line with the age grouping in 2013 up to 2020. The consolidated data for Finland, consequently, has yearly information from 1978 up to 2020, with uniform ten-year age groups (20-29, …, 80-89, 90+).

Figure 1. Extrapolation of missing information for those aged 65 and over in Finland in the years 1978-1992 based on data from 1993 onwards. Trends by educational level and age group

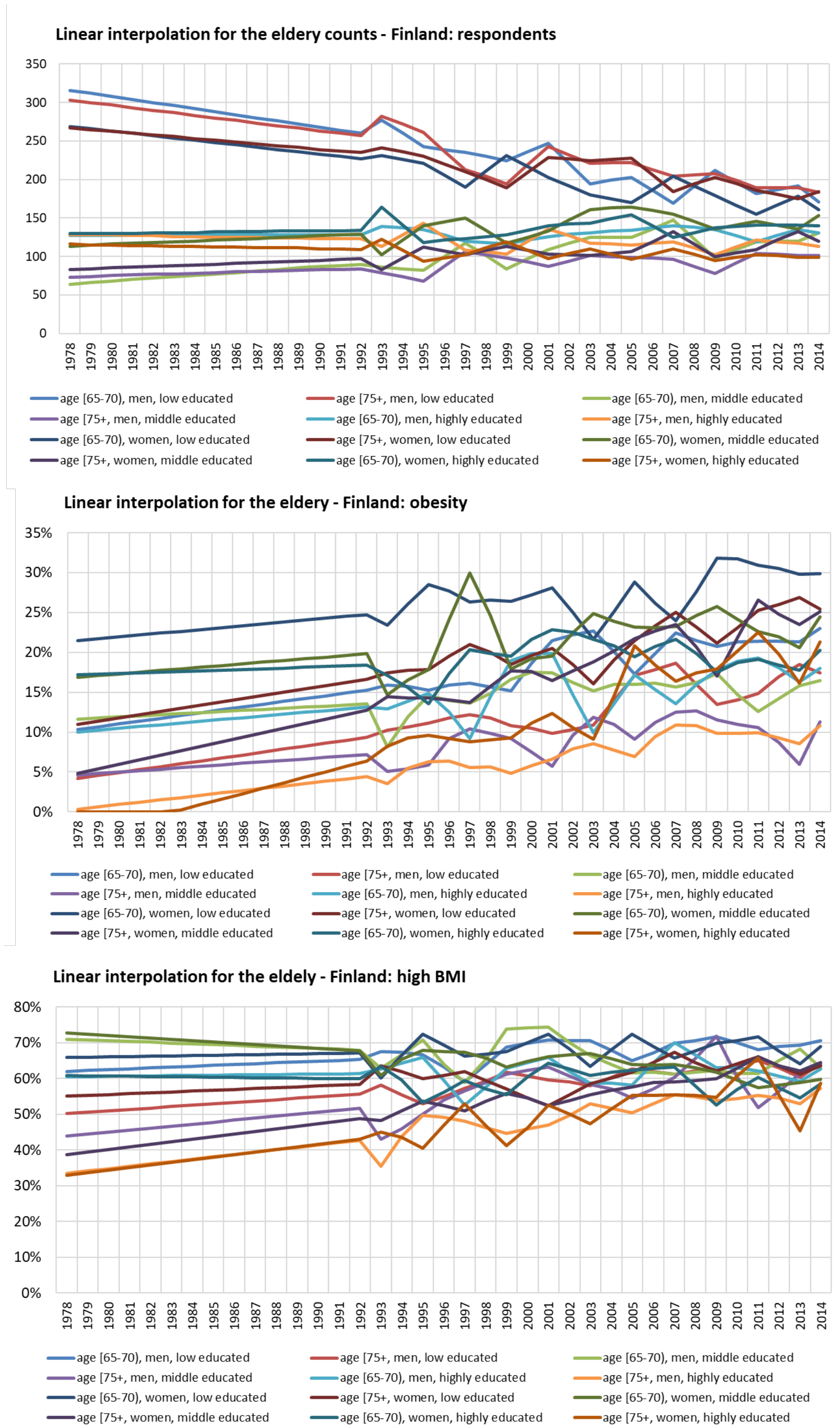


Figure 2.1 Extrapolation of missing information for those aged 65 and over in Finland in the years 1978-1992 based on data from 1993 onwards
Trends by educational level and age group

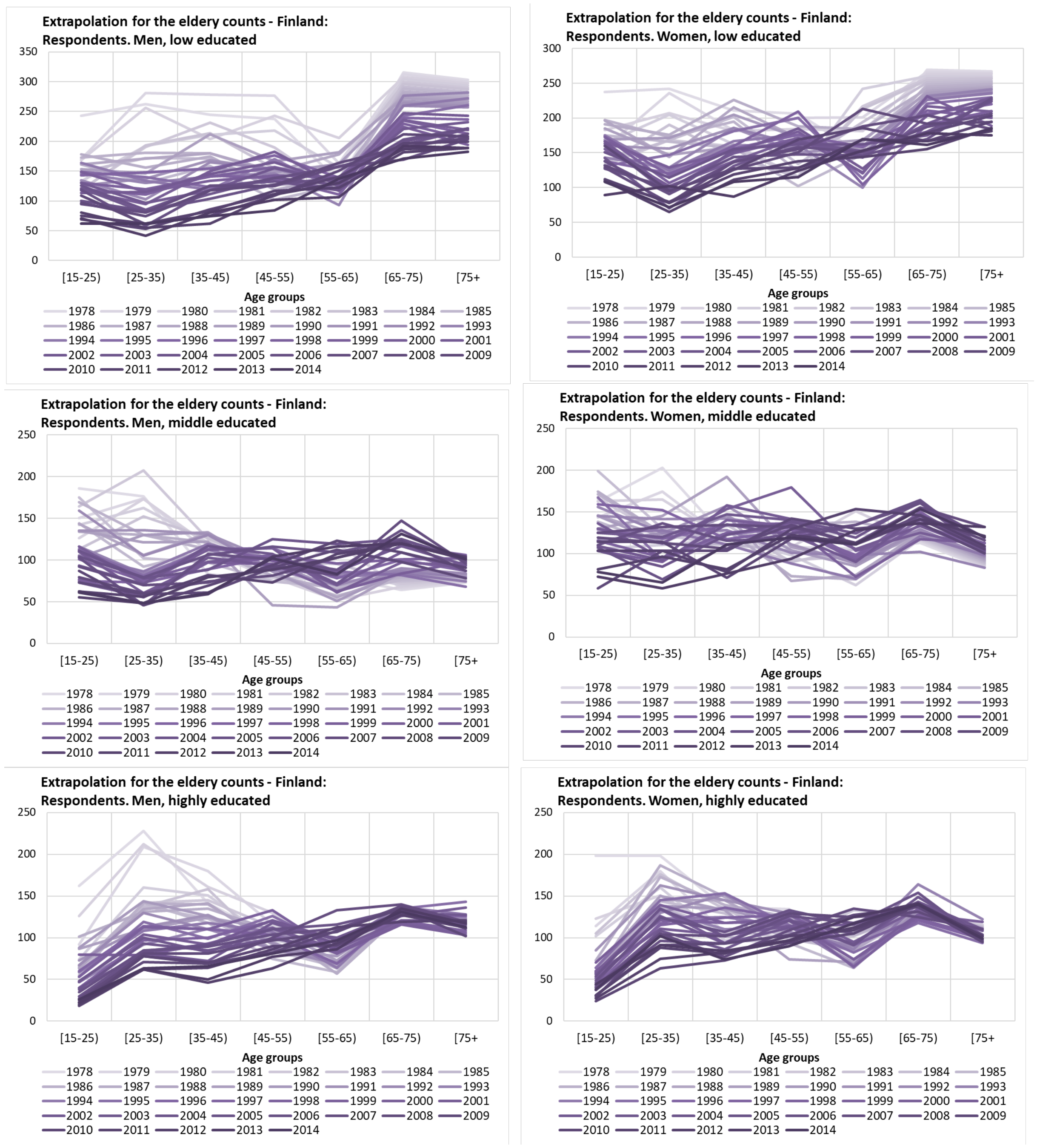


Figure 2.2 Extrapolation of missing information for those aged 65 and over in Finland in the years 1978-1992 based on data from 1993 onwards: obesity.
Trends by educational level and age group

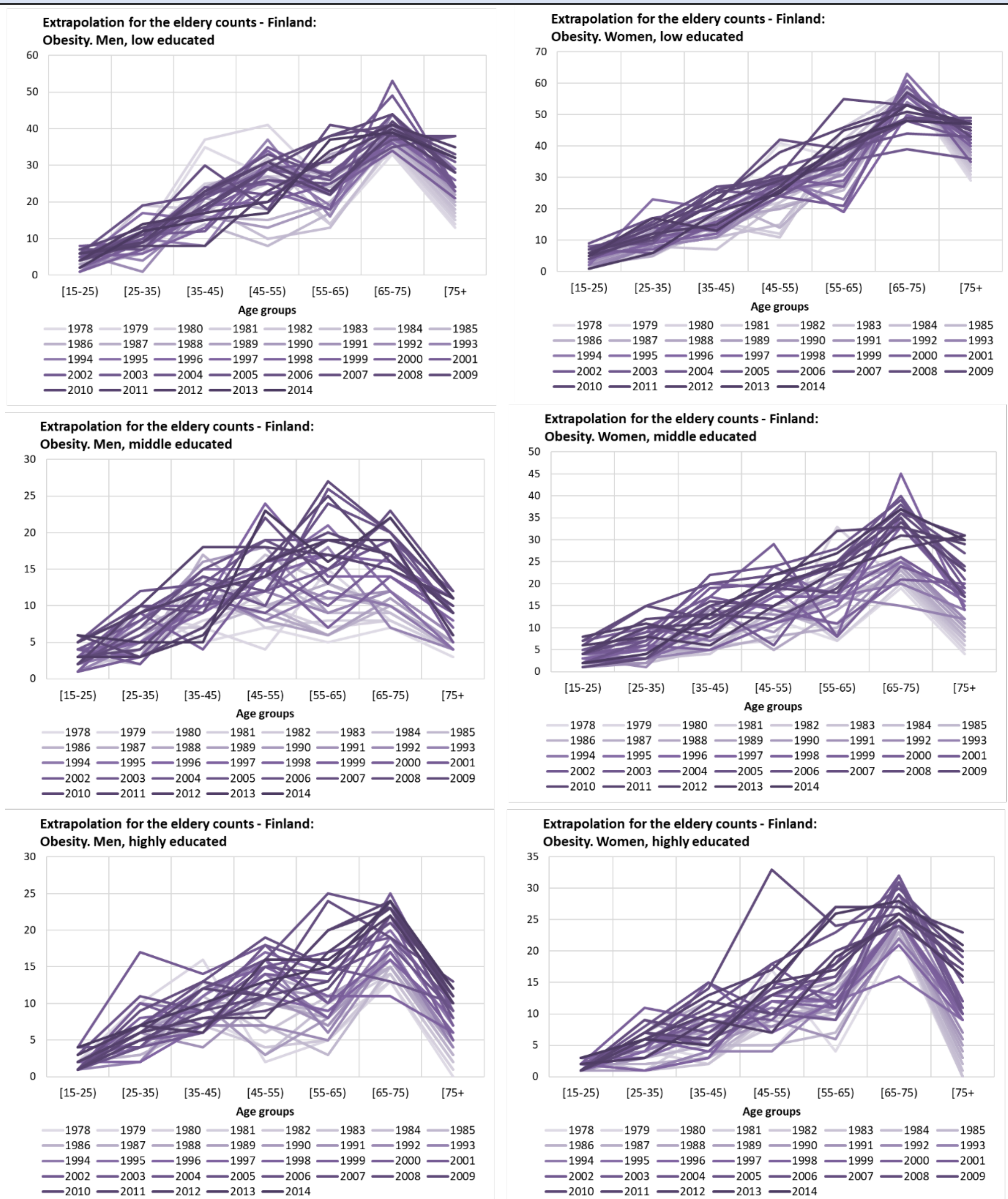
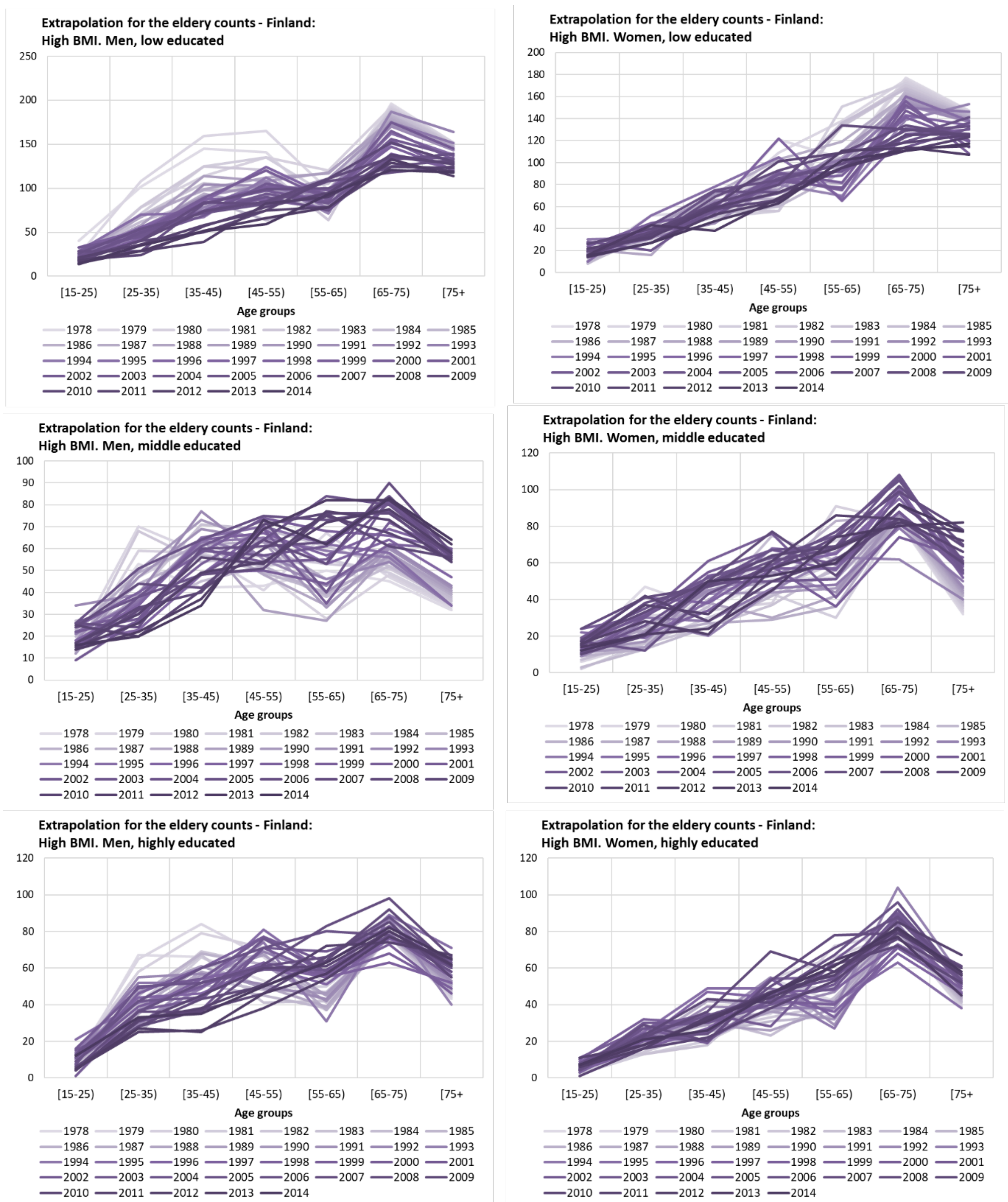


Figure 2.3 Extrapolation of missing information for those aged 65 and over in Finland in the years 1978-1992 based on data from 1993 onwards: high BMI
Trends by educational level and age group



In England, the smoothed counts by single ages (15-99) for the year 2014 were aggregated to five-year age-groups starting at age 25, with an open-ended age group of 80+, in line with the age grouping in all other years from 1991 up to 2008. The consolidated data for England, consequently, has yearly information from 1991 up to 2018, with uniform five-year age groups (25-29, …, 75-79, 80+). Finally, for Italy, the smoothed counts by single ages (18-99) for the years 2014 to 2018 were aggregated to five-year age groups starting at age 25, with an open-ended age group of 85+. The consolidated data for Italy, consequently, has yearly information from 1990 up to 2018, with uniform five-year age groups (25-29, …, 80-84, 85+).

Two-dimensional (2D) smoothing with the algorithm by Rizzi et al. (2019) was applied to the consolidated data for Finland, England, and Italy, with different age groupings by country, in order to obtain the desired database with both calendar-year-specific and age-specific (25-95+) obesity and high BMI prevalence by educational level and sex. The 2D Rizzi et al. (2019) smoothing algorithm produces results that are robust to the presence of outliers, an advantage over other smoothing algorithms such as LOESS (locally estimated scatterplot smoothing) that are distorted by the presence of outliers (Cleveland, 1979). Optimal values of the smoothing parameters were chosen as those that minimize the Bayesian Information Criterion (BIC). A pseudo-out-of-sample extrapolation experiment was performed to calibrate the hyperparameters of the 2D Rizzi algorithm, based on obesity data for Finland.

Figure 3.1. Example of surfaces estimated with discontinuities when using survey data with dissimilar age groups: AVTK+EVTK vs. ATH/FinSote for low educated men, Finland

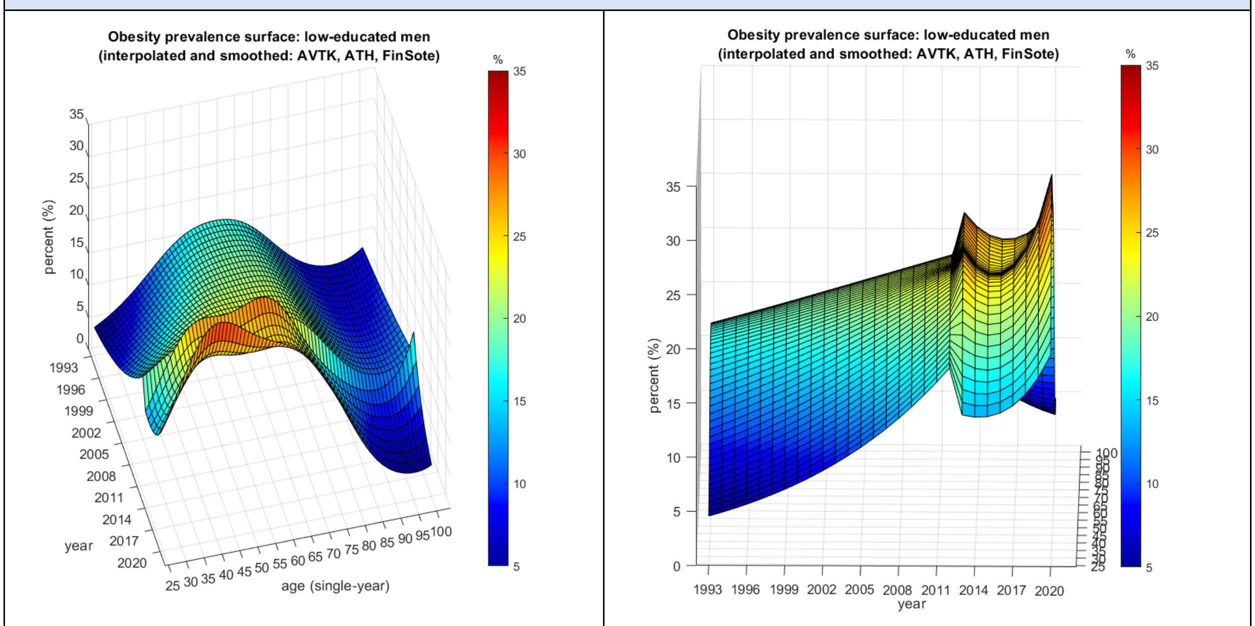
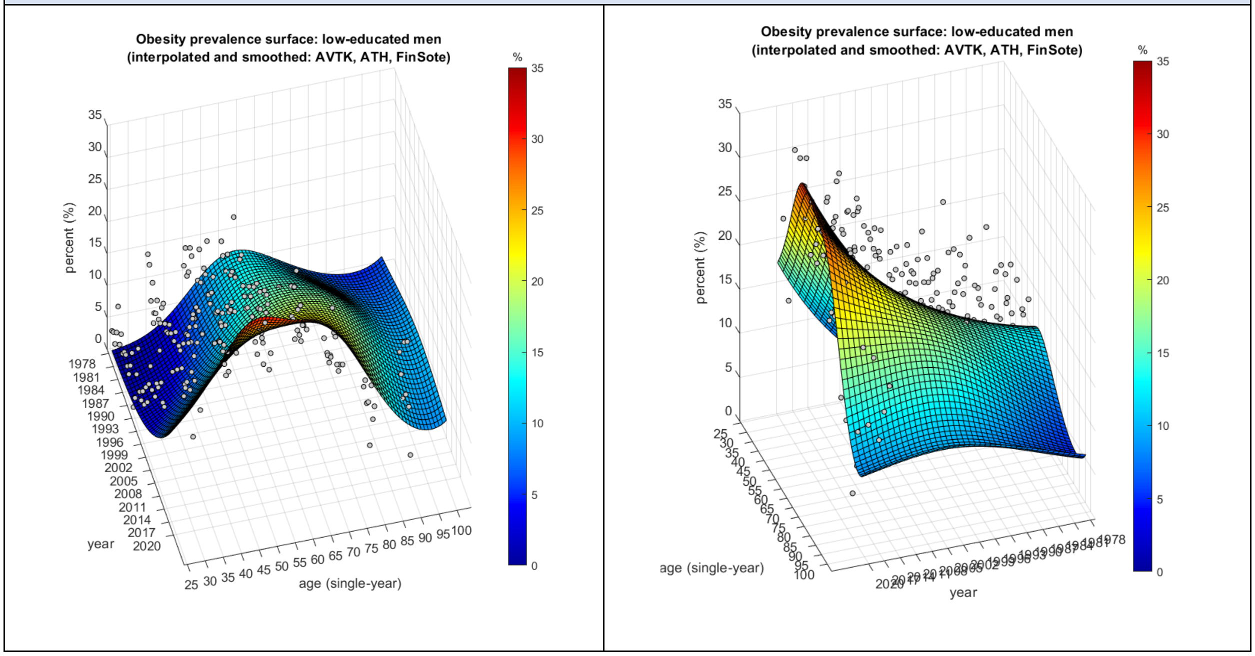


Figure 3.2. Example of surfaces estimated with survey data with similar age groups: AVTK+EVTK vs. ATH/FinSote for low educated men, Finland



The purpose of the experiment was to choose the optimal values of the polynomial degree (*d*), the number of knots (*k*) in the B-splines, as well as to decide and decide if it is more convenient to create artificial data before applying the smoothing or rather find which amplitude use for the last open-ended age interval. The experiment was aimed to identify which values of *d* and *k* can be used to recover the patterns of obesity prevalence for the elderly. As only Finland has complete information for the older age groups up to 90+, the data of this country was used to calibrate the Rizzi 2D algorithm in the pseudo-out-of-sample extrapolation experiment. The data of Finland for the years 2013 up to 2020 for each stratum were divided into one subsample with data comprising those aged 25-79 years old (the train sample) and another dataset with those aged 80-90+ (the test sample). The estimates of obesity prevalence for those aged 80 and over obtained through the train sample –using different experiments– were compared with the real prevalence for those aged 80 and over that was hold out (the test sample). We applied the following experiments:

- **An artificial endpoint equal to zero for 110 years old or 130 years old.** This implied generating artificial data based on an extrapolation of the data for the last observation until an artificial zero as the final observation at either age 110 or age 130.
- **No artificial endpoint, and instead discarding values (burn-in).** In the burn-in method the end age for the open-ended age interval (which is a parameter in the Rizzi et al. 2019 method) was chosen as 110 years and –subsequently– the smoothed values above 100 years were discarded. To come to 110 as the end age for the open-ended age interval, we performed experiments with different end ages. It proved that an end age of 110 years minimizes the root mean squared error and the mean absolute error in the pseudo-out-of-sample extrapolation experiment, and therefore this end age of 110 years is used as part of "burn-in".

— **Different number of knots (k) in the splines (from 3 to 8).**
— **Different values of the polynomial degree (d) in the splines (from 2 to 12).**

We used the following measures of accuracy to compare the results: the root-mean square error (RMSE), the mean absolute error (MAE) and the R-square between the fitted and the observed data. Table 3 below indicates that a good approximation to end-of-life obesity prevalence is obtained using a higher number or knots (=8), a polynomial of degree 6, and using a burn-in, without endpoint imputation, that discards smoothed values above 100 years. The resulting values of $d = 6$ and $k = 8$ that minimized the root mean square error and the mean absolute error in the test sample were consequently used when applying the 2D Rizzi filter in Finland, Italy, and England, for both obesity and high-BMI. Values equal to or above 100 years old were disregarded due to the presence of the Runge (1901) phenomenon. Also, BMI is not considered a precise measure of obesity in the elderly, due to age-related height declines in older adults, due to the compression of vertebral bodies and kyphosis, i.e., the posterior convex angulation of the spine (Villareal et al., 2005), which will cause BMI to increase, even with minimal changes in body weight (Decaria et al., 2012). As with advancing age, fat tends to be redistributed towards more abdominal fat, central adiposity measures such as absolute girth, waist circumference, body shape and waist-to-hip ratio are considered to be more useful than BMI in assessing levels of body composition in the elderly.

Table 3. Performance metrics for values of the parameters of the Rizzi et al. algorithm

			low educated men			highly educated women			Average		
End point	knot	degree	RMSE	MAE	R2	RMSE	MAE	R2	RMSE	MAE	R2
110	7	3	21.5	17.0	20.0	13.9	12.1	21.0	17.7	14.6	20.5
130	7	3	11.8	9.2	13.9	13.3	11.1	19.4	12.6	10.1	16.7
130	8	6	9.8	8.2	11.5	9.9	8.7	24.9	9.8	8.4	18.2
burn-in	7	3	8.8	7.7	12.0	13.3	11.1	19.4	11.1	9.4	15.7
burn-in	3	3	9.6	8.1	18.3	12.4	10.9	7.6	11.0	9.5	13.0
burn-in	7	2	10.3	7.0	12.7	20.1	17.0	19.0	15.2	12.0	15.9
burn-in	7	4	14.7	10.0	0.3	17.3	14.0	15.9	16.0	12.0	8.1
burn-in	3	4	9.0	7.9	16.6	13.4	11.5	9.4	11.2	9.7	13.0
burn-in	8	2	10.9	7.5	13.8	20.6	16.1	16.6	15.7	11.8	15.2
burn-in	8	6	7.5	6.6	15.3	10.4	9.1	27.5	9.0	7.8	21.4
burn-in	8	12	12.5	11.0	9.3	9.8	7.8	30.8	11.1	9.4	20.1

Note: In the table above, the red color indicates the worst values of RMSE, MAE and R2 (higher values in the case of RMSE and MAE, and lower values in the case of R2), while the green values indicate the best values of RMSE, MAE and R2 (lower values of RMSE and MAE, and higher values of R2). Yellow and orange colors show intermediate cases between the worst and the best values.

Table 5. R^2 (fit) of the smoothing trends in Italy, England & Wales, and Finland (by sex and educational level)						
	male			**female**		
	low	**middle**	**high**	**low**	**middle**	**high**
Obesity						
Italy: Before fine tuning*	0.909	0.782	0.821	0.237	0.733	0.652
Italy: After fine tuning**	0.903	0.869	0.872	0.911	0.797	0.648
England & Wales	0.403	0.981	0.945	0.575	0.988	0.898
Finland	0.002	0.848	0.900	0.696	0.842	0.883
High BMI						
Italy: Before fine tuning*	0.986	0.779	0.972	0.953	0.667	0.745
Italy: After fine tuning**	0.988	0.884	0.979	0.970	0.657	0.829
England & Wales	0.932	0.996	0.980	0.941	0.993	0.967
Finland	0.976	0.962	0.944	0.960	0.910	0.915

(*) Before fine tuning: Same hyper-parameters for all strata (final age interval: 25 years, spline knots: 8, polynomial degree: 6)
(**) After fine tuning: Different hyper-parameters for each stratum (Table 4)

3. Results

Figures 4.1 (Finland), 4.2 (Italy) and 4.3 (England) show the surfaces of prevalence estimated with the observed data of obesity prevalence in Finland, Italy, and England, by sex and educational level, for the age categories and calendar years available for each country. We used the central age to depict the prevalence for a specific age group. For example, the observation for age 27 depicts the age group 25-29. The figures also show the smoothed surfaces that we obtained in the end, and, as well, a measure of smoothing fit (R^2).

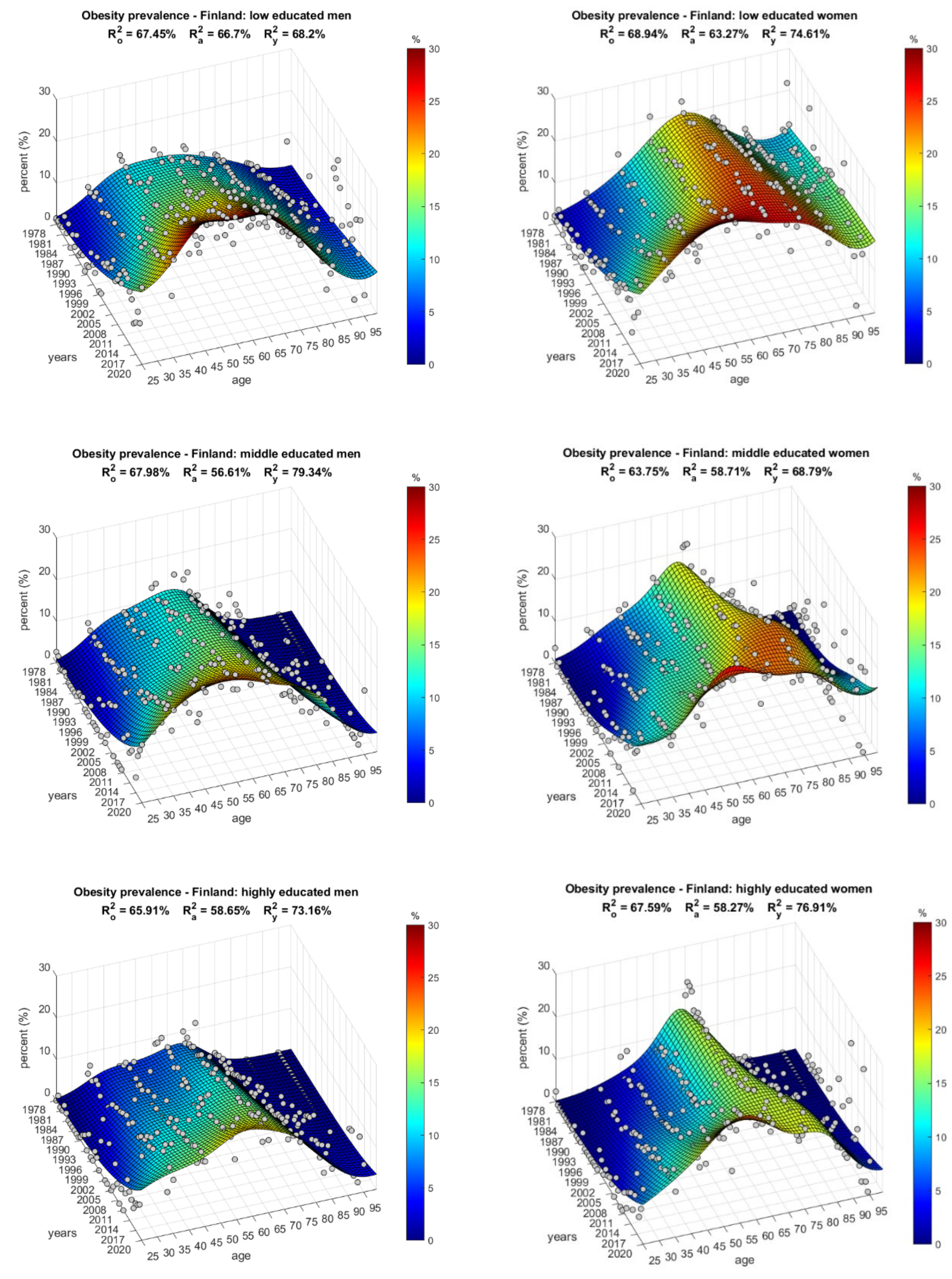
The average of overall R^2 for obesity prevalence is 70% in the case of Finland, 82% in the case of Italy, and 80% in the of England. However, since the purpose of the smoothing is not to maximize the fit but rather to reduce the irregularities (the noise) in the dataset, the measures of goodness fit should be considered only indicative and not conclusive of the quality of the smoothing (since, for example, other algorithms can maximize R^2 but at the cost of producing less smoothed results). More importantly, it can be observed that the smoothed surfaces closely follow the patterns of the observed data in all countries, and at the same the 2D smoothing algorithm produces results that are robust to the presence of outliers, as those observed for example for low educated men and women in Finland (Figure 4.1), and for high educated men and women in England (Figure 4.3).

Figures 5.1, 5.2 and 5.3 show the treated and smoothed trends in age-standardized obesity prevalence (30+), by educational level and sex, in Finland (Figure 5.1), Italy (Figure 5.2) and England & Wales (Figure 5.3). Age-standardization was performed with the revised European Standard Population (ESP) estimates provided by the European Commission (2013). The ESP is based on the projected total population (male + female combined) of the European Union (EU)-27 plus the European Free Trade Association (EFTA) countries, based on the Eurostat 2010-based population projections, averaged over the period 2011-2030. The smoothed trends of obesity prevalence reproduce the trajectories of obesity prevalence treated to account for missing values but reducing the noise of the treated data. A good fit of the smoothed age-standardized obesity prevalence to the treated age-standardized obesity prevalence is observed particularly for Italy and England & Wales.

Figures 5.1, 5.2 and 5.3 show the treated and smoothed trends in age-standardized obesity prevalence (30+), by educational level and sex, in Finland (Figure 5.1, for the years 1978-2017), Italy (Figure 5.2, 1990-2018) and England & Wales (Figure 5.3, 1991-2017). Age-standardization was performed with the revised European Standard Population (ESP) weights provided by the European Commission (2013). The ESP is based on the projected total population (male + female combined) of the European Union (EU)-27 plus the European Free Trade Association (EFTA) countries, based on the Eurostat 2010-based population projections, averaged over the period 2011-2030. The smoothed trends of obesity prevalence reproduce the direction of the trends of obesity prevalence treated to account for missing values, but the smoothed trends reduce the noise of the treated data. A particularly good match of the smoothed age-standardized obesity prevalence is observed compared to the treated age-standardized obesity prevalence in Italy and England & Wales.

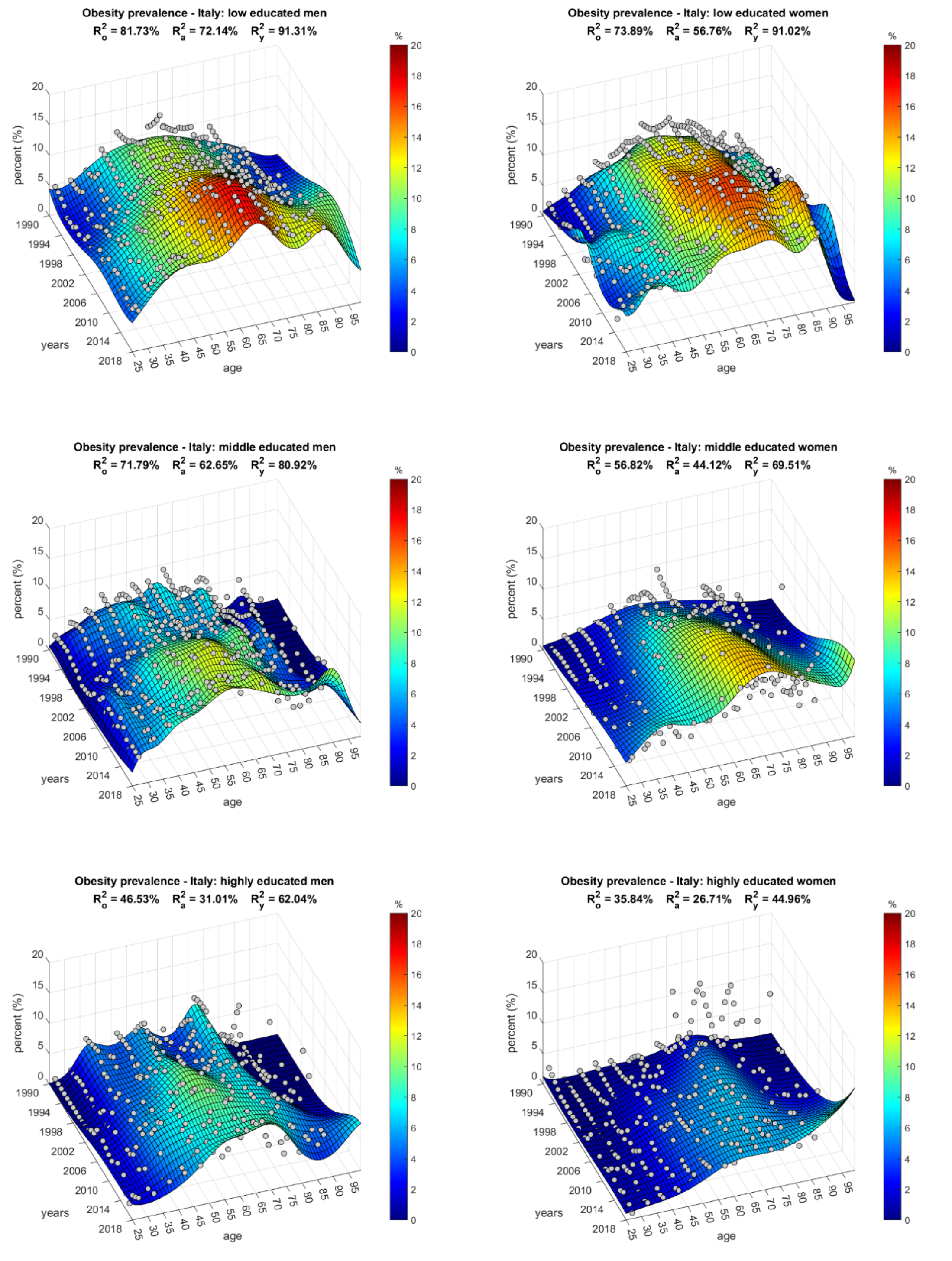
Figures 6.1, 6.2 and 6.3 show the treated and smoothed trends in age-standardized high BMI prevalence (30+), by educational level and sex, in Finland (Figure 6.1, 1978-2017), Italy (Figure 6.2, 1990-2018) and England & Wales (Figure 6.3, 1991-2017). Age-standardization was performed again with the ESP weights provided by the European Commission (2013). The smoothed trends of high-BMI prevalence are in line with the direction of the trajectories of high-BMI prevalence treated to account for missing values, but as in the case of obesity prevalence, the smoothed trends reducing the noise of the treated data. A particularly good match of the smoothed age-standardized high-BMI prevalence to the is observed again for Italy and England & Wales.

Figure 4.1. Observed data and smoothed surfaces of obesity prevalence, by educational level and sex: Finland, 1978-2020



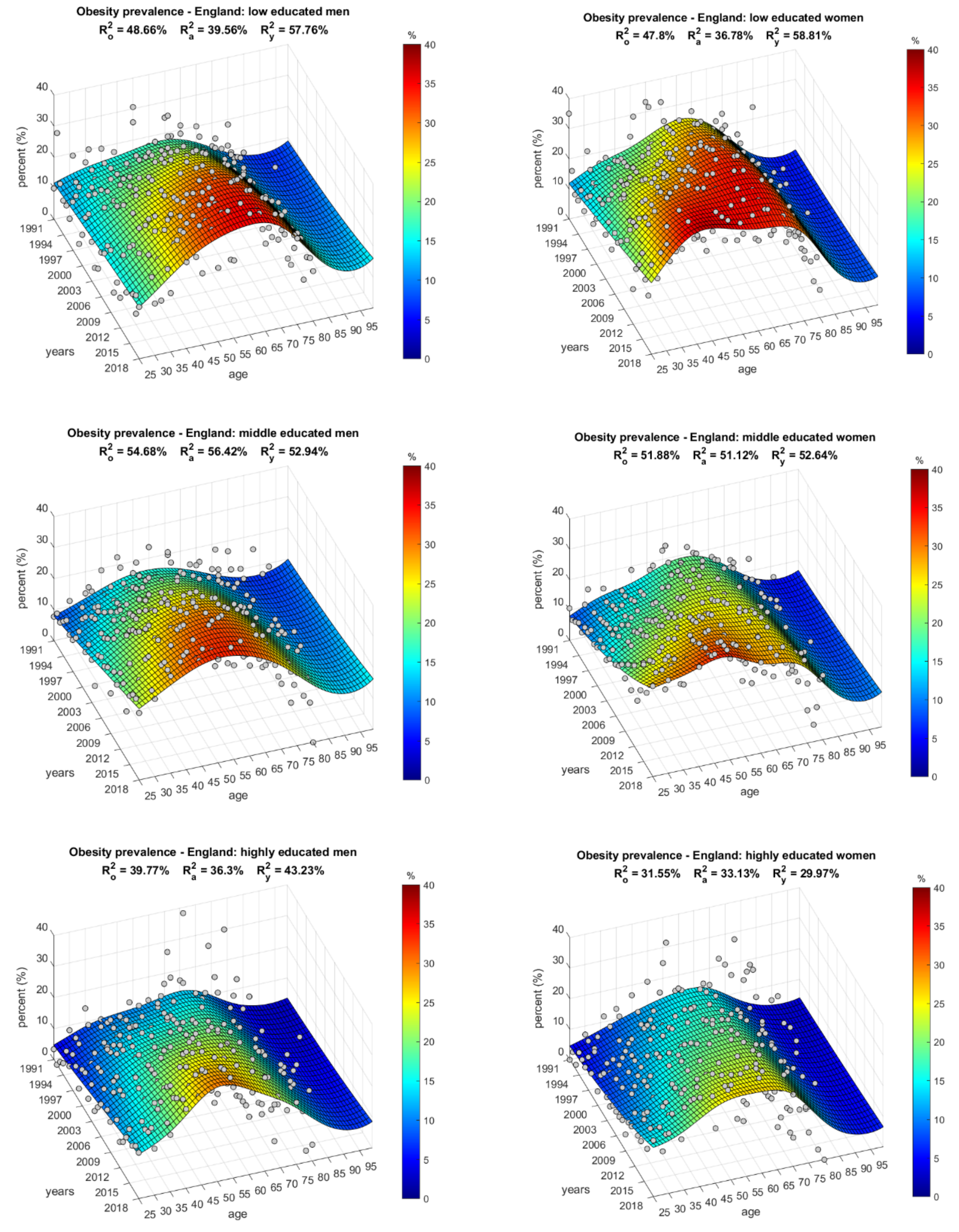
Note: R_o^2: Overall R-squared (average across age categories and calendar years). R_a^2: Average R-squared across age categories. R_y^2: Average R-squared across calendar years. AVTK & EVTK survey: 1978-2014, ATH survey: 2013-2017, FinSote: 2018-2020. Left column: men, right column: women. We used the central age to depict the prevalence for a specific age group. For example, the observation for age 27 depicts the age group 25-29.

Figure 4.2. Observed data and smoothed surfaces of obesity prevalence, by educational level and sex: Italy, 1990-2018



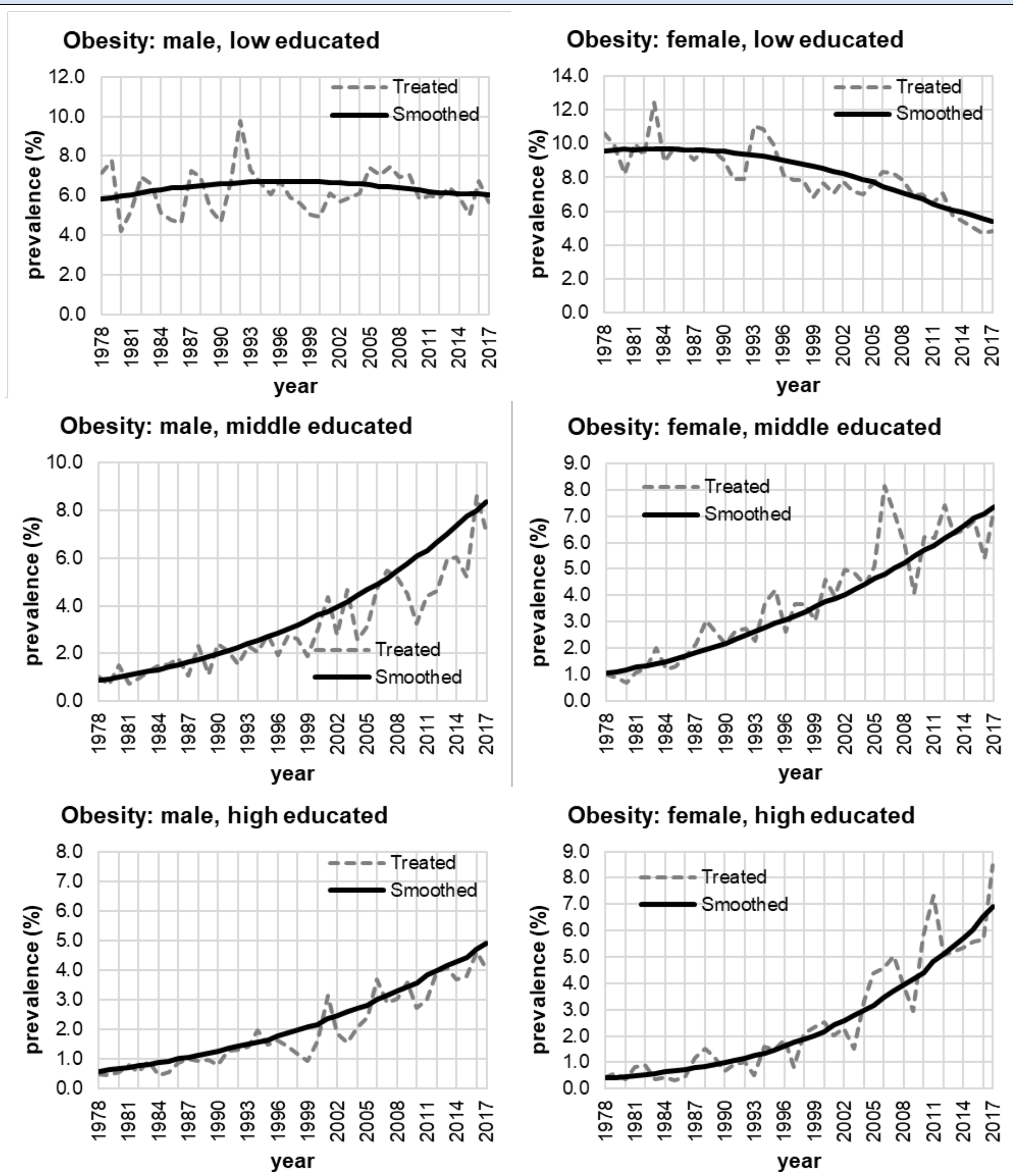
Note: R^2_o: Overall R-squared (average across age categories and calendar years). R^2_a: Average R-squared across age categories. R^2_y: Average R-squared across calendar years. NMSS survey: 1990, HCHS: 1994, 1999/2000, 2004/2005, 2013, AVQ survey: 2001-2018. Left column: men, right column: women We used the central age to depict the prevalence for a specific age group. For example, the observation for age 27 depicts the age group 25-29.

Figure 4.3. Observed data and smoothed surfaces of obesity prevalence, by educational level and sex: England, 1991-2018



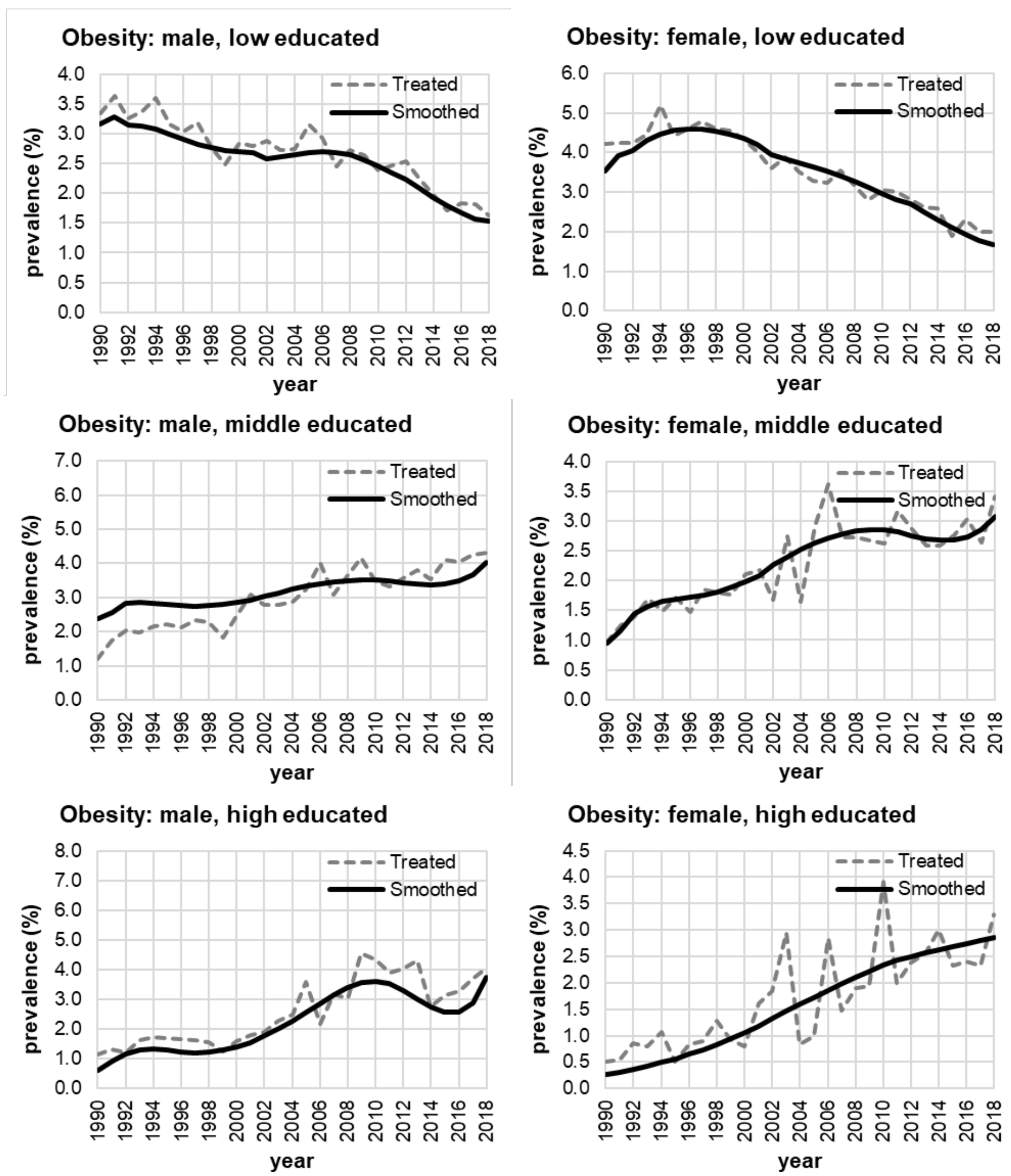
Note: R^2_o: Overall R-squared (average across age categories and calendar years). R^2_a: Average R-squared across age categories. R^2_y: Average R-squared across calendar years. HSE survey: 1991-2018. Left column: men, right column: women. We used the central age to depict the prevalence for a specific age group. For example, the observation for age 27 depicts the age group 25-29.

Figure 5.1. Trends in age-standardized obesity prevalence (30+), by educational level and sex: Finland, 1978-2017



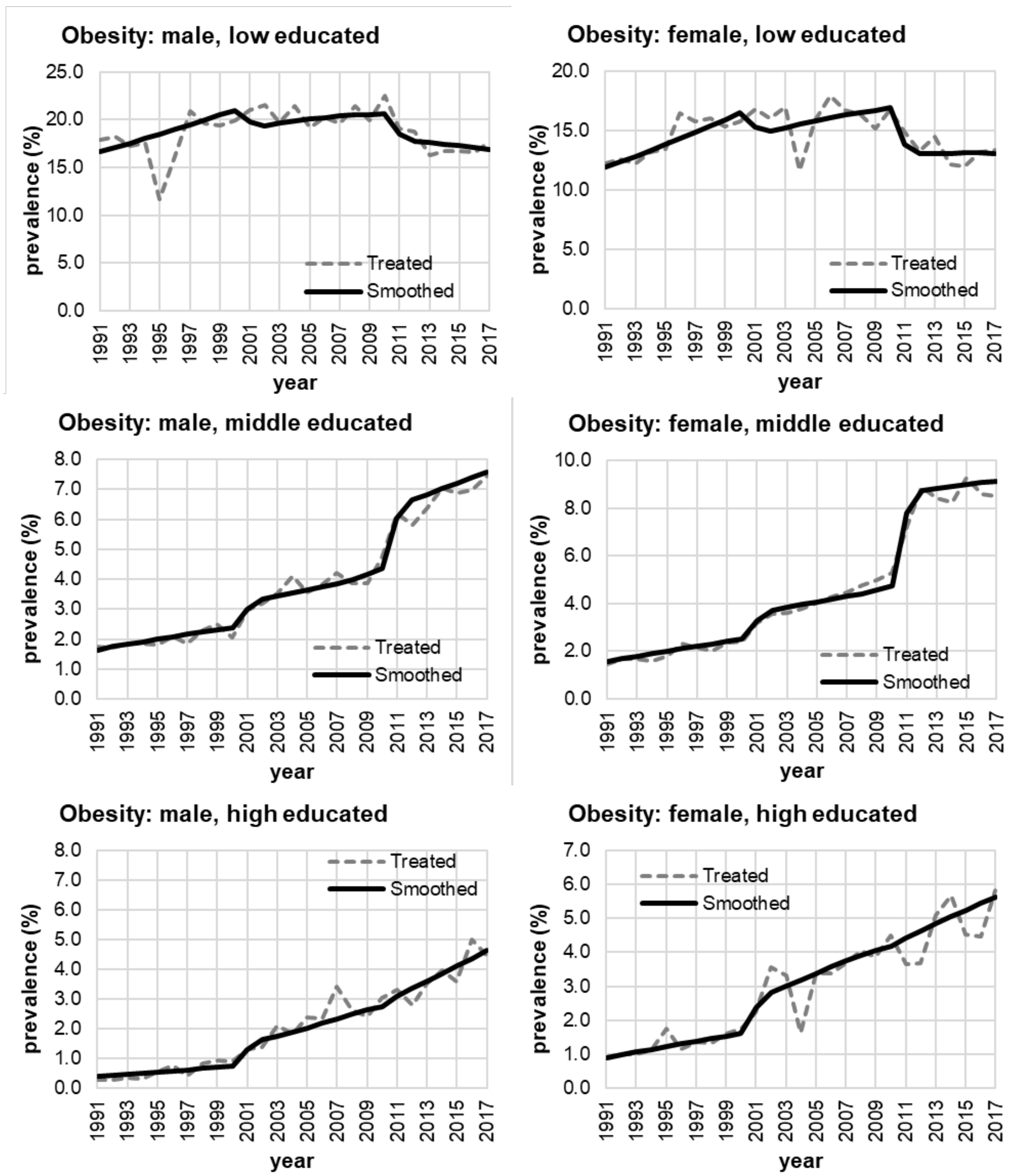
Note: Treated data are the original information of the surveys that was interpolated to account for missing values. Smoothed data is the treated data that was smoothed and extrapolated with the Rizzi et al. algorithms.

Figure 5.2. Trends in age-standardized obesity prevalence (30+), by educational level and sex: Italy, 1990-2018 (after fine tuning the Rizzi et al. hyper-parameters)



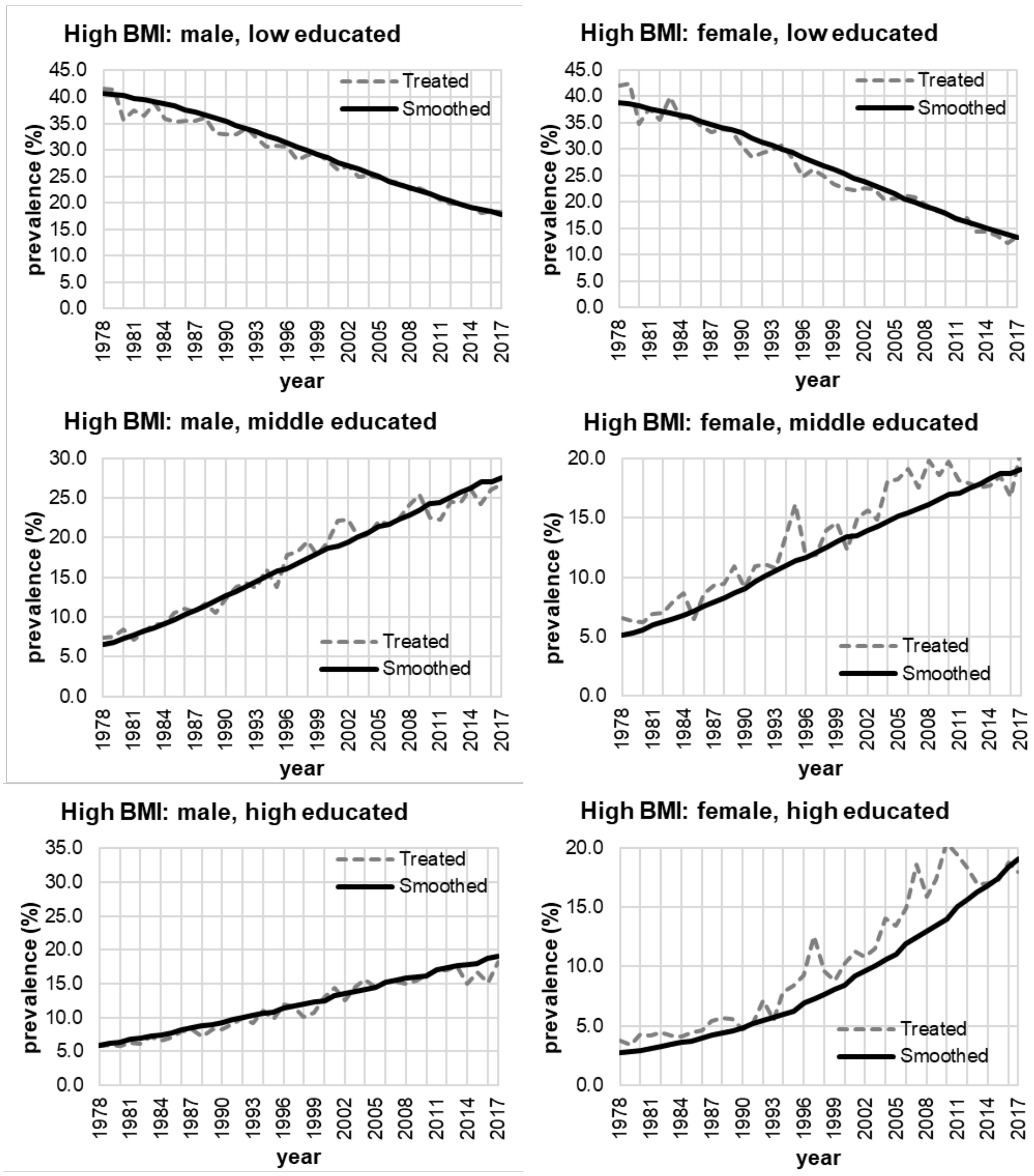
Note: Treated data are the original information of the surveys that was interpolated to account for missing values. Smoothed data is the treated data that was smoothed and extrapolated with the Rizzi et al. algorithms.

Figure 5.3. Trends in age-standardized obesity prevalence (30+), by educational level and sex: England & Wales, 1991-2017



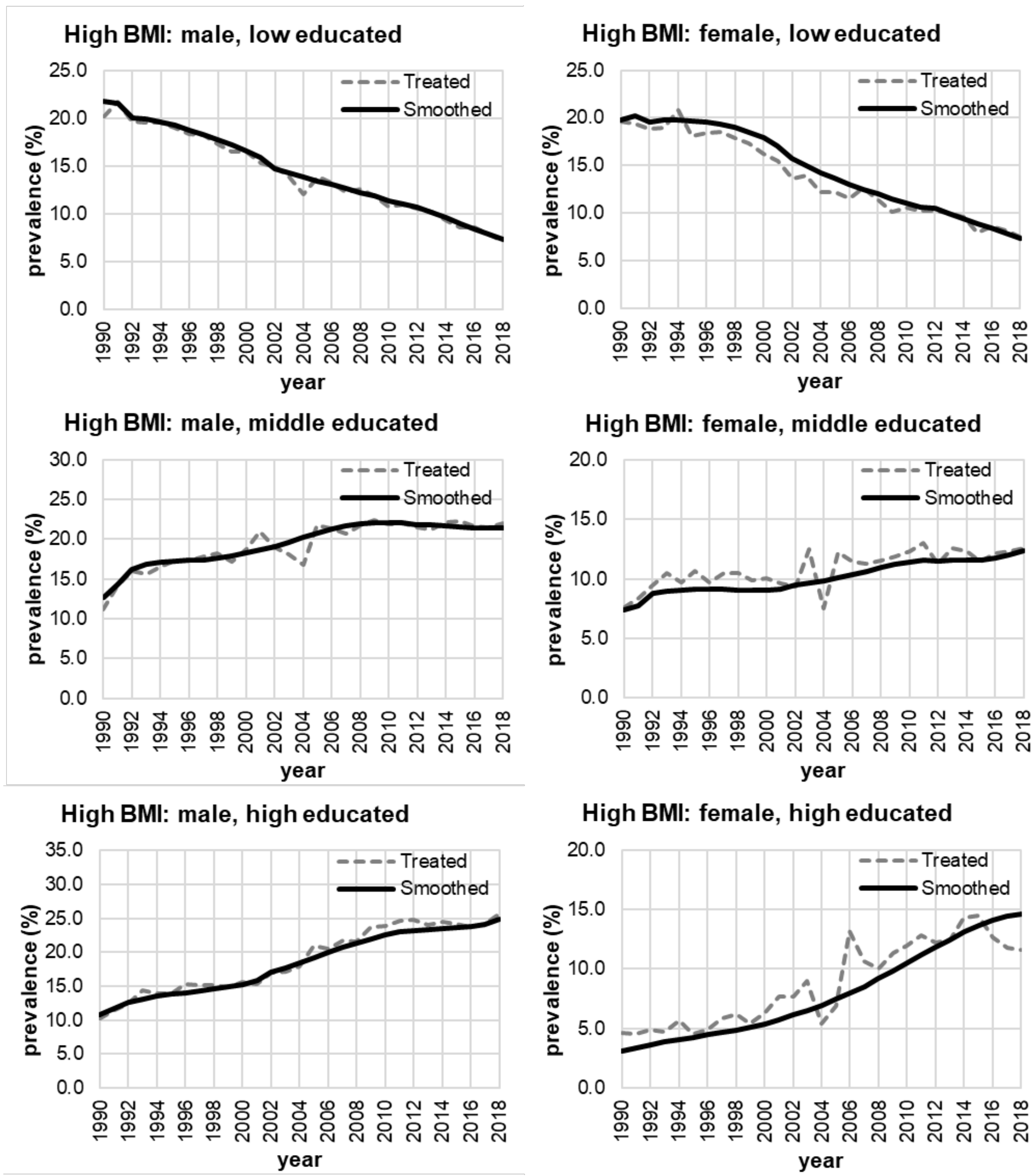
Note: Treated data are the original information of the surveys that was interpolated to account for missing values. Smoothed data is the treated data that was smoothed and extrapolated with the Rizzi et al. algorithms.

Figure 6.1. Trends in age-standardized high BMI prevalence (30+), by educational level and sex: Finland, 1978-2017



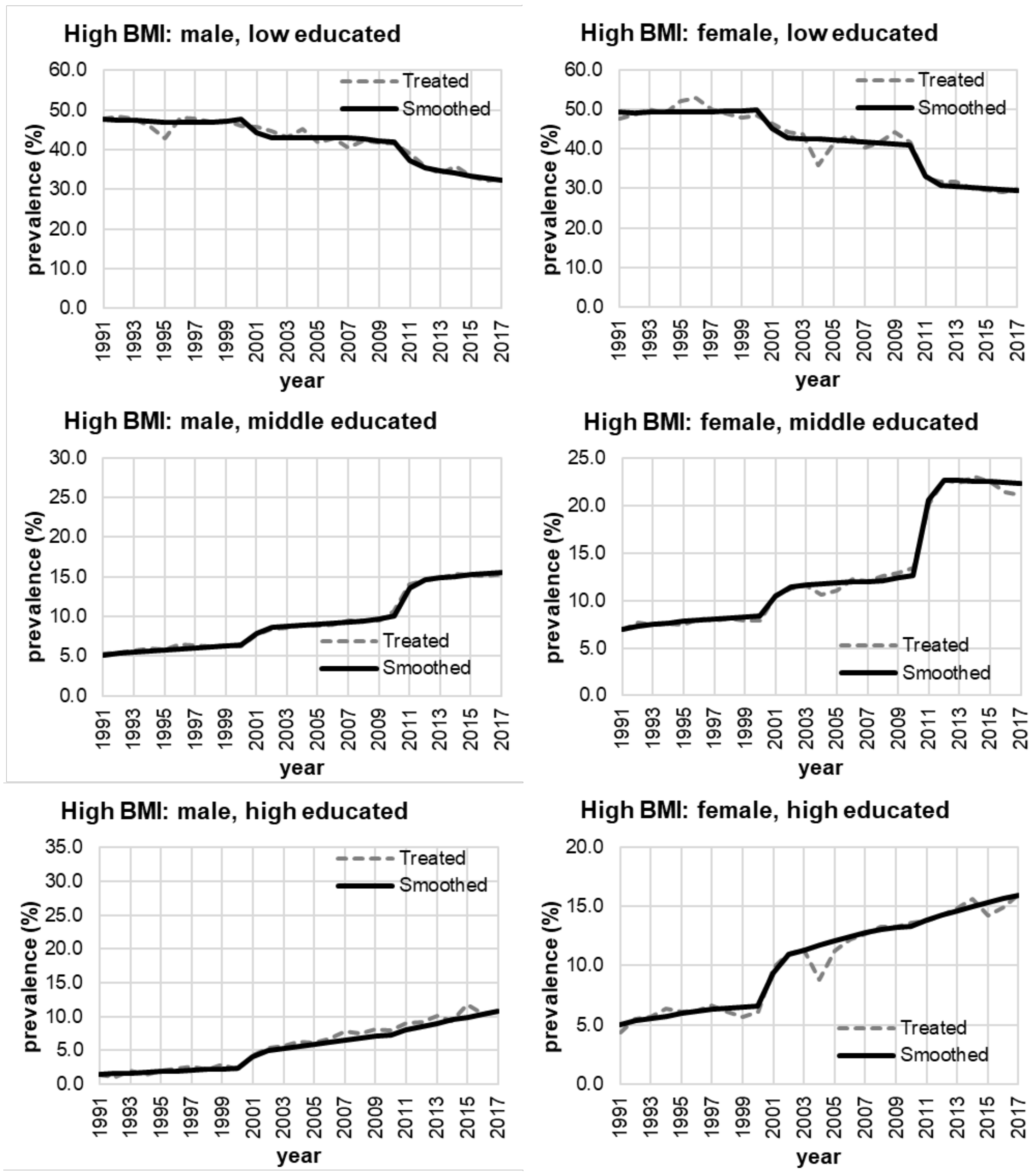
Note: Treated data are the original information of the surveys that was interpolated to account for missing values. Smoothed data is the treated data that was smoothed and extrapolated with the Rizzi et al. algorithms.

Figure 6.2. Trends in age-standardized high BMI prevalence (30+), by educational level and sex: Italy, 1990-2018 (after fine tuning the Rizzi et al. hyper-parameters)



Note: Treated data are the original information of the surveys that was interpolated to account for missing values. Smoothed data is the treated data that was smoothed and extrapolated with the Rizzi et al. algorithms.

Figure 6.3. Trends in age-standardized high BMI prevalence (30+), by educational level and sex: England & Wales, 1991-2017



Note: Treated data are the original information of the surveys that was interpolated to account for missing values. Smoothed data is the treated data that was smoothed and extrapolated with the Rizzi et al. algorithms.

A validation of our results is carried out through a comparison of our findings by educational level against those obtained by Kagenaar et al. (2022), as well as a comparison against the OECD information on high-BMI and obesity prevalence for the general population in Finland, the United Kingdom, and Italy (OECD 2022).

Kagenaar et al. (2022) used essentially the same raw data compared to us. For Finland however, data by five-year age groups (including more missing strata) and not 10-year age groups (which came available later) was used. Kagenaar et al. (2022) calculated age-standardized obesity prevalence using the observed obesity prevalence by the available age groups and available years as input, after applying linear interpolation to obtain estimates for missing strata within the data. Subsequently, they applied LOESS smoothing to the age-standardized prevalence to obtain estimates for each consequent year.

Figure 7 shows trends over time in smoothed age-standardized obesity prevalence by educational level and sex for different European countries from Kagenaar et al. (2022). Like Kagenaar et al., we applied age standardization using the in 2003 revised European Standard Population (ESP; Eurostat, 2003). Contrary to Kagenaar et al. (2022), which applied age-standardization to data for age groups 25-64 for Finland, data for age groups 25-75+ for Italy, and data for age groups 25-80+ for England, we were able –after employing our methodology– to obtain uniform age groups and apply the age standardization to data with age groups in the intervals 25-95+ for the different countries.

In the case of England, we obtained very similar values and trends compared to Kagenaar et al. (2022). For Finnish men also largely similar values and trends are obtained, except that our outcomes do not show the overlap at the onset of the observation period between the low educated and the middle educated. For Finnish women, our results are also different from those by Kagenaar et al. (2022). That is despite increasing age-standardised obesity prevalence for the three educational groups in both outcomes, educational differences diverged based on Kagenaar et al. (2022), whereas in our outcomes this divergence is not observed. These differences for Finland could –at least partly– be explained by differences in the original data that was treated, and the range to which the age-standardised prevalence applies, but potentially as well the size of the age groups (we used data by ten-year age groups to avoid missing strata). For Italian men, largely similar values and trends are obtained, except for the middle educated in the period 1994-2000, whom –in our results– have lower values overlapping with the high educated. This difference can most likely be explained by the different approaches employed to deal with years with missing data; specifically, the decline for the middle educated that we obtain might be related to the fact that we performed linear interpolation on the age-standardized outcomes. For Italian women, values are largely the same, and in both outcomes an increasing gap between middle and high educated women is observed. However, based on our outcomes, this gap is wider, and our outcomes show a convergence between middle and low educated women, which is not observed in Kagenaar et al. (2022).

In Figures 8.1, 8.2, and 8.3, we make an additional comparison of our trends in age-standardized obesity and high-BMI prevalence (30+) for the general population (= the three educational groups combined) against the available information on this within the OECD

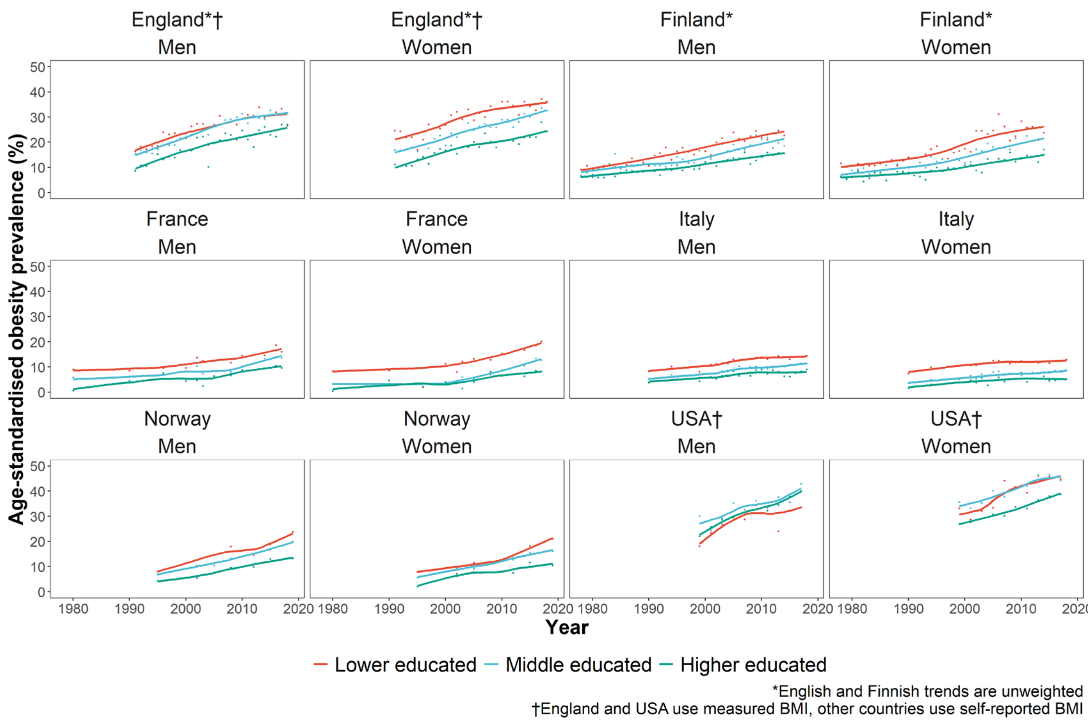
Health Statistics database (OECD, 2022). In interpreting the findings, please note the difference in the age range of the prevalence data between us and the OECD, and the application of age-standardization in our data but –seemingly– not in the OECD data.

In the case of Italy (Figure 8.1), our levels of age-standardized obesity prevalence for males and females are below the levels of obesity prevalence of the OECD. In the case of high-BMI, our smoothed levels for males are almost exactly the same as the OECD trend, but our smoothed high-BMI prevalence for females is below the OECD levels. However, our smoothed trends follow the trends of the treated data (this is, the original survey data that was treated to account for missing values). The difference between our results and the OECD values is related to the fact that we are using more information and a different age range, since the OECD data is for individuals in the age range 15/18+, while in our case our calculations are for individuals aged 30+.

In the case of Finland (Figure 8.2), our estimated levels of high-BMI prevalence are above the OECD levels, both for males and females, and our estimated levels of obesity prevalence for females are above the OECD levels of obesity prevalence for females. Our estimated levels of obesity prevalence for males are similar to the OECD levels of obesity prevalence for males. Our estimated smoothed trends, however, are similar to those of the OECD data, and our estimated smoothed trends follow the treated data based on survey information. The difference between the OECD results and our results is related again to the different age ranges, since the OECD data for Finland is for individuals aged 15-20-64+, while in our case our calculations include the elderly aged 30-90+ (treated data) and 30-95+ (extrapolated and smoothed data).

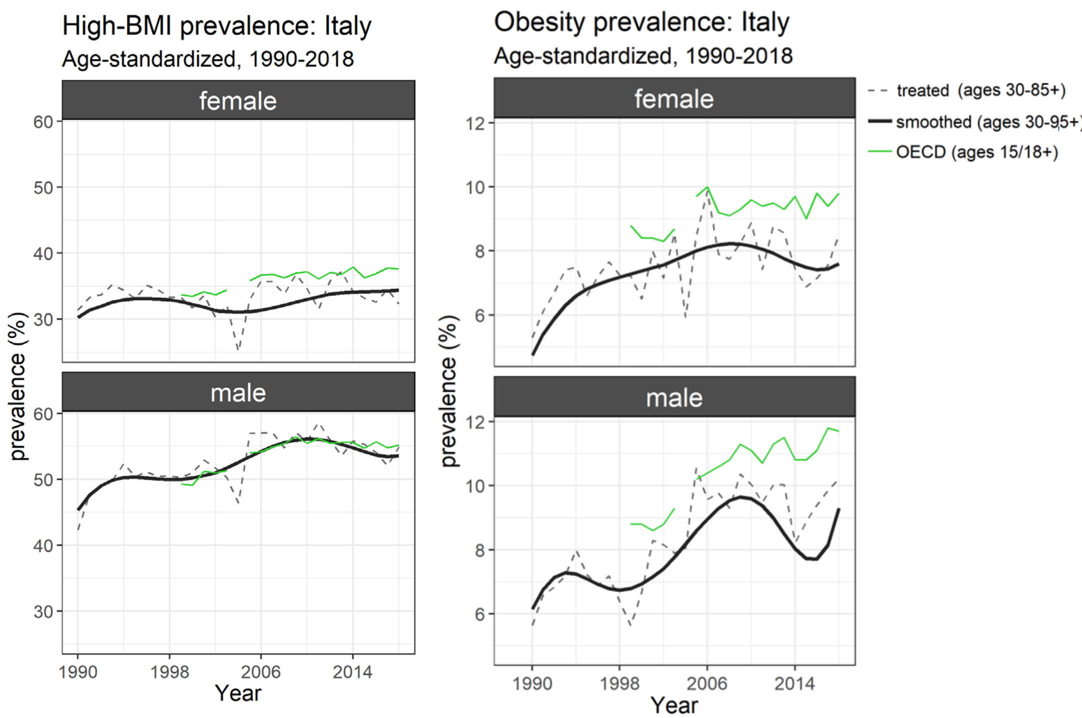
In relation to England & Wales (Figure 8.3), our estimates of the levels of high BMI and obesity prevalence are very similar to the OECD levels, particularly for high-BMI and obesity prevalence of males. In the case of females, our estimated levels of high-BMI and obesity prevalence are above the OECD levels. Our smoothed trends of obesity and high BMI prevalence, however, follow closely the direction of the trends of the OECD data. The OECD is for UK individuals aged 18+; our calculations are based on data of England & Wales for individuals aged 30-80+ (treated data) and 30-95+ (extrapolated and smoothed data).

Figure 7. Loess-smoothed age-standardized prevalence (%) of obesity (BMI ≥30 kg/m2) by educational attainment and sex, in six countries from 1978 to 2019 (source: Kagenaar et al. 2022)



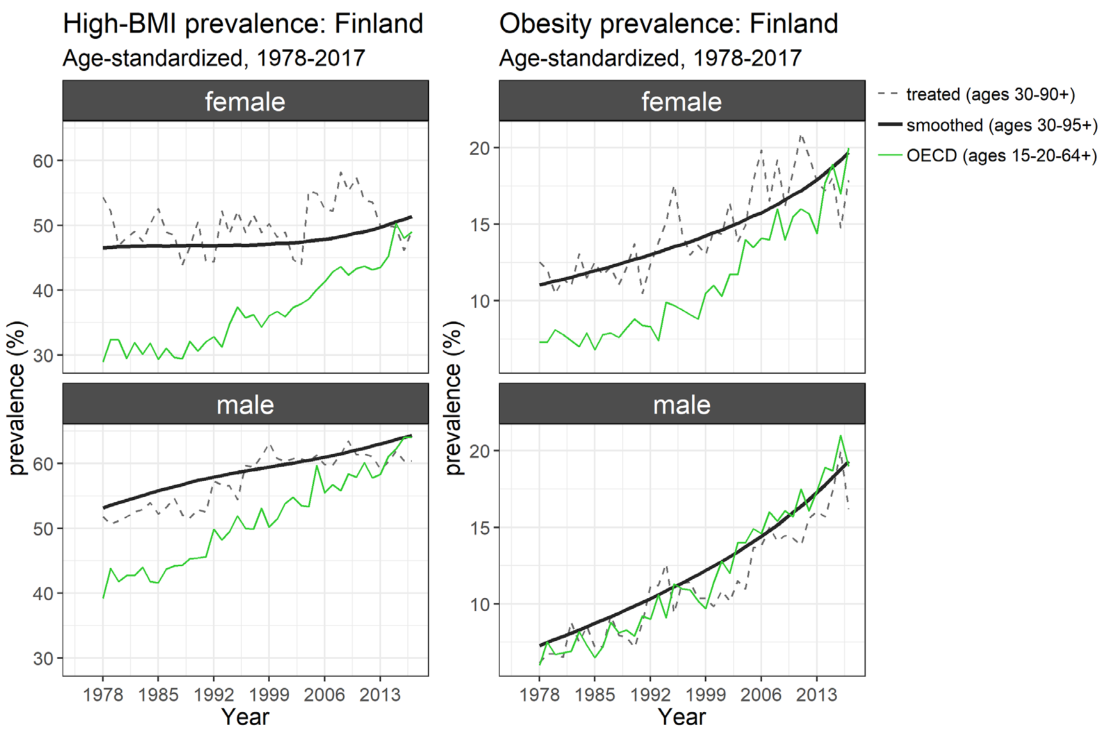
Note: The age-standardized obesity prevalence applies to different age ranges in the different countries: for Finland to 25-64, for France to 25-74, for Italy to 25-75+, and for England, USA, and Norway to 25-80+. The age-standardized obesity prevalence was calculated by applying to the smoothed age-specific prevalence the in 2013 revised European Standard Population (European Commission, 2013).

Figure 8.1. Comparison of treated and smoothed trends in age-standardized high BMI and obesity prevalence for the three educational levels combined with the OECD Health Statistics 2022, by sex: Italy, 1990-2018



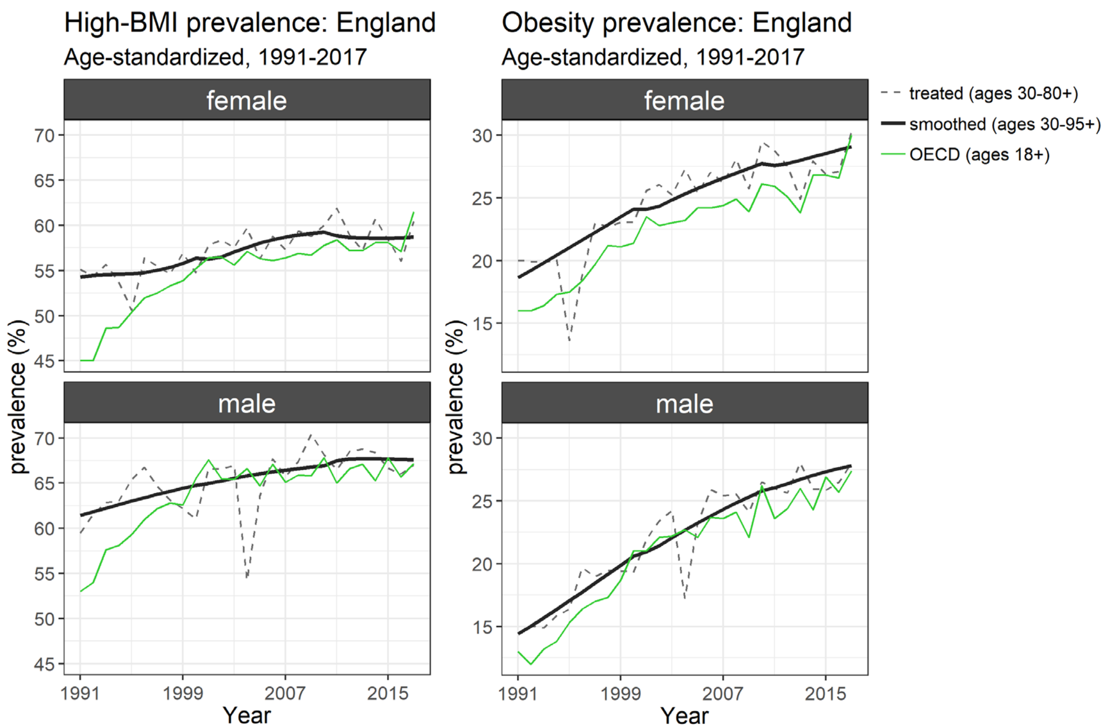
Note: Our age-standardized prevalences are calculated by applying the in 2013revised European Standard Population (European Commission, 2013) to the age-specific prevalences for the total population. The age-specific prevalence for the total population was obtained by weighing the age-specific prevalences by educational level with age-specific population numbers by educational level from the Turin Longitudinal Study. The source of the OECD prevalence data was obtained directly from the OECD website, without additional calculation. The source of the OECD data is detailed in Appendix I.

Figure 8.2. Comparison of treated and smoothed trends in age-standardized high BMI and obesity prevalence for the three educational levels combined with the OECD Health Statistics 2022, by sex: Finland, 1978-2017



Note: Our age-standardized prevalences are calculated by applying the in 2013revised European Standard Population (European Commission, 2013) to the age-specific prevalences for the total population. The age-specific prevalence for the total population was obtained by weighing the age-specific prevalences by educational level with age-specific population numbers by educational level from the Turin Longitudinal Study. The source of the OECD prevalence data was obtained directly from the OECD website, without additional calculation. The source of the OECD data is detailed in Appendix I.

Figure 8.3. Comparison of treated and smoothed trends in age-standardized high BMI and obesity prevalence for the three educational levels combined with the OECD Health Statistics 2022, by sex: England & Wales, 1991-2017



Note: Our age-standardized prevalences are calculated by applying the in 2013revised European Standard Population (European Commission, 2013) to the age-specific prevalences for the total population. The age-specific prevalence for the total population was obtained by weighing the age-specific prevalences by educational level with age-specific population numbers by educational level from the Turin Longitudinal Study. The source of the OECD prevalence data was obtained directly from the OECD website, without additional calculation. The source of the OECD data is detailed in Appendix I.

4. Conclusion

We created a database on obesity and high BMI prevalence by educational level and sex for adjacent calendar years and uniform ages for England, Finland, and Italy. The estimates of obesity and high BMI prevalence were obtained with the two-dimensional Rizzi et al. (2019) smoothing algorithm, applied to data with similar age groups across time and without missing values, which we obtained through interpolation/extrapolation across years and one-dimensional Rizzi et al. (2015) smoothing across age groups.

We selected the Rizzi et al. (2019) 2D algorithm because of its clear advantages over other smoothing procedures. That is, the method is theoretically consistent and simultaneously smooths across age and time, thereby producing results that are robust to outliers, without overfitting the data. A drawback of the 2D algorithm is however that the results are sensitive to the choice of the last age interval, the number of knots and the degree of the polynomial of the splines in the algorithm. It was observed also that the 2D algorithm tends to produce explosive trends for older age groups, in line with the Runge phenomenon. We dealt with this by extending the last age interval until 110 years old and by dropping the observations above 100 years that suffer from the Runge phenomenon.

Nevertheless, our results must be interpreted with care because our procedure relies on the imputation of missing values to generate the input needed for the 2D dimensional smoothing. This applies especially for the elderly in Finland for the years up to 2012, since data regarding the older age groups were mostly missing, and for Italy for data for the years between 1990 and 2001, which essentially rely on data for four survey years only (1990/91, 1994, 1999/2000, 2001). Although we performed the imputation with care and carefully reviewed the outcomes, the outcomes remain estimates based on a limited number of observations. For England & Wales, the smoothed prevalence can be regarded as the most precise, because the data did not require imputation and only the year 2014 received a treatment with the 1D algorithm.

All in all, we managed to deal –in a systematic manner– with the different types of missing and inconsistent information in the data, thereby making full advantage of the available data and using recent methodological improvements in smoothing algorithms. The produced smooth prevalence surfaces across age and time for the low, middle, and high educated in England, Finland and Italy match the treated data reasonably well, and are consistent with previous evidence regarding obesity and high BMI prevalence by educational level. Our database facilitates the detailed analysis of long-term trends of obesity prevalence and high-BMI prevalence by socio-economic status and can be used for further analysis regarding its causes and consequences.

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Appendix I: Sources of the OECD data of obesity and high-BMI prevalence

Country	OECD Source*
Finland	Finnish Institute for Health and Welfare (THL). 2020: “National FinSote Survey”, Mikko Valtanen. 2019: “National FinSote Survey/European Health Interview Survey wave 3”, Jonna Ikonen. 2018: “National FinSote Survey”, Suvi Parikka. 2015-2017: “Regional Health and Wellbeing study”, Jukka Murto. 1978-2014: “Health Behaviour and Health among the Finnish Adult Population”, Satu Helakorpi. Coverage: 2020: Population aged 20 to 64 years old. 2019: Population aged 15 to 64 years old. 2015-2018: Population aged 20 to 64 years old. 1978-2014: Population aged 15 to 64 years old. Methodology: 2020: A random sample of 61600 of the population aged 20 years or older. The average response rate was 46%. 2019: A random sample of 15000 of the population aged 15 years or older. 2015-2018: A random sample of 38000 of the population aged 20 years or older. The average response rate was 54%. 1978-2014: Annual postal survey for a random sample of the population of Finnish adults aged 15-64 years old. The sample size was 5000. The average response rate was 72%. Further information: http://www.thl.fi/en_US/web/en.
Italy	Source: ISTAT, Instituto Nazionale di Statistica (National Institute of Statistics). From 2000: Survey “Aspect of daily living.” 1994 and 1999: Survey of health conditions and recourse to health services, 1994 and 1999-2000. Coverage: Starting in 2001, data refer to the population aged 18 years old and over. Until 2000, data refer to the population aged 15 years old and over. Further information: http://dati.istat.it//Index.aspx?QueryId=42614
United Kingdom	2017: Eurostat database, European Union Survey on Income and Living Conditions (EU-SILC). Population aged 18 years old and over. Extracted via http://ec.europa.eu/eurostat/data/database?node_code=ilc_hch10. 2014: Eurostat EHIS 2014 survey.

The increasing trends in obesity and high body mass index (BMI) create a burden for health services and economic productivity worldwide. However, long-term trends of obesity prevalence and high-BMI prevalence by socio-economic status remain largely under-researched, in part due to limitations in data availability by educational level. In this document we describe the creation of a database on obesity prevalence (OP) and high-BMI prevalence (HBP) by educational level and sex for adjacent calendar years and uniform ages for England, Finland, and Italy. Using interpolation across years and smoothing across age, we consolidated the data from available national health surveys from the 1970s onwards, into data without missing years and with similar age groups across time. Subsequently, we applied the two-dimensional Rizzi et al. (2019) smoothing algorithm to obtain prevalence data by educational level (low, middle, high), sex, five-year age groups (25-95+) and single calendar years. The resulting smooth prevalence surfaces across age and time for the low, middle, and high educated in England, Finland and Italy match the treated data reasonably well, and are consistent with previous evidence regarding obesity and high BMI prevalence by educational level. With our procedure, we managed to deal –in a systematic manner– with the different types of missing and inconsistent information in the obesity and high-BMI prevalence data by educational level, thereby making full advantage of the available data and using recent methodological improvements in smoothing algorithms. Our database facilitates the detailed analysis of long-term trends of obesity prevalence and high-BMI prevalence by socio-economic status and are the basis of further analysis regarding obesity attributable mortality and high-BMI attributable mortality.

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