Parametric and Non-Parametric Analysis of the Role of Economic Factors on Obesity Prevalence in Spain

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1. Introduction

Poor diets and rising obesity rates dominate the current food, nutrition and health policy debate in many countries, including Spain. Obesity is partly a result of an energy imbalance caused by consumption of too many calories and/or low expenditures of calories (i.e., low physical activity) over a considerable period. Consequently, most published economic research has examined the increased growth of obesity rates by analyzing several factors that may contribute to this imbalance of caloric consumption and usage (see Cutler et al., 2003; Chou et al., 2004; Lakdawalla and Philipson, 2007; Philipson and Posner, 1999; Loureiro and Nayga, 2005).

Due to rising concerns about obesity, the availability, accessibility and choice of foods to meet an adequate diet are becoming key challenges to our food system today. Good nutrition is essential to obtaining optimum health and productivity and in reducing the risk for chronic and infectious diseases. Understanding factors influencing food consumption and obesity is needed to gain a clearer picture of the mechanisms that would cause individuals to eat unhealthful or become over weighted. Hence, knowledge about how people make food choices and how economic and non-economic factors influence food consumption and obesity is critically important to improve policy interventions and developing agricultural and food programs that can assure a safe, affordable, reliable and nutritious food supply and promote health.

Previous economic studies have analyzed the role played by income on health. In general, there seems to be a consensus about the positive effect of income on health (Smith, 1999). Consequently, we would expect, all things being equal, a negative effect on obesity, although this may not be necessarily the case, since obesity is in some cultures a sign of status and wealth. Furthermore, several recent economic studies explain the role played by different cultural and socio-demographic factors on obesity rates. Leaving genetics aside, obesity is caused by consumption of too much calories and/or low expenditures of calories (i.e. low physical activity). For example, Schlosser (2002) showed that the fast growth of fast food and soda drinks has increased the dietary intake of saturated fats, sugars, and calories and then, the prevalence of obesity. Other researchers argue that female labour participation is a leading factor in increasing obesity rates (Garcia et al., 2006), mainly in childhood.

Most of the literature in Spain has concentrated on the adequacy of alternative instruments to measure obesity or on educational and environmental factors (i.e. food consumption) affecting obesity. However, up to now, limited attention has been paid to the role of economic factors (income and prices) on food choices, physical activity and, consequently, on the prevalence of obesity.

Despite the increasing obesity rate in Spain, there has been no known published research in Spain that has analyzed the economic factors affecting food consumption, the quality of diet and obesity. The main aim of our work is analyzing the relevance of economic factors (mainly income and other socioeconomic characteristics of Spanish households and market prices) on the prevalence of obesity in Spain and to what extent market intervention prices are effective to reduce obesity and improve diet quality and under what circumstances.

Our methodological approach depending upon the estimation of a multinomial logit model Combined with the estimation of a non-parametric model, the Multivariate

Adaptive Regression Splines (MARS), to judge the role of different socioeconomic factors on the obesity prevalence in Spain. Despite the desirable advantages of the use of non-parametric models such as MARS, our paper is the first attempt to use this type of models to analyze the determinant factors of obesity prevalence.

Our data come from the 2006 National Health Survey (NHS), the last survey available at national level. In order to take into account the effect of economic factors we augment the data set with regional consumer price indices for food, the food away-from-home index and the regional disposable income index. Our data set consists of 25459 adults (16 years old or more).

To achieve the paper' objective, the rest of the paper is organized as follows. Section 2 provides a brief description on the obesity prevalence in Spain. The methodological approach applied in our analysis is explained in section 3. Our empirical application and the main results are discussed in sections 4 and 5, respectively. Finally, the paper ends with some concluding remarks.

2. Obesity prevalence in Spain

Following the 2006 National Health Survey (NHS) the prevalence of overweight and obesity among Spanish adults aged 18 years old or more was about 37.13% and 15.37% respectively. While the prevalence of obesity was quite similar between men and women (15.6% among men and 15.2% among women), the overweight prevalence was quite higher in men representing almost 44.7% in men and only 29.4 in women. The lowest obesity prevalence rate in both men and women detected in the youngest category including people aged between 18 and 24 years with a prevalence rate of about 5.4% for both genders. Elder people aged between 65 and 74 years was the category with the highest rate of obesity prevalence among the two genders with a prevalence rate of 25.5% and 28.3% among men and women, respectively. Also the prevalence of obesity was higher in persons with no education than in those with higher education. The prevalence of obesity in Spain has increased at an alarming rate in 20 years as it has passed from 6.9% and 7.9% in men and women, respectively, in 1987, to the above mentioned 15.6% and 15.2%, in 2006.

3. Methodological approach

Few studies have used multinomial logit model to analyze the determinant factors of obesity prevalence (see Cavaliere and Banterle, 2008; Warner, 2003; Asfaw, 2007 among others). Previous studies found that age has a positive effect on obesity prevalence and that overweight prevalence rate was higher among men than among women while in the case of obesity prevalence the opposite trend has been found (Miljkovic et al., 2008).A substantial percentage of studies has found that obesity is more frequent among low social classes and among adults with non or low education levels (Loureiro and Nayga, 2005). However, only in a very limited number of studies food prices have been considered as a main determinant of obesity prevalence (Schroeter and lusk, 2005 among others). This paper is one of the first attempts to consider this issue. Moreover, it is the first attempt to conducting this analysis in Spain. From methodological point of view, this paper compares the results obtained from the use of parametric and non parametric models to tackle with this issue. While previous literature has focused in parametric methods, like the multinomial logit we use the

Multivariate Adaptive Regression Splines (MARS), which is flexible enough to provide more insight on how covariates interact with the prevalence of obesity. In the next section we provide a brief description of MARS models.

MARS Model

MARS is a non-parametric regression technique developed by Friedman (Friedman, 1991). MARS allows covariates to enter in the model as a single variable or as interacting with other covariates generating unbiased parameter estimations with strong algorithms. MARS could be viewed as a generalization of the repeated discriminate method and stepwise linear regression to improve the performance of a covariate set. This method first divides data into locales and then forms a regression equation for each one. Each obtained linear region is called “knot”.

MARS uses both forward and backward progresses for robust and unbiased parameter estimations. It starts by maximizing all possible effects of explanatory variables in the forward model and then removes the least effective functions in the backward model using Ordinary Least Squares method.

The main advantage of MARS comparing with other regressions such as logistic regression is that MARS is a data driven technique. Instead of fitting a single regression equation for the model, MARS get many piecewise regression equations which allow the researcher to obtain more consistent and unbiased estimates of the covariates.

The main principle of MARS is based on searching for every point where linearity breaks. Then this point is taken as a knot and extrapolative variables, which have an effect until that point, are modeled using a new regression equation. Then, the number of obtained regression equations is the same as the number of knots defined in the process. MARS reaches the final model taking the obtained combination of basic functions into account (these functions are called Basis Functions) based on minimizing the Generalized cross validation (GCV) (Kayri, 2007).[1] MARS uses GCV to compare the performance of obtained models. lower values of GCV are better. The GCV can be considered as a form of regularization by trading off between goodness-of-fit against model complexity. For MARS models we cannot use the raw residual sum of squares (RSS) for comparing models, because the RSS always increases as MARS terms are dropped which means that if the RSS were used to compare models the backward step of model construction would always choose the largest model.

As it is designed, this method overcomes the shortcoming of other nonparametric methods by obtaining readable regression curves and generates unbiased parameter estimates by using the split method and a solution approach (Deconinckb et al., 2008).

The main disadvantage of MARS is the low prediction power with insufficient sample size. This is not the case in our analysis as we have a quite big data set. Moreover, Briand et al. (2007) mentioned that the model may suffer from multicollinearities as MARS gets interaction between predictive variables involved in the model.

[1] Mathematical expressions have been omitted due to space limitations.

4. Empirical application

Our data come from the 2006 National Health Survey (NHS). The NHS is a cross-section survey that provides micro data on the health status of citizens and its determinants. It is carried out by the National Institute of Statistics (INE) in cooperation with the Ministry of Health and Consumption. The survey collects information on the individual socioeconomic characteristics, morbidity, food habits and the demand for health care of respondents. Food habits refer to two main issues: type of breakfast and frequency of consumption of selected food groups. However, the data set does not provide information on quantities consumed (or purchased) neither on prices. In order to take into account the effect of economic factors we augment the data set with regional consumer price indices for food, the food away-from-home index and the regional disposable income index. Our data set consists of 25459 adults (16 years old or more). Table 1 show some descriptive statistics of the variables used in our analysis.

Table 1 Description and descriptive statistics of the analyzed variables

Variable	Units	Mean	S.deviation
Body Mass Index (BMI)	Kg/m2	25.85	4.44
Categorical BMI (CBMI)	1= normal 2=overweighed 3=obese	1.69	0.73
Perceived BMI (PBMI)	1= normal 2=overweighed 3=obese	1.53	0.64
Age	Years	49.01	17.9
Male	1=male 0=female	0.41	0.49
Food at Home Price (FAP)	Ratio of CPI of food at home and CPI of all items	1.033	0.007
Relative food out of home price(FOP)	Ratio of CPI of food out of home and CPI of food at home	1.025	0.019
Income	Regional Disposable Income index (national=100)	101.23	15.38
Physical exercise	1=doing the sufficient physical exercise 0=not doing	0.404	0.491
Last medical visit	1=last medical visit was less than four weeks ago 0=last medical visit was more than four weeks ago	0.408	0.492
Complete breakfast	1= having a complete breakfast 0= not having complete breakfast	0.763	0.425

We have distinguished between calculated body mass index (CBMI) which we have calculated using the reported weight and height collected from the participants and perceived (PBMI) which is reported directly by the participants. Both indices are split in the same categories for the purpose of making comparisons feasible. Categorical variables have been used also to reduce the potential bias in BMI estimates as it is not measured but self reported. Table 2 compares statistics for CBMI and PBMI.

Table 2 Frequency of normal, overweight and obese people in our data sample depending upon CBMI and PBMI

Categories	Categorical BMI		Perceived BMI	
	Frequency	%	Frequency	%
Normal	11942	46.91	13956	54.94
Over weighted	9454	37.13	9329	36.73

Obese	4063	15.96	2117	8.33
Total	25459	100	25402	100

As our dependent variables are categorical and unordered, first, we have estimated a multinomial logit model (see Greene, 2003). To overcome the shortcoming of using parametric models when the relation between variables is non-linear or when there is an interaction between covariates we have estimated two MARS models taking CBMI and PBMI as dependent variables with the same covariates than in the parametric model. However, in the case of the nonparametric we have jointly considered overweight and obese people. In other words, the dependent variable is binary taking the value one if the person is overweight or obese, and zero, otherwise.

5. Results

Main results from the multinomial logit model suggest that regarding the Calculated Body Mass Index (CBMI) all variables except prices have a significant marginal effect on the probability of being overweight, being the most relevant the sex (men) (in a positive way) and disposable income (negative effect). In the equation corresponding to obesity, all variables have a significant marginal effect on the probability of being obese. Parameter estimates from the model with the Perceived Body Mass Index (PBMI), as the dependent variable, seem to be less significant and, in some cases with some marginal effects with a non-expected sign.

It is also interesting to note that there are significant differences between the calculated BMI and the perceived BMI with a correlation coefficient between both two of only 0.45. Table 3 presents estimates and marginal effects of CBMI and PBMI.

Table 3. Estimates and marginal effects from Multinomial logit models for Calculated BMI and Perceived BMI.

	CBMI		PBMI	
Overweight				
Constant	1.104**	(0.532)	0.231	(0.503)
Age2	0.000**	(0.000)	0.000**	(0.000)
Male	0.823**	(0.030)	-0.138**	(0.028)
Ln FAP	4.976*	(2.770)	-3.929	(2.597)
Ln FOP	1.452	(1.229)	1.960*	(1.145)
Ln Income	-0.549**	(0.105)	-0.098	(0.100)
Physical exercise	-0.237**	(0.030)	-0.290**	(0.028)
Last medical visit	0.158**	(0.030)	0.198**	(0.028)
Complete breakfast	-0.131**	(0.034)	-0.237**	(0.032)
Obesity				
Constant	2.217**	(0.717)	-1.000	(0.899)
Age2	0.000**	(0.000)	0.000**	(0.000)
Male	0.553**	(0.039)	-0.288**	(0.050)
Ln FAP	8.225**	(3.575)	-17.691**	(4.549)

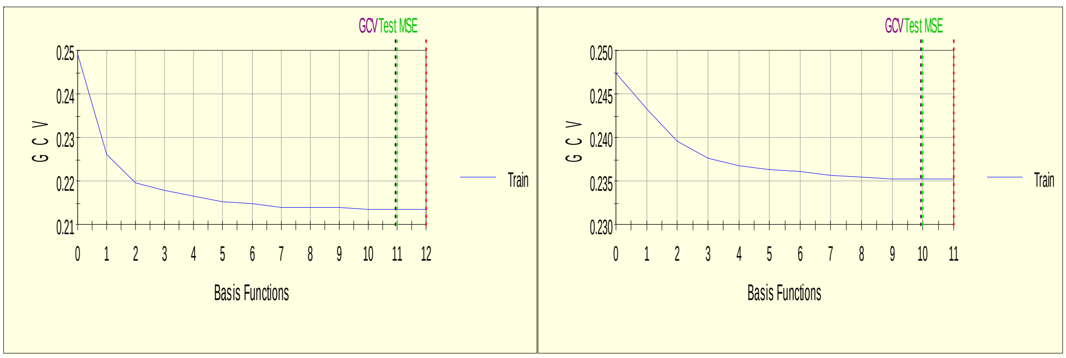
Ln FOP	4.217**	(1.599)	0.046	(2.028)
Ln wage	-1.019**	(0.143)	-0.034	(0.179)
Physical exercise	-0.451**	(0.040)	-0.556**	(0.051)
Last medical visit	0.409**	(0.039)	0.496**	(0.049)
Complete breakfast	-0.259**	(0.044)	-0.371**	(0.054)
Marginal effects				
Overweight				
Age2	0.000**	(0.000)	0.000**	(0.000)
Male	0.160**	(0.006)	-0.024**	(0.006)
Ln FAP	0.685	(0.603)	-0.396	(0.586)
Ln FOP	0.092	(0.269)	0.455*	(0.259)
Ln wage	-0.069**	(0.023)	-0.022	(0.023)
Physical exercise	-0.030**	(0.006)	-0.051**	(0.006)
Last medical visit	0.012*	(0.007)	0.031**	(0.006)
Complete breakfast	-0.015**	(0.007)	-0.044**	(0.007)
Obesity				
Age2	0.000**	(0.000)	0.000**	(0.000)
Male	0.022**	(0.005)	-0.017**	(0.003)
Ln FAP	0.788*	(0.435)	-1.178**	(0.322)
Ln FOP	0.469**	(0.195)	-0.054	(0.144)
Ln wage	-0.102**	(0.017)	0.000	(0.013)
Physical exercise	-0.044**	(0.005)	-0.031**	(0.003)
Last medical visit	0.045**	(0.005)	0.031**	(0.004)
Complete breakfast	-0.027**	(0.006)	-0.021**	(0.004)

Note: Standard Error in parentheses

** and * denotes statistical significance at 5 and 10 per cent significance level respectively.

Let us now concentrate on the results obtained from the non parametric approach. Figure 1 represents the minimized MSE of GCV for the CBMI and PBMI which use to choose the optimum number of base functions. As it was explained above in the backward step the best model is used by minimizing the GCV. It can be observed that the MARS model of CBMI reached the final model with 11 basis function while the MARS model with PBMI reached the best model with only 10 basis functions. Annex 1 represents the basis functions and the final model for both CBMI and PBMI MARS models respectively.

Figure 1 Minimized MSE of GVC for model with CBMI and PBMI



Tables 4 and 5 represent the basis function estimates for the final models in the case of CBMI and PBMI. MARS models have a better goodness of fit than the parametric logit model (adjusted R^2=0.02 and 0.15 for logit and MARS models, respectively)

Table 4. Parameter estimates from MARS model for CBMI

Basis Function	Coefficient	Variable	Sign	Parent Sign	Parent	Knot
0	0.7276					
1	-0.0043	AGE	+			66.0000
2	-0.0133	AGE	-			66.0000
3	0.2532	MALE	+			SubSet1
5	-0.0061	AGE	-	-	MALE	32.0000
6	-0.0144	AGE	+	+	MALE	32.0000
7	0.0682	PHYSICALEXERCISE	-			SubSet1
9	-0.0027	INCOME	+	-	MALE	90.7600
10	0.0048	INCOME	-	-	MALE	90.7600
11	-0.0650	LASTMEDICALVISIT	+	+	MALE	SubSet1
14	0.0002	AGE	-	+	INCOME	43.0000

Table 5. Parameter estimates from the MARS model for PBMI

Basis Function	Coefficient	Variable	Sign	Parent Sign	Parent	Knot
0	0.6115					
1	-0.0105	AGE	+			60.0000
2	-0.0081	AGE	-			60.0000
3	0.0853	PHYSICALEXERCISE	+			SubSet1
5	-0.0543	LASTMEDICALVISIT	-			SubSet1
7	0.0034	INCOME	+			108.5700
8	0.0028	INCOME	-			108.5700
9	-0.0400	COMPLETEBREAKFAST	+			SubSet1
11	-1.7744	FOP	-			1.0560
13	-0.0405	MALE	+	-	COMPLETEBREAKFAST	SubSet1
15	-98.6532	FAP	-	-	FOP	1.0150

From estimated parameters, we can calculate the variable importance of covariates in each model (CBMI and PBMI). Tables 6 and 7 summarize main results. As can be observed, the variables age, male, doing physical exercise, income and having a good health are important in both models, while in the case of PBMI also having a complete breakfast and relative food prices to consume both at home and away from home are important. As in the parametric logit models best performance has been obtained in the CBMI equation relative to the PBMI.

Table 6 Variable importance for CBMI MARS model

Variable	Score	
AGE	100.00	
MALE	63.50	
PHYSICALEXERCISE	19.72	
INCOME	18.60	
LASTMEDICALVISIT	14.30	

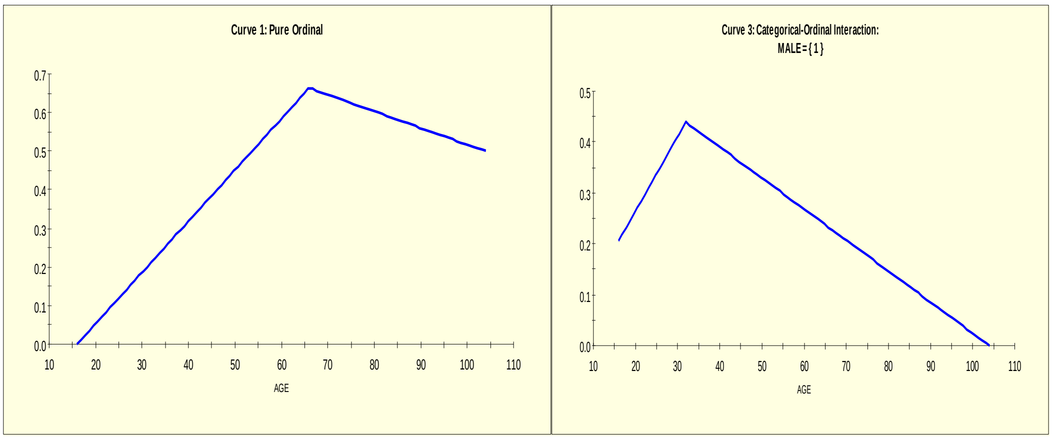
Table 7 Variable importance for PBMI MARS model

Variable	Score	
AGE	100.00	
PHYSICALEXERCISE	45.49	
COMPLETEBREAKFAST	30.26	
LASTMEDICALVISIT	27.83	
INCOME	25.52	
FAP	20.40	
FOP	19.05	
MALE	17.19	

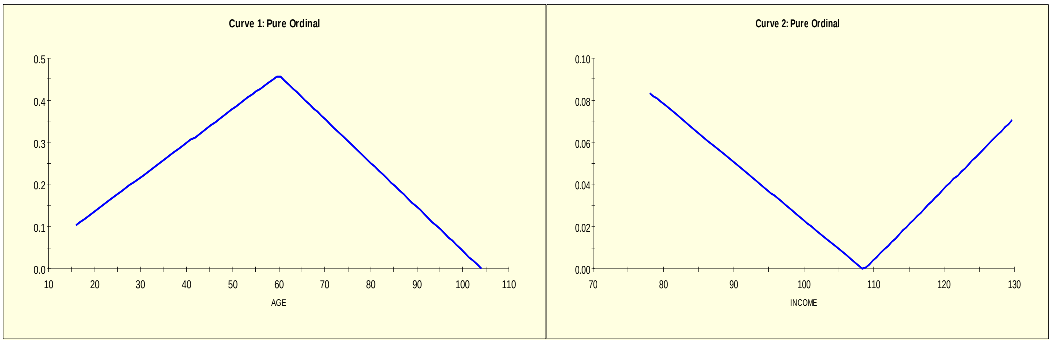
As mentioned above, the MARS method is more flexible as, among other issues, does not impose linearity between the dependent variable and its covariates. In fact, results obtained from the MARS model are quite similar to those obtained in the parametric approach, when the relationship is linear, but significant differences have been found when this is not the case. Moreover, we have found more consistency with expected results in the case of variables that have a non-linear relationship (i.e. age). While in the parametric multinomial logit the age does not have a significant effect on the prevalence of obesity, in the MARS it is the most important variable. The different results between logit and MARS model is owing to the non linear nature of the data in figure 2 we can see some example of this non linear nature. In 2A it can be observed that in CBMI MARS model the age has two patterns for people has more and less than 65 years for the whole sample. In 2B we can see similar relation but with the knot located at 32 years and only for males. 2C and 2D represent these non linear relationships for the PBMI in the case of age and income.

Figure 2 Relationship between age and income with obesity in CBMI and PBMI MARS models

A B



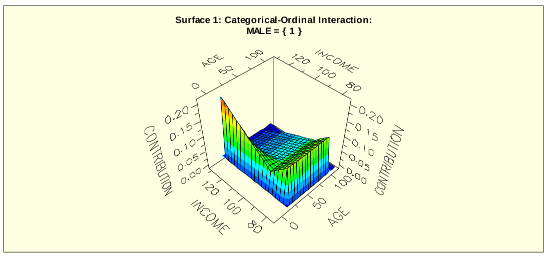
C D



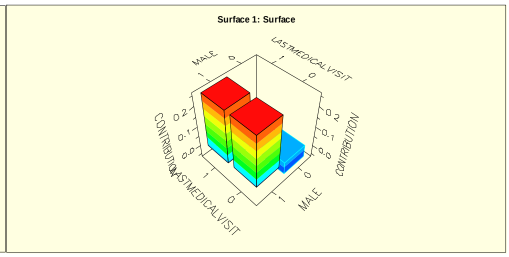
Another interesting result from MARS models is the three dimension figures which can help in understanding the interaction between the different independent variables. Figure 3 represents some examples of these three dimension figures for both models. 3A and 3B represent the joint effect of age and income and the conjoint effect of being a male and having a complete breakfast respectively for CBMI model, while 3C represent the same joint effect as 3B but for PBMI and 3D represents the conjoint effect of prices of food at and out of home for the PBMI model. In figure 3A it can be observed that higher disposable income resulted in higher obesity prevalence only in young people while higher income has an opposite effect in the case of elders and because of that the lowest obesity prevalence can be observed among older people with higher income level. In figure 3B we can see that being a male leads to a higher obesity prevalence rate and not having a complete breakfast enhances a little bid this effect while the smallest obesity prevalence rate observed in the case of women that have a complete breakfast. Regarding the PBMI MARS model figure 3C shows that being a male and having a complete breakfast lowers heavily the perception of being obese or overweighed while not having a breakfast does not have a significant effect on the perceived obesity. Figure 3Dindicated that increase food at home prices and decrease out of home prices increased the perceived obesity rate while decreasing food at home prices and increase out of home prices has an opposite effect on the perceived obesity.

Figure 3 Some three dimensions figures of MARS model results

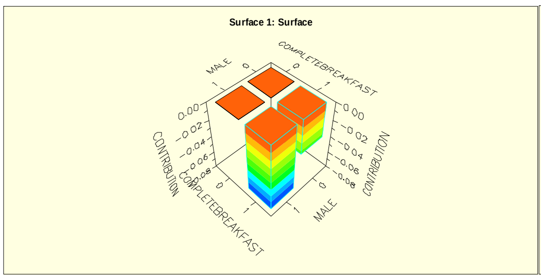
A



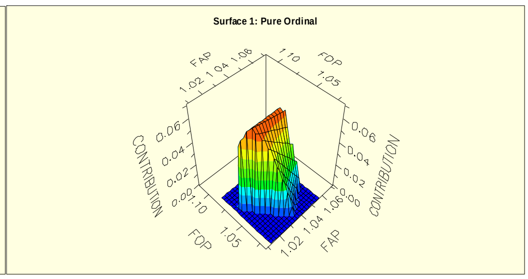
B



C



D



6. Concluding remarks

There are significant differences between CBMI and PBMI. For instance while about 16% of the sample are obese only about 8% recognize it, which emphasize the need of educational policies to increase awareness about this issue. Economic factors seem to have a significant impact on the prevalence of obesity. In general, increasing prices, being male, being older and have a bad health increase the probability of being obese. On the other hand, increasing income, doing sufficient physical exercise and having a more completed breakfast decrease the probability of being obese. The most limiting point of this type of analysis is the data availability.

MARS models outperform the traditional multinomial logit and could be a helpful tool for understanding the nature of the relationship and the importance of the different variables to be introduced into the model.

Although our study gives a first look on the effect of economic factors on the prevalence obesity, at the same time it opens number of interesting future research lines such as: Use different years of the NHS estimating a panel data model, Combine the NHS with the continuous household budget survey so we can get a richer data base, Develop a food quality index to be included in the analysis and Compare results from the NHS and the Catalan Health Survey which include estimated instead of reported weights and heights.

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Annex 1 The basis functions and the final model for both CBMI and PBMI MARS models.

```
BF4 = ( MALE in ( "0" ));
BF5 = max(0, AGE - 32) * BF3;
BF6 = max(0, 32 - AGE) * BF3;
BF7 = ( PHYSICALEXERCISE in ( "0" ));
BF9 = max(0, INCOME - 90.76) * BF4;
BF10 = max(0, 90.76 - INCOME) * BF4;
BF11 = ( LASTMEDICALVISIT in ( "0" )) * BF4;
BF14 = max(0, 43 - AGE) * BF9;

Y = 0.727617 - 0.00433466 * BF1 - 0.0132806 * BF2   + 0.253192 * BF3 - 0.00608167 * BF5
     - 0.0143866 * BF6 + 0.0681755 * BF7  - 0.00265792 * BF9 + 0.00484387 * BF10
       - 0.0650067 * BF11 + 0.000187387 * BF14;

MODEL CBMI = BF1 BF2 BF3 BF5 BF6 BF7 BF9 BF10 BF11 BF14;

BF5 = ( LASTMEDICALVISIT in ( "0" ));
BF7 = max(0, INCOME - 108.57);
BF8 = max(0, 108.57 - INCOME);
BF9 = ( COMPLETEBREAKFAST in ( "1" ));
BF11 = max(0, FOP - 1.056);
BF12 = max(0, 1.056 - FOP);
BF13 = ( MALE in ( "1" )) * BF9;
BF15 = max(0, FAP - 1.015) * BF12;

Y = 0.61147 - 0.0104528 * BF1 - 0.00809142 * BF2 + 0.0852657 * BF3 - 0.0542966 * BF5
    + 0.00336802 * BF7 + 0.00276152 * BF8  - 0.0400022 * BF9 - 1.77435 * BF11 - 0.0404502 * BF13
           - 98.6532 * BF15;
MODEL PBMI = BF1 BF2 BF3 BF5 BF7 BF8 BF9 BF11 BF13 BF15;
```