HEDONIC HOUSING PRICES AND AGRICULTURAL POLLUTION: AN EMPIRICAL INVESTIGATION ON SEMIPARAMETRIC MODELS

Abstract :

The objective of this paper is to assess the impact of agricultural pollution in a livestock intensive region of France using alternative semiparametric hedonic price models. A parametric, a fully nonparametric, a nonparametric additive, and a single index specifications are estimated using appropriate econometric procedures. A general-to-specific specification search procedure is performed, selecting only the nonparametric additive specification. Willingness to pay for pollution reduction are then computed. The main result is that the pollution due to livestock operations in rural townships is a more crucial environmental issue than the pollution due to intensive agricultural practices, although both affect significantly and in a non-linear way house prices.
Keywords : Hedonic pricing, semiparametric models, agricultural pollution.
JEL : C14, R21, R32

1 Introduction

The first order derivatives of an hedonic price function with respect to some pollution indicators give an estimate of the prices of these environmental attributes and, indirectly, an estimate of consumers' willingness to pay for these "disamenities". Up to now, the study of the relationships between agricultural pollution and house prices has been conducted using parametric model specifications (see, for instance, Herriges et al., 2003, Huang et al., 2003, Vukina and Vossink, 2000, and Palmquist et al., 1997), and to the authors' knowledge, nonparametric and/or semiparametric models have never been employed to address this problem of agricultural pollution in housing price models. The objective of this paper is to fill this gap by using a partially linear semiparametric hedonic price function in order to assess the impact of agricultural pollution on the prices of residential houses in a livestock-intensive region of France. Three alternative specifications - a fully nonparametric one, a nonparametric additive one, and a single index one - are used to capture different possible forms of non-linearity associated with these pollution variables in a hedonic price function. We also consider the parametric counterpart of the three aforementioned non and semiparametric model specifications. Indeed, the performances of non and semi-parametric models are usually investigated by comparing their goodness of fit to the parametric model "benchmark". This work differs from previous studies in two respects. First the "true" model benchmark is the fully nonparametric model, and second specification tests are performed in order to compare these specifications (fully parametric, non parametric additive and single index) with respect to this former model benchmark.

The empirical application deals with a set of transaction prices of residential houses sold in 1996 and 1997 in Brittany, France, the leading French region for a number of livestock products and vegetables. Agriculture in this region has two major impacts on the environment. First, the existence of intensive livestock units induce harmful effects on the environment in various forms such as the emergence of unpleasant odors and the emissions of nitrate which pollute soil, affect water quality and seep into the underground water table. The second effect of agriculture on the environment concerns the degradation of the country's landscape resulting from intensive agricultural practices and operations. In our study, these two effects are captured by two aggregate indicators : The per hectare of arable land amount of nitrogen emissions of livestock operations in the rural townships where the residential house is located, and the proportion of permanent pasture land converted into tilled land.

In the hedonic price model, we specify the prices of residential houses as a function of its physical characteristics, of the two environmental indicators but also of variables representing the economic structure of rural townships where the residential houses are located. Since many housing characteristics are discrete and since our main interest in this work hinges on measuring the impact of environmental variables on house prices, all the explanatory variables but the two former environmental indicators enter the hedonic price function in a linear fashion. This makes up the linear part of the hedonic price function. The two pollution indicators enter the hedonic price function in a nonparametric or semiparametric way and this constitutes the nonlinear part of the model.

The empirical strategy to estimate our housing price model follows a general-to-specific specification search involving three stages. In the first stage, the parameters involved in the linear part of the hedonic price models are estimated using Robinson's (1988) approach of partial linear model. In the second stage, the four - parametric, nonparametric, additive and single index - specifications of the non linear part of the hedonic price function are estimated using the residuals of the first stage estimation. The econometric procedures involve local polynomial regression (Fan and Gijbels, 1996), average derivative estimation (Horowitz and Hardle, 1996) and marginal integration (Linton and Nielsen, 1995). Finally, specification tests similar to those of Fan and Li (1996), Horowitz and Spokoiny (2001), and Gozalo and Linton (2001), are performed. The three (parametric, nonparametric additive and single index) specifications are thus compared to the more general one, i.e. the fully nonparametric one.

The specification search selects only the nonparametric additive specification. Willingness to pay for pollution reduction are then computed for this selected specification using the Severance-Lossin and Sperlich (1999) estimation procedure of derivatives for additive separable models. The main result is that the pollution due to livestock operations in rural townships is a more crucial environmental issue than the pollution due to intensive agricultural practices, although both affect significantly and in a non-linear way house prices.

The rest of the paper is organized as follows : The semi-parametric house price models are defined in Section 2. In Section 3, our general-to-specific specification search procedure is described. Section 4 is devoted to the presentation of data, while the estimation results of the proposed models are examined and discussed in Section 5. The paper ends by a concluding section highlighting the main finding of this empirical exercise.

2 Semiparametric house price models

2.1 Identification issues

This section provides a discussion of the different specifications for the hedonic price function and the estimations procedures. Let X represent a vector of observed characteristics of the house and of its surrounding environment (e.g. number of rooms, state of repair, age of the house, population of the city, stock of existing houses, ...), and let Z a vector of observed environmental characteristics (defining the impact of agricultural pollution). The housing market is assumed to be in equilibrium, which requires that individuals optimize their housing choice based on the prices of alternative prices. Prices are assumed to be market clearing, given the inventory of housing choices and their characteristics. Thus the price of any house Y can be described as a function of the different observed (X, Z) and unobserved (ξ) characteristics of the house :

$$Y = m(X, Z, \xi) \tag{1}$$

This equation is referred to as the hedonic price equation and $m(.)$ is a function of unknown form. Making additional assumptions on individuals' utility function and differentiating the hedonic price function with respect to a given characteristic enables us to derive the marginal willingness to pay for that characteristic (see Rosen, 1974).

2.2 Semiparametric models

Nonparametric regression estimator would provide a natural way to estimate equation 1. Unfortunately in this process, we thus would face two main problems : *(i)* The curse of dimensionality given that the vectors X and Z may involve a large number of characteristics, and *(ii)* the fact that the vector ξ cannot be observed. The latter problem can be avoided by assuming that $Y = m(X, Z) + \varepsilon$ where the error term contains the unobserved characteristics, but the first problem still remains. Since many housing characteristics are discrete and since our main interest in this work hinges on measuring the impact of environmental variables on house prices, we can assume a partial linear model specification given by :

$$Y = \beta' X + m(Z) + \varepsilon \tag{2}$$

where ε denotes an error term with zero mean and finite variance.

The crux now is to find the coefficients β and to estimate the function $m(z)$ in equation 2. To do so, we estimate this unknown function using $Y - \beta X$ as the dependent variable. Even though β has to be estimated, our estimation approach will follow this former and simple idea using a two-stage procedure. In the first stage, we estimate with the less restrictive available model specification, that is the specification proposed by Robinson (1988), where the function $m(.)$ is left unspecified. In the second stage, we investigate four models corresponding to four alternative specifications of the function $m(.)$ defined as follows :

Specification of $m(z)$		**Resulting model specification**	
Parametric specification		Linear and parametric model	
$m(Z) = \gamma' Z$	$\hookrightarrow$	$Y = \beta' X + \gamma' Z + \varepsilon$	(M1)
Nonparametric specification		Partially linear and nonparametric model	
$m(Z) = m(Z_1, \cdots, Z_L)$	$\hookrightarrow$	$Y = \beta' X + m(Z_1, \cdots, Z_L) + \varepsilon$	(M2)
Additive specification		Partially linear and additive model	
$m(Z) = \sum_{l=1}^{L} g_l(Z_l)$	$\hookrightarrow$	$Y = \beta' X + \sum_{l=1}^{L} g_l(Z_l) + \varepsilon$	(M3)
Single index specification		Partially linear and single index model	
$m(Z) = G(\gamma' Z)$	$\hookrightarrow$	$Y = \beta' X + G(\gamma' Z) + \varepsilon$	(M4)

3 Specification search procedure

3.1 First stage: The linear part

The first stage leading to the estimation of β is based on the procedure proposed by Robinson (1988). It is motivated by observing that, if we subtract on both side of (2) the conditional expectation relative to z, we obtain :

$$Y - E(Y|Z = z) = \beta' \Big(X - E(X|Z = z) \Big) + \varepsilon \tag{3}$$

The estimation procedure is thus as follows :

1. Regress both y_i and x_i on z_i nonparametrically to obtain residuals $\tilde{Y}_i \equiv y_i - E(Y|Z = z_i)$ and $\tilde{X}_i \equiv x_i - E(X|Z = z_i)$.

2. Then perform OLS on these residuals to get an estimate of β in (3).

Robinson (1988) showed that, under regularity conditions, this procedure yields to a $\sqrt{N}$-consistent and asymptotically normal estimator $\widetilde{\beta}$ for β, and that there exists a consistent estimator of its limiting covariance matrix.

Once β is estimated, we use $W = Y - \widetilde{\beta}X$ for dependent variable in all of the models proposed, and only specify the function $m(z)$ according to models M1-M4.

3.2 Second stage: The non-linear part

3.2.1 Fully nonparametric model

This model is used as benchmark for our investigation on the ability of semi-parametric model to estimate hedonic functions for real datasets. The function $m(z)$ is estimated using the second stage of Robinson's procedure based on a nonparametric regression of $Y - \widetilde{\beta}\ X$ on Z leading to an estimate of $m(\cdot)$. As a nonparametric estimator of $m(z)$, we use a local polynomial estimator. As any nonparametric estimator, $\widehat{m}_h(z)$ strongly depends on the bandwidth choice h. We built a grid search for the bandwidth choice and use a cross-validation criterion. Thus, we solved the following program.

$$\min_h CV(h) = \frac{1}{N} \sum_{i=1}^{N} \left(W_i - \widehat{m}_h^{-i}(z_i) \right)^2 \tag{4}$$

where :

- $(W_i)_{i=1,\ldots,n}$ are the first step residuals $(Y_i - \widetilde{\beta}X_i)_{i=1,\ldots,n}$.
- $\widehat{m}_h^{-i}(z_i)$ denotes the *leave-one out* local polynomial estimator used for the cross validation.
- Each of the bandwidths is computed with respect to the distribution of z_i (through its standard deviation $\sigma(z_i)$) and the theoretical rate of convergence, so that $h_i = h_{0i}\sigma(z_i)n^{-\frac{1}{6}}$ for $i = 1, 2$

3.2.2 Additive model

The additive house price model is of the form :

$$m(Z) = \sum_{l=1}^{L} g_l(Z_l) \tag{5}$$

where $\Big(g_l(.)_{l=1}^{L}, \text{ resp.}\Big)$ is a set of L unknown functions satisfying the identifiability condition $E(g_l(Z_l)) = 0$, for every $l = 1, \ldots, L$.

Additive models are usually estimated using the backfitting algorithm proposed by Hastie and Tibshirani (1990) (see, for instance, Pace, 1998, Iwata *et al.*, 2000, and Martins-Filho and Bin, 2003). Here, we use an alternative procedure for estimation of additive models based on marginal integration which has been proposed by Linton and Nielsen (1995) in the case of two independent variables and extended by Tjøstheim and Auestad (1995) and Chen *et al.* (1996) to larger dimensions.

3.2.3 Single-index model

A single-index house price model rests on the assumption that all the information conveyed by the independent variables can be summarized into a single index $\gamma' Z$ where γ is a vector of unknown coefficients, linked to the endogenous variable through an unknown link function $G(.)$ as :

$$m(z) = G(\gamma' Z) \tag{6}$$

The main idea underlying these models is to avoid the *curse of dimensionality*, by reducing the dimension of the regressor space to one, through the index. The cost is paid in terms of identification since for any arbitrary δ and ν, equation (6) is equivalent to $m(z) = G^*\Big(\nu + \delta(\gamma' Z)\Big) + \varepsilon$, and thus size and scale normalization are needed.

3.3 Third stage: Specification tests

3.3.1 Parametric vs nonparametric

Several papers have proposed tests of a parametric specification of a regression model against a nonparametric alternative (see among other Lavergne and Vuong, 1996 or Härdle and Mammen, 1993). Recently, Horowitz and Spokoiny (2001) have developed a new test used here. We test the null hypothesis, H_0, that $m(Z)$ belongs to some parametric family i.e. there exists some $\theta \in \Theta$ such that $m(Z) = M(Z, \theta)$ against the alternative, H_1 that there is no such θ. The test is based on the distance between the kernel estimation of $m(Z)$ and the kernel-smoothed estimation of the parametric regression $M(X_i, \theta)$. The distance is computed using rate-optimal and adaptative bandwidth, based on set of bandwidth values, and is centered and studentized.

3.3.2 Additive vs nonparametric

Gozalo and Linton (2001) propose several nonparametric tests of a very general additive structure in nonparametric regression. The null hypothesis H_0 is set in a more general framework than the additive model we are testing here and allows for discrete covariates and unknown link function $G(\cdot)$. In this framework, under H_0 it is assumed that for some parameters θ, $G_\theta(m(Z)) = \theta_0 + \sum_{d=1}^{D} m_d(Z_d)$, where G_θ, $\theta \in \Theta$ is a parametric family of transformations. Four tests statistics are proposed based on Hausman-like statistics, U-statistics or Lavergne and Vuong-like statistics to measure the distance between the nonparametric estimates of the function (or its residuals) under the null and under the general alternative that H_0 is false.

3.3.3 Single index vs nonparametric

To test the single index specification of the regression function $m(z)$, we use the procedure proposed by Fan and Li (1996). it is based on the null H_0 that $m(z) = G(\gamma z)$, for some $\gamma \in \Re^d$ and some $G(\cdot) \; : \; \Re \to \Re$ against the general alternative that H_o is not true. The test is based on U-statistics constructed as moments of the residuals of the estimated regression under the null. Under H_o the asymptotic distribution of the statistic is the Normal.

4 Data

The variables used in the hedonic regression analysis fall into three broad categories: *(i)* the price and the physical attributes of the home and the lot, *(ii)* the characteristics of the surrounding community, and *(iii)* the environmental "disamenities". Data on house sales were obtained from the MIN *(Marché Immobilier des Notaires)* data base. This data base provides a very detailed description of every house sale including the sale price and the physical attributes of the home and lot. Taxes and various fees linked to the sale were incorporated in the computation of the price really paid by the buyer of the house. This variable is denoted by *PRICE*. Four physical characteristics of the home and lot are used in the empirical analysis: The age of the house, *AGE*, its state of repair, *REPAIR*, the number of rooms, *ROOMS*, and the lot size, *LOT*. A description of these five variables is given in table 1.

The second category of explanatory variables are characteristics of the surrounding community. We associated each home with the community where the house is located, and used the INSEE (*Institut National de la Statistique et des Études Économiques*) data base to obtain the total population of the community (*POP*) and the average family income (*AVINC*). The MIN data base allowed us to compute for each community the percentage of vacant houses. This variable, denoted by *VACANT*, measures the state of the property market in each community. The last variable in this category, we denoted by *COUNTY*, is a dummy variable indicating the location of the community in the *Ille et Vilaine* county or not. The Brittany region is composed of four counties the *Ille et Vilaine* county being the less rural one. This variable also measures the state of the property market but now in the Brittany area. A description of the four variables : *POP*, *AVINC*, *VACANT*, and *COUNTY*, is given in table 1.

To measure consumer's willingness to pay for environmental "disaminities" generated by agriculture would require to dispose of, not only personal and confidential information on consumers' views on such issues, but also of detailed information on the location of livestock operations relative to the consumers' residential houses. Collecting such quantitative information is so sensitive that it is impossible to undertake relevant surveys to generate the relevant data. Given this situation, agricultural pollution is measured by two aggregate indicators which were provided by the French *Direction Régionale de l'Agriculture et de la Forêt de Bretagne*:

- The first one (*NITRO*) is the per hectare of arable land amount of nitrogen emissions of livestock operations in the rural community where the residential house is located.

Table 1: Variables and Descriptive Statistics

Variable	Description	Units	Min	Max	Mean	Std. Dev.
PRICE	Market Price	FF(10,000s)	10.102	106.648	50.177	22.259
AGE	Age	Year	0	298	47.835	42.018
REPAIR	State of repair	= 1 if good	0	1	0.687	0.464
ROOMS	Number of rooms	#	1	7	4.429	1.353
LOT	Lot size	(1000s)	0.102	21.880	1.793	2.551
COUNTY	County location	= 1 if *"Ille et Vilaine"*	0	1	0.478	0.499
VACANT	Vacant Housing	Percent	0.000	20.000	6.275	3.157
POP	County population	# (x1000)	0.104	4.972	2.047	1.215
AVINC	Average income	FF(1,000s)	3.751	18.726	7.103	1.644
TMEAD	Temporary meadows	Percent	0.010	70.143	29.420	9.972
NITRO	Nitrogen concentration	kg/ha	0.000	339.48	45.169	51.118

N=2092 observations

- The second indicator considered ($TMEAD$) is the proportion of permanent pasture land converted into tilled land. A high value associated with this variable would indicate a degradation of country's landscape.

Deriving the first order derivatives of house prices with respect to these variables will give an estimate of the prices of these two environmental attributes and indirectly an estimate of consumers' willingness to pay for these two agricultural "disamenities".

A description of the two pollution indicators is given in table 1. We also report in figure 1 the results of the nonparametric estimation of the joint density of these two indicators[1]. This joint density appears to be single peaked density and the majority of the observations corresponds to values of $TMEAD$ belonging to the $[20, 45]$ interval and of $NITRO$ in $[0, 50]$.

5 Empirical results

In the hedonic price models, we specify the prices of residential houses as a function of its physical characteristics, of the two environmental indicators but also of variables representing the economic structure of rural townships

[1] A bivariate normal kernel was used and the bandwidth was chosen using the Silverman's rule. See Silverman, 1986.

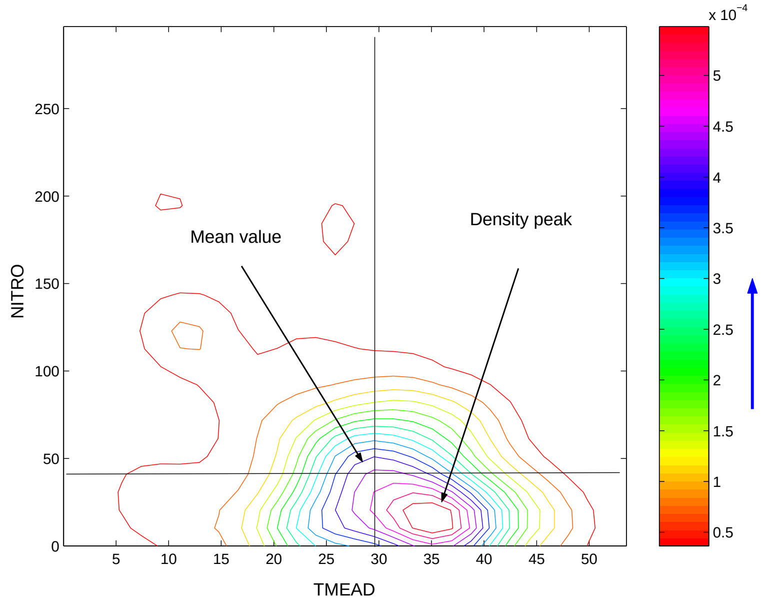


Figure 1: *Joint iso-density curves for the two environmental variables* (z_1, z_2)

where the residential houses are located. All the explanatory variables but the two former environmental indicators enter the hedonic price models in a linear fashion. This makes up the linear part of the hedonic price function. The two pollution indicators enter the hedonic price function in a nonparametric or semiparametric way and this constitutes the nonlinear part of the model.

5.1 Linear part

The estimates of the several parameters involved in the linear part of the first step estimation are reported in table 2. In the second part of this table we report the parametric parameters involved in the fully parametric and single index models. All the parameters have the expected sign and are significant.

5.2 Nonlinear part or depiction of nonlinearities

We report the estimated surfaces linking housing prices to the two pollution indicators for the four specifications in figure 3. We have restricted the repre-

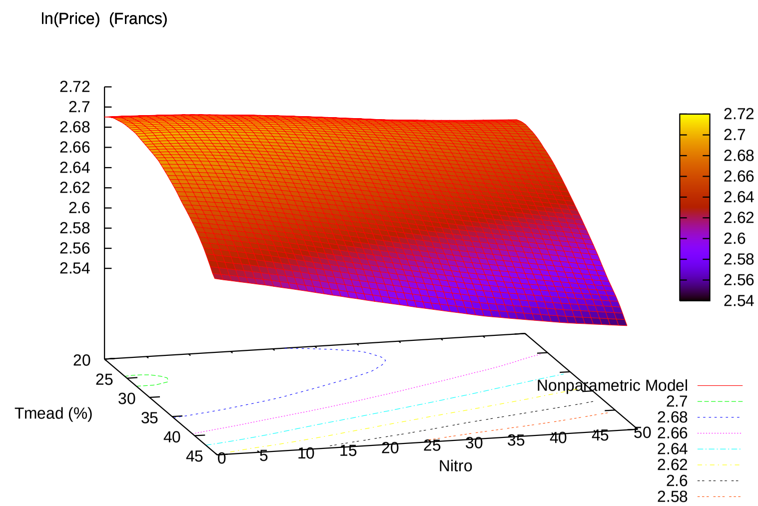
Table 2: Estimates of the parameters the first step and of the linear and Single index models

	Variable	Partial linear
First step estimates	Age	-0.002
		(*0.0002*)
	Repair	0.359
		(*0.0174*)
	Rooms	0.140
		(*0.0057*)
	Lot	0.029
		(*0.0028*)
	County	0.091
		(*0.0169*)
	Vacant	-0.017
		(*0.0032*)
	Pop	0.016
		(*0.0074*)
	Avinc	0.050
		(*0.0061*)

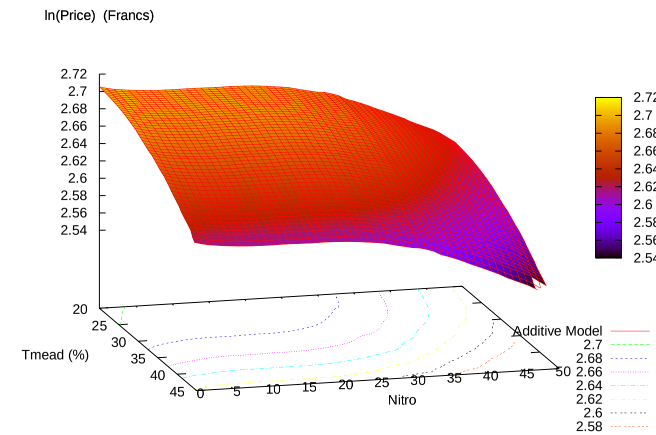
	Variable	Fully parametric model	Single Index model
Second step estimates	Constant	2.777	—
		(*0.0253*)	
	Tmead	-0.003	**-0.003**
		(*0.0007*)	
	Nitro	-0.0006	-0.003
		(*0.0001*)	

For comparison purpose, the coefficient in the Single index model γ_{Tmead} has been normalized to its corresponding value in the linear model. Standard error are presented in the parentheses.

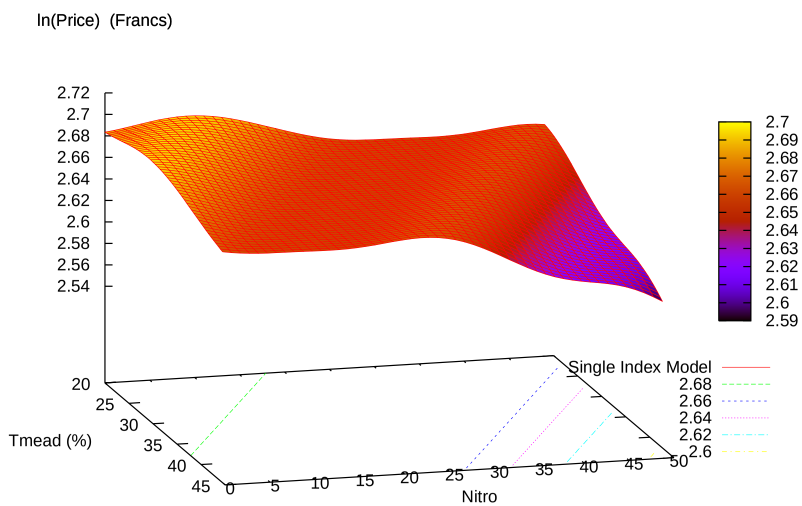
sentation of these curves to an area were the density of the joined distribution of the environmental variables z_1 and z_2 was high (see figure 1). A visual inspection of the four estimated surfaces suggests that the non parametric additive specification looks similar to the fully nonparametric one, while the two others (e.g. fully parametric and single index) do not. The fully parametric specification of the hedonic price function seems to be unable to capture all the features of our data sample; the same applies to the partial linear specification involving a single index in the non linear part of the hedonic price function. Moreover, the specification tests leads us to conclude that the null hypothesis of an nonparametric additive specification compared to the fully nonparametric one is not rejected, while the two other specifications are not accepted.



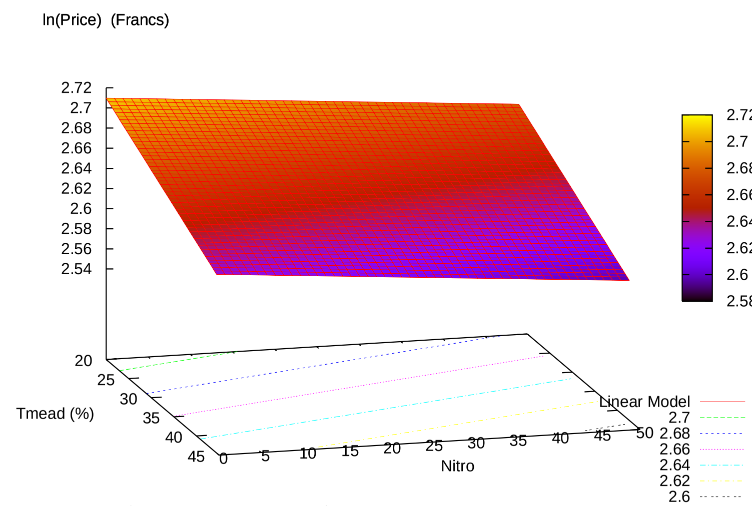
$H(Tmead, Nitro)$, nonparametric specification



$H(Tmead, Nitro)$, nonparametric additive specification



$H(Tmead, Nitro)$, Single index specification



$H(Tmead, Nitro)$, parametric specification

Table 3: Estimation of $H(z_1, z_2)$ for the four specifications

Table 4: Specification Tests

	$H_1 : Y = \beta' X + m(Z_1, \cdots, Z_L) + \varepsilon$		
	Test	Stat value	p-value
H_0			
Parametric specification	Reject H_0	$T^* = 6.107$	0.001
Single index specification	Reject H_0	$H_\alpha = 5.3289$	0.001
Nonparametric additive specification	Do not Reject H_0	$\tau_0 = 0.3353$	0.371

5.3 Specification tests

We have performed three specification tests, comparing the three restricted models to the nonparametric model. The results, presented in table 4, show that the nonparametric additive model is clearly not rejected, while the two others are.

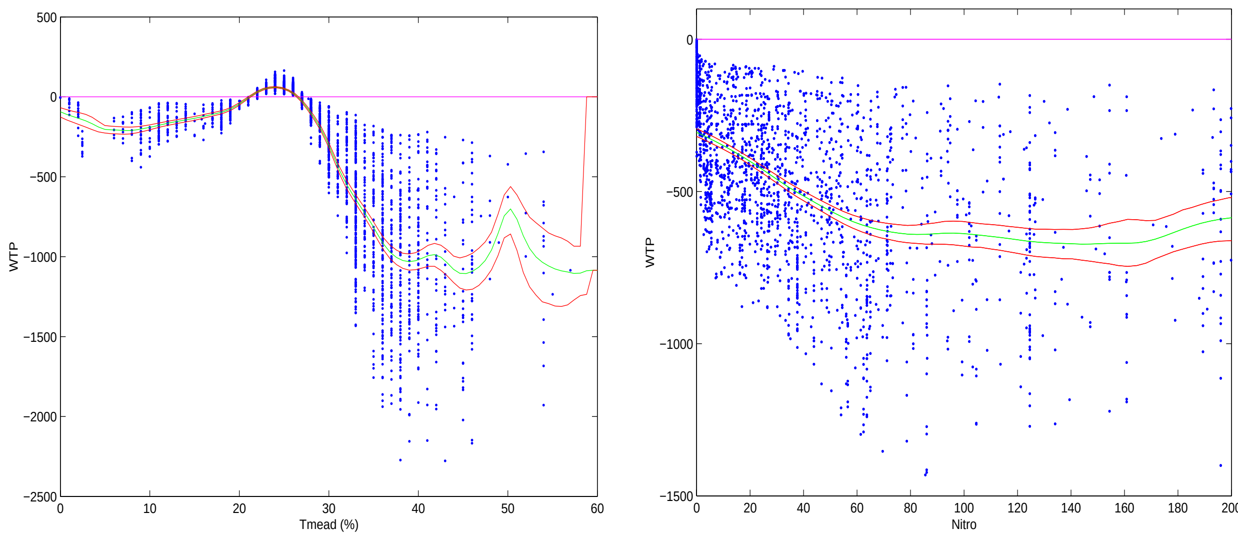
5.4 Marginal prices

Table 5 reports the willingness to pay for pollution reduction for the nonparametric additive specification. These estimates are obtained using the Severance-Losin and Sperlich (1999) estimator :

$$\widehat{g'}_l(z_l) = \frac{1}{N} \sum_{i=1}^{N} m'(Z_{i1}, \ldots, Z_{i,l-1}, z_l, Z_{i,l+1}, \ldots, Z_{iL}) \tag{7}$$

An estimate of the function $\widehat{g'}_l(z_l)$ can be obtained by replacing the unknown multivariate function $m(Z_{i1}, \ldots, Z_{i,l-1}, z_l, Z_{i,l+1}, \ldots, Z_{iL})$ by a nonparametric estimate. As a nonparametric estimator, we can use a local polynomial estimator.

In each of the graphs we report the estimated values of the willingness to pay for each housing transaction, as well as a nonparametric estimation of the mean willingness to pay function and its 95% confidence bounds. It can be seen from the table 5, that the relationships linking the willingness to pay to the pollution indicators are highly nonlinear. Up to a certain threshold that is significantly different from zero, the derivative of the hedonic price



WTP for Tmead WTP for Nitro

Table 5: Willingness to pay for pollution reduction for the nonparametric additive specification (dots), and nonparametric estimation of the mean willingness to pay function with its 95% confidence bounds (lines).

function with respect to the environment indicator "TMEAD" is small relative to average observed house prices, but exhibiting a marked decline for larger values. By contrast, the derivative with respect to the other environment indicator "NITRO" shows a clear and more significant impact even for small values of this explanatory variable. Moreover, the range of willingness to pay values for the latter is much larger than for "TMEAD".

6 Concluding remarks

to be completed

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