Can we explain pesticide price trend by the regulation changes ?

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This article estimates a hedonic pesticide price model using 151 pesticide products linked to more than 39 chemical families over the period 1996 to 2006 in France. To take into account the chemical family as well as the unbalanced structure of the panel a nested error component model is estimated. This approach embeddes the successive components of the error term into the preceding component thus capturing the unobservable heterogeneity. Based on the predicted prices, the decrease of indices in 2001, corresponding to the setting of a toxicity-tax, suggests that pesticide turnover and innovativeness is more important than toxicity-tax effect.

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Keywords: Pesticide Prices, Hedonic Functions, Unbalanced Panel Data, Double Nested Error Components Model.

JEL Classification: C23, L11, L51, Q11.

1 Introduction

In 2008, the French government committed to reduce pesticide use by 50% over the following ten years. France is the first user of pesticide in Europe and has developed agricultural systems that are highly dependent on pesticides. These products are highly regulated because they have potential harmful impacts on the environment (Fenner et al., 2013) and human health (Baldi et al., 2013). In a context where the use of these products is challenged, it is important to understand how the pesticides characteristics explain their prices and how the regulation requirements influenced their turnover. Only few analysis of the impact of regulation on pesticide supply has been provided and most of them were concentrated on the U.S. market[1] (Lichtenberg, 1992; Ollinger et al., 1998). They aimed at measuring the impact of regulation change on the behavior of firms, and the quality of products available for farmers (Fernandez-Cornejo and Jans, 1995). These researches showed that pesticide quality increases in terms of safety under the pressure of new sustainable development requirements into regulation. However, the pesticide performance is limited over time. The development of pest resistance is a key challenge for firms. It requires high levels of Research and Development (R&D) to find new active ingredient (a.i.) In a context where a large number of heterogeneous products are available it is useful to analyze how regulation influenced the turnover of products on the pesticide market through the analysis of their prices and characteristics.

The literature on pesticides focuses primarily on modeling the impact of pesticides on agricultural productivity and economic evaluation of reducing their use; see Jacquet et al. (2011); Skevas et al. (2012). Research show that farmers are very dependent on pesticide inputs, and relate their use to better control of pest damage to maintain yields (Fernandez-Cornejo et al., 1998; Sexton et al., 2007). Reducing pesticide use is difficult farmers' demand is weakly sensitive to pesticide prices (Skevas et al., 2013). Few studies have addressed the impact of regulation on pesticide supply. In the U.S. market, reinforcement of the marketing authorization process has increased the regulatory costs and decreased the number and toxicity of pesticides in the market (Ollinger and Fernandez-Cornejo, 1998a,b).[2] However, we do not know how regulation influences firms' pricing strategies and their incentive to innovate. Since firms' willingness to register a pesticide is related strongly to regulatory constraints and the potential revenue generated by pesticide sales, an increase in regulatory constraints should affect pesticide prices.

This article uses a hedonic framework to analyze the pesticide prices. The pesticide market involves more than a hundred different active ingredients that are embedded within chemical families. First, this means that within a chemical family, pesticide prices might be correlated. Second, in the case of some pesticide products, we observe a price that applies to several retailers and various different sales conditions. Third, the dataset used for this analysis covers the period 1996-2006 when regulation was heavily influencing the pesticide market and was resulting in several products being banned. Hence, the analysis

[1] Nowadays, the analysis of the U.S. pesticide market are widely concentrated on the gains or looses due to genetic engineering introduction (e.g. GMOs) into the agricultural process. Hence researches switched to the analysis of complementarities and/or substitutions between GMOs and pesticides. In the European context, where GMOs cannot be cultivated, the pesticide use reduction is a key issue in terms of public policies.

[2] 2Most studies focus on the U.S. market and the gains or losses due to the introduction of genetic engineering (e.g. genetically modified organisms - GMOs) in the agricultural process. Most research analyses the complementarities and/or substitution between GMOs and pesticides. In the European context, where GMOs are banned from cultivation, reducing pesticide use is a key issue in public policy.

of pesticide prices requires consideration of the hierarchical structure of the data in order to obtain consistent parameter estimates. Our hedonic functions deal with three levels of intra-group correlation. At the lower level, for each time period, we observe *series* of price per hectare of application. This level gives, for one pesticide, several prices depending, for example on packaging size. The second level nests all the series by pesticide products. Here, we identify the regulatory mentions, and labeling informations. Finally, the higher level nests the pesticide product within its chemical family. This description enables to define a nested structure to the random error to consider the intra-group correlation for the estimations to control the bias generated by neglecting groups correlations Moulton (1987).[3] Moreover, the empirical application is made on the French market with panel data over the period 1996-2006. This period enables to cover both the implementation of the the directive 91/414/ECC that contributes to ban the most toxic products, especially in 2003 with the banning of the most toxic products. It also covers the implementation in 2000 of an excise tax based on the toxicity of products. The 151 pesticides of our sample contain more than 110 a.i. that cannot be introduced directly for the estimation; however, neglecting this intra-group correlation may lead to biased estimation results Moulton (1986).

In such a context, it is relevant to consider the nested structure of the data to define the hedonic functions. The nested effects are defined through disturbance *via* a double nested error component structure Antweiler (2001). This decomposition enables to capture the relative part of the unobserved heterogeneity with respect to: the series, the products and the chemical families. The structure of the pesticide dataset implies three levels of intra-group correlation, which bias estimation of the variance components (Moulton, 1987). First, to control for this bias, we consider a nested structure of the random error because this allows us to model the proximity of hedonic price determinants among products in the same "group" (Moulton, 1986, 1987). Second, because regulation influences the turnover of pesticide products, we exploit the unbalanced structure of the data. To solve these two issues simultaneously, nested effects are defined through disturbance via a double nested error component structure (Antweiler, 2001) by extending the estimators proposed in Baltagi et al. (2002)). This article proposes ANOVA estimators for the situations where the Maximum Likelihood estimator does not have a unique solution. Based on these estimates, predicted prices are used to compute adjusted prices that are corrected from quality changes, and illustrate how the turnover of the pesticide products influenced the price indices.

The remainder of this article is organized as follows. Section 4 presents the data. Section 3 describes the double nested error component model, the corresponding ANalysis Of VAriance (ANOVA) estimator. The estimation procedures and their results are presented and discussed in section 5. The paper ends with some concluding remarks.

2 Related literature

An extensive part of the literature analyzed pesticide use and the impact of their reduction on agricultural productivity; but firms supply has been seldom addressed. This literature

[3]This framework has been applied by Moulton (1986, 1987) and extended by **?** to the Harison and Rubinfeld data (1978) for the estimation of households willingness to pay for clean air. This structure applied to the housing market enables to carry on the grouped structure of the data, and the proximity of hedonic prices determinants when the houses are in the same "group".

emerged with data availability in the 1990's and focused on the economic evaluation of the strengthening of the registration process. In the U.S, it occurred by the amendment of the FIFRA Act of 1972.[4] Researchers analyzed how the introduction of environmental requirements affect firms strategies: in term of innovation process and/or product characteristics. For example, Cropper et al. (1992) showed that probability of cancellation by the EPA is positively dependent on the risks to human health or environment. Hence, firms are encouraged to develop less toxic pesticides Ollinger and Fernandez-Cornejo (1998a). This is confirmed by a survey made by the European Crop Protection Association in 2012 (McDougall, 2011). The report underlined that R&D and registration cost to introduce a new a.i. increased by 68% from 1995 to 2005 because of an increase of development costs, i.e. field trials and toxicology evaluations. In other words regulation amendment increases the cost of development of new products and slope on the cost functions.

The regulation has two consequences on the pesticide market: First, it leads firms to focus on the larger harvested crops for the first registration leaving technical "holes" for farmers (Jaffe and Palmer (1997), Ollinger et al.(1998)). Thus, the potential revenue generated by each products depends on: the total area of each crop, and the application rate for which the product is registered (Fernandez-Cornejo et al., 1998). Indeed, the increase of sunk costs and research expenditures favors the largest firms over the small ones (Ollinger and Fernandez-Cornejo, 1998a). Hence, the likelihood for firms to merge innovation process with one of its competitor rises. For example, in 2006, BASF and Monsanto, or Syngenta and DuPont made joint ventures on R&D for pesticide creation (See Agrow reports). This illustrates the fact that suppliers are multinational firms that are subject to a combination of various regulatory process to market pesticides. Their willingness to register a pesticide is highly related to the regulatory constraints and the potential revenue generated by pesticide sales. So, the increase of regulatory constraints should affect the prices of pesticides to reveal their safety as well as their chemical performance. Moreover, due to the high levels of cost to introduce a new a.i. these substances are patented giving a monopoly advantage for firms on the first years of commercialization and confirming their trend to choose the larger markets. Finally, the high levels of R&D to develop new pesticides are also explained by the fact that pesticide efficacy is negatively related with the development of pest resistance (Lichtenberg and Zilberman, 1986).

Hedonic functions have been widely adopted to explain the prices; we survey here some of the relevant hedonic approaches (Griliches, 1961; Rosen, 1974). Griliches argued that the hedonic coefficients illustrate firms strategies in terms of prices and quality of products[5]. Werle et al. (1997) applied this framework to the French pharmaceutical drugs market, which share a very close mechanism of registration and innovativeness with the pesticide market. They estimated a random coefficient model by chemical family of the drug. They conclude that the strategic effect on prices depends on the innovativeness of drugs. This can be explained by the possibilities of substitutions with more recent, but more expensive products.

Relative to the pesticide market, Fernandez-Cornejo and Jans (1995, hereafter FJ)

[4]In 1972, the U.S. Congress amended the Federal Insecticides, Fungicide, and Rotenticide (FIFRA) Act of 1947. This amendment increases regulatory stringency on pesticides authorizations to raise health and environmental safety of plant protection products. It had direct effect on product registrations by firms.

[5]Theoretical literature mainly focus on the demand side to define the hedonic functions (see Triplett (2004) for a survey on hedonic functions) or a more global approach that consider the market equilibrium, in the sense defined by Rosen (1974). But rather few analyses addressed the supply side functions that enables to address the problem of firms cost functions, and thus reflect the producers' costs (Griliches, 1961; Nerlove, 1995).

computed for the period 1968-1981 a quality adjusted price indices for the U.S. pesticide prices. By using a pooled time series to explain the prices of the a.i., they showed that the pesticide quality increased in terms of safety through the introduction of sustainable development requirements into the regulation process. They showed that the "*rapid changes in pesticide quality*"(FJ, p. 657) is explained by a change in firms supply, mainly driven by regulation and its environmental requirements.

3 The model

The specification introduces hierarchical error components which represents the impact of packaging effects embedded within pesticide products which are embedded within their chemical compounds. This hierarchical structure deals with unobserved heterogeneity which is related to the chemical family of pesticide products. The dependent variable y_{cjit} denotes, for each time period t, the logarithm of average price of the *serie* i corresponding to product j in the chemical class c. Let consider the unbalanced panel data regression model:

$$(1) \quad y_{cjit} = \mathrm{X}_{cjit}\beta + u_{cjit}, \text{where } c = 1, ..., C,\ j = 1, ..., M_c;\ i = 1, ..., N_{cj};\ t = 1, ..., T_{cji}.$$

X_{cjit} denotes a vector of k non-stochastic covariates.[6] There are $m(= \sum_{c=1}^{C} M_c)$ pesticides, and $n(= \sum_{c=1}^{C} \sum_{j=1}^{M_c} N_{cj})$ series of prices. The number of chemical classes is C. Each serie of prices is observed during T_{cji} time periods which are not necessarily identical for all series of prices. This means there are C pesticide classes and each class has M_c pesticides in which N_{cj} series of prices are observed. In other words, the N_{cj} series of prices are nested by the M_c pesticides. These pesticides are nested by the chemical class, C. The total number of observations is given by $S(= \sum_{c=1}^{C} \sum_{j=1}^{M_c} \sum_{i=1}^{N_{cj}} T_{cji})$.

Following Antweiler (2001), the remainder term u_{cjit} follows a nested errors components structure:

$$(2) \quad u_{cjit} = \alpha_c + \mu_{cj} + \nu_{cji} + \epsilon_{cjit},$$

where $\alpha_c \sim \mathrm{IID}(0, \sigma_\alpha^2)$, $\mu_{cj} \sim \mathrm{IID}(0, \sigma_\mu^2)$, $\nu_{cji} \sim \mathrm{IID}(0, \sigma_\nu^2)$, $\epsilon_{cjit} \sim \mathrm{IID}(0, \sigma_\epsilon^2)$, and α_c, μ_{cj}, ν_{cij} and ϵ_{cijt} are independent of each other and among themselves.

In notation matrix equations (1) and (2) are equivalent to

$$(3) \quad y = X\beta + u,$$
$$(4) \quad u = Z_\alpha \alpha + Z_\mu \mu + Z_\nu \nu + \epsilon,$$

where Z_α is a matrix of dimension (S, C) taking ones when i is in class c and 0 otherwise; α is a $(C, 1)$ of ones; Z_μ is a matrix with dimension (S, m) taking ones for i and 0 otherwise; μ is a $(m, 1)$; Z_ν is a matrix with dimension (S, n) taking ones when j is in i and 0 otherwise; ν is a $(n, 1)$. The covariance matrix of the disturbance is given by:

$$(5) \quad \Omega = \sigma_\alpha^2 Z_\alpha Z_\alpha' + \sigma_\mu^2 Z_\mu Z_\mu' + \sigma_\nu^2 Z_\nu Z_\nu' + \sigma_\epsilon^2 I_S.$$

[6] More precisely, each product is defined by a bundle of k pesticide characteristics. Thus, the vector x_{cjit} includes physical and technical characteristics, see section 4.

The estimation of equation (3) through Ordinary Least Square (OLS) gives unbiased and consistent estimates of the parameters. However, this estimator provides biased standard error because some disturbances are correlated (due to the nested structure of error components). Generalized Least Square (GLS) on (3) are obtained by estimating OLS on the transformed model which incorporates between weights among the nests, and given the number of observations they contain. The unbalancedness structure of the dataset complicate the generalization of Ω because the Kronecker products is problematic due to the fact that each nest does not include the same number of observations.[7]

Antweiler (2001) showed, through Monte Carlo simulations, the link of both the degree of unbalancedness and variance ratios on the consistency of estimates. In such a situation, the double error component should be preferred to the single Maximum Likelihood (ML) estimator to minimize Moulton bias. For example, with high variance ratios and high degree of unbalancedness, variance ratios have much more influence on the consistency of estimates than the degree of unbalancedness. Through simulations, he underlined that when the variance component ratios are higher than 0.4 a benchmark between estimators is needed. Moreover, the nonlinearity of the Likelihood function can lead to unstable maximization routines. Hence, the function value cannot be improved when the number of nests of the smaller group is important and/or covariates get higher. In this context, the ANOVA estimators can be an interesting alternative because they perform well for the estimation of coefficients[8], see Baltagi and Chang (1994). Their unbiasedness properties are relative in context of unbalancedness, but their results are close from those of ML estimators (see Baltagi et al., 2001, p. 370-371, Table 2). Thus, we follow Baltagi et al. (2001) whom computed ANOVA-type estimators with single nested error components structure.Wansbeek and Kapteyn (1989) and Swamy and Arora (1972) estimators are extended for the double nested disturbance structure, following the computation of the error components with nested models derived by Xiong (1995) and using Khatri-Rao products (Khatri and Rao, 1968). This product enables to generalize the kronecker products with matrix constructed from blocks of different size[9];

Let define M_u a vector which contains the exact number of products of each class c, i.e. each element is m_{cjit}; N_u a vector which contains the number of product per serie of price n_{cjit}, and T_u the number of time period per *serie* (i.e. t_{cjit}). These vectors, in which is element is a scalar enables to use the Theorem 1 of Liu (1999), to obtain:

$$(7) \quad \bar{J}_{M_u} = \frac{1}{M_u} * J_{M_u}, \bar{J}_{N_u} = \frac{1}{N_u} * J_{N_u}, \bar{J}_{T_u} = \frac{1}{T_u} * J_{T_u},$$

where $*$, is the Katri-Rao product; $J_A = \iota_A \iota_A^{'}$, $\bar{J}_A = J_A/A$ and for any positive integers $J_{AB} = J_A * J_B$, $I_{AB} = I_A * I_B$. Thus by replacing I_A by $E_A + \bar{J}_A$, where $E_A = I_A - \bar{J}_A$,

[7]Computations in the balanced situation are available upon request. We focus here on the unbalanced situation which is more accurate for our analysis.

[8]If we consider a balanced panel, ANOVA estimators are the best quadratic unbiased estimators, see Baltagi and Chang (1994); Searle (1995) for overviews. The comparison is based on the mean square error (MSE) of the parameter estimates, (Baltagi and Chang, 1994), Table 1, p. 81.

[9] Let: $\mathbf{A} = (\mathbf{A}_{ij})$ a partitioned matrix with $\mathbf{A}_{ij}$ of order $m_i \times n_j$ as the (i,j)th block submatrix; $\mathbf{B} = (\mathbf{B}_{lk})$ a partitioned matrix with $\mathbf{B}_{lk}$ of order $p_k \times q_l$ as the (k,l)th block submatrix. The Khatri-Rao product (Khatri and Rao, 1968; Liu and Trenkler, 2008a), generalize the kronecker products. It is defined as follow:

$$(6) \quad \mathbf{A} * \mathbf{B} = (\mathbf{A}_{ij} * \mathbf{B}_{ij})_{ij} = \left[\begin{array}{c|c} \mathbf{A}_{11} \otimes \mathbf{B}_{11} & \mathbf{A}_{12} \otimes \mathbf{B}_{12} \\ \hline \mathbf{A}_{21} \otimes \mathbf{B}_{21} & \mathbf{A}_{22} \otimes \mathbf{B}_{22} \end{array} \right].$$

Note that when considering non partitioned matrix : $\mathbf{A} * \mathbf{B} = \mathbf{A} \otimes \mathbf{B}$ (**?**).

and collecting terms with the same matrices. This enables to write Ω such that:

$$\begin{aligned}\Omega =&(\sigma_\alpha^2 M_u * N_u * T_u + \sigma_\mu^2 N_u * T_u + \sigma_\nu^2 T_u + \sigma_\epsilon^2)Q_4 \\ &+ (\sigma_\mu^2 N_u * T_u + \sigma_\nu^2 T_u + \sigma_\epsilon^2)Q_3 + (\sigma_\nu^2 T_u + \sigma_\epsilon^2)Q_2 + \sigma_\epsilon^2 Q_1,\end{aligned} \tag{8}$$

with

$$\begin{aligned}&Q_1 = I_C * I_{M_u} * I_{N_u} * E_{T_u}, Q_2 = I_C * I_{M_u} * E_{N_u} * \bar{J}_{T_u}, \\ &Q_3 = I_C * E_{M_u} * \bar{J}_{N_u} * \bar{J}_{T_u}, Q_4 = I_C * \bar{J}_{M_u} * \bar{J}_{N_u} * \bar{J}_{T_u}.\end{aligned} \tag{9}$$

First, consider the modified Wansbeek and Kapteyn estimator of Baltagi et al. (2001), denoted WK. The $\tilde{q}_1$, $\tilde{q}_2$, $\tilde{q}_3$ and $\tilde{q}_4$ are given by equating their expected values, respectively $E(\tilde{q}_1)$, $E(\tilde{q}_2)$, $E(\tilde{q}_3)$ and $E(\tilde{q}_4)$, i.e.

$$\begin{aligned}&E(\tilde{q}_1) = E(\tilde{u}_{WTN}^{'} Q_1 \tilde{u}_{WTN}), E(\tilde{q}_2) = E(\tilde{u}_{WTN}^{'} Q_2 \tilde{u}_{WTN}), \\ &E(\tilde{q}_3) = E(\tilde{u}_{WTN}^{'} Q_3 \tilde{u}_{WTN}), E(\tilde{q}_4) = E(\tilde{u}_{WTN}^{'} Q_4 \tilde{u}_{WTN}),\end{aligned} \tag{10}$$

where $\tilde{u}_{WTN}$ are the within residuals. We define X_1 a $(S \times k_1)$ matrix, which incorporates the k_1 variables that vary within time dimension. The within estimator is given by pre-multipling the equation (3) by Q_1.[10] So, the variance components are:[11]

$$\begin{aligned}\hat{\sigma}_\epsilon^2 =& \frac{\tilde{u}_{WTN}^{'} Q_1 \tilde{u}_{WTN}}{(S-n-k_1)}, \\ \hat{\sigma}_\nu^2 =& \frac{1}{S-t}\left\{\tilde{u}_{WTN}^{'} Q_2 \tilde{u}_{WTN} - \hat{\sigma}_\epsilon^2 \left[n - m + tr((X_1^{'} Q_1 X_1)^{-1} X_1^{'} Q_2 X_1)\right]\right\}, \\ \hat{\sigma}_\mu^2 =& \frac{1}{S-n}\left\{\tilde{u}_{WTN}^{'} Q_3 \tilde{u}_{WTN} - \hat{\sigma}_\epsilon^2 \left(m - c + tr\left[(X_1^{'} Q_1 X_1)^{-1} X_1^{'} Q_3 X_1\right]\right) - \hat{\sigma}_\nu^2 (t-c)\right\}, \\ \hat{\sigma}_\alpha^2 =& \frac{1}{S}\left\{\tilde{u}_{WTN}^{'} Q_4 \tilde{u}_{WTN} - \hat{\sigma}_\epsilon^2 \left(C + tr((X_1^{'} Q_1 X_1)^{-1} X_1^{'} Q_4 X_1)\right) - \hat{\sigma}_\mu^2 \left(\frac{S}{M}\right) - \hat{\sigma}_\nu^2 \frac{S}{MN}\right\}.\end{aligned} \tag{11}$$

Remember that the within estimator wiped out the time invariant variables, however, these variables are relevant to define the hedonic functions. In other word, the within residual may overestimate variances if the dimension of variation of the variables is higher. Thus, we extended the Swamy-Arora-estimator to the double nested error component (denoted SA). Variances for such an estimator are obtained by transforming the equation (3) with Q_p, for $p = 1, ..., 4$:

$$\begin{aligned}&E(\tilde{q}_1^+) = E(\tilde{u}_{WTN}^{'} Q_1 \tilde{u}_{WTN}), E(\tilde{q}_2^+) = E(\tilde{u}_2^{'} Q_2 \tilde{u}_2), \\ &E(\tilde{q}_3^+) = E(\tilde{u}_3^{'} Q_3 \tilde{u}_3), E(\tilde{q}_4^+) = E(\tilde{u}_4^{'} Q_4 \tilde{u}_4).\end{aligned} \tag{12}$$

[10] When computing the intercept, the centered residuals on the full sample should be computed as in WK.

[11] The proofs are available upon request

Thus we have:

$$\hat{\sigma}_{\epsilon}^{2} = \frac{\tilde{u}_{WTN}^{'} Q_1 \tilde{u}_{WTN}}{(S-n-k_1)},$$

$$\hat{\sigma}_{\nu}^{2} = \frac{\tilde{u}_2^{'} Q_2 \tilde{u}_2 - \hat{\sigma}_{\epsilon}^{2}\,(n-m-k_2)}{S-t-tr\left((X_2^{'} Q_2 X_2)^{-1} X_2^{'} Z_{\nu} Z_{\nu}^{'} X_2\right)},$$

$$\hat{\sigma}_{\mu}^{2} = \frac{\tilde{u}_3^{'} Q_3 \tilde{u}_3 - \hat{\sigma}_{\nu}^{2}[t-c-tr(Q_3 X_3 (X_3^{'} Q_3 X_3)^{-1} X_3^{'} \frac{Z_{\mu} Z_{\mu}^{'}}{N})] - \hat{\sigma}_{\epsilon}^{2}(m-c-k_3)}{S-n-tr(Q_3 X_3 (X_3^{'} Q_3 X_3)^{-1} X_3^{'} Z_{\mu} Z_{\mu}^{'})},$$

$$\hat{\sigma}_{\alpha}^{2} = \Bigg\{ \tilde{u}_4^{'} Q_4 \tilde{u}_4 - \hat{\sigma}_{\mu}^{2}(tr(Z_{\alpha} Z_{\alpha}^{'})/M - tr((X_4^{'} Q_4 X_4)^{-1} X_4^{'} Z_{\alpha} Z_{\alpha}^{'} X_4)/M) - \hat{\sigma}_{\nu}^{2}(tr(Z_{\alpha} Z_{\alpha}^{'})/MN$$

$$- tr((X_4^{'} Q_4 X_4)^{-1} X_4^{'} Z_{\alpha} Z_{\alpha}^{'} X_4)/MN) - \hat{\sigma}_{\epsilon}^{2}(C-k_4) \Bigg\} \Bigg/ \Big\{ S - tr((X_4^{'} Q_4 X_4)^{-1} X_4^{'} Z_{\alpha} Z_{\alpha}^{'} X_4) \Big\}, \tag{13}$$

where $X_2 = Q_2 X$, $X_3 = Q_3 X$ and $X_4 = Q_4 X$ are the $(S \times k)$ matrix of explanatory variables.

4 The Data

A new original dataset has been constructed to analyze pesticide prices. This section first describes the several data sources and presents a range of descriptive statistics. Prices come from the French Ministry of Agriculture; Then three data sources have been merged to recover the technical, regulatory and commercial pesticide characteristics. One enables to recover the regulatory mentions and identify the firm owner of the product: *E-Phy* (French Ministry of Agriculture). *E-Phy* reports regulatory mentions imposed for each pesticide. It contains the specific quantity of application with respect to each crop for the specific disease. Besides, it reports information on the registrants firms, the date of registration and/or canceling, the level of toxicity of each product and the safety precautions for farmers. One identifies, yearly, the patent portfolio of firms: "*Index phytosanitaire*", indicating whether or not the active ingredient is patented or not. The last one gives the chemical families of the active ingredients included into each pesticide: Pesticide Properties DataBase (PPDB), see Appendix-Table 7. The chemical class enables to group the pesticides as in Integrated Pest Management programs (IPM), illustrating possible substitutions based on the mode of action of each active ingredient. The Herbicides, Insecticides and Fungicides Resistance Action Committees published a uniform classification by pesticide category: Herbicide Resistance Classification (HRAC), Insecticide Resistance Classification (IRAC), and Fungicide Resistance Classification (FRAC).

Table 1 presents the descriptive statistics by category of pesticides, i.e. herbicides, insecticides and fungicides. The "Dim" column reports the dimensions of the variables with M, N and T respectively indicating that the variable changes at the product, serie and time levels. A total of 4,968 observations are obtained from 675 series of prices representing 151 products grouped into 39 chemical classes. The number of observations are reported in Table 2 by category of pesticide, and considering each level. The dataset is an unbalanced panel of 11 years from 1996 to 2006 because some product are no longer marketed during the observed period.

To measure the degree of unbalancedness, we compute Ahrens and Pincus (1981)

statistics which are the ratio, by group, between harmonic mean and arithmetic mean. When these ratios are smaller than one, it indicates that the sample is highly unbalanced. The ratio is given by:

$$(14) \quad \omega = \frac{N/\sum_{i=1}^{N_i}(1/T_i)}{S/N}.$$

The introduction of nests implies to compute these ratios at the level of each nest. Thus following Antweiler, they are given by:

$$(15) \quad \omega_\alpha = \frac{C/\sum_{c=1}^{C}(1/M_c)}{M/C}, \omega_\mu = \frac{M/\sum_{c=1}^{C}\sum_{j=1}^{M_c}(1/N_{cj})}{N/M}, \omega_\nu = \frac{NT/\sum_{c=1}^{C}\sum_{j=1}^{M_c}\sum_{t=1}^{N_{cj}}(1/T_{cji})}{S/N}.$$

The degree of unbalancedness is reported in Table 3. For the entire sample, 83 % of the series are observed for each of the 11 years. The remainder sample is only observed for less periods illustrating the entry and exit of pesticides from the market. Moreover, it enables to measure how the unbalancedness should affect the properties of our estimates. More precisely, the structure of unbalancedness is quite different among the different categories of pesticides. A better understanding of these ratios is completed by chemicals grouping distribution of pesticide detailed in the Appendix A (see Table 7).

Table 1: Descriptive Statistics

Variable	Symbol	Unit	Dim.	Herbicides	Insecticides	Fungicides
				Mean (SD)	Mean (SD)	Mean (SD)
logPrice	log p	€/hectare	. . N T	3.79 (0.44)	2.38 (0.73)	3.63 (0.33)
Concentration	concent	0=liter/1=kg	. . N .	0.92 (0.28)	0.74 (0.44)	0.80 (0.40)
Weight	weight	Unity	. . N .	7.69 (7.74)	4.04 (3.50)	5.57 (5.69)
30 d. pay	pay	0=No/1=Yes	. . N .	0.19 (0.39)	0.28 (0.45)	0.19 (0.39)
Age	age	years	. M . T	12.53 (5.01)	13.86 (7.05)	9.54 (3.93)
Patent	pat	0=No/1=Yes	. M . T	0.91 (0.28)	0.94 (0.23)	0.97 (0.17)
Nb a.i.	# a.i.	Unity	. M . .	1.69 (0.81)	1.25 (0.44)	1.59 (0.59)
Nb diseases	# dis	Unity	. M . .	14.51 (6.46)	11.60 (3.91)	8.46 (2.36)
Nb crops	# crop	Unity	. M . .	2.47 (1.47)	5.25 (1.49)	4.31 (1.95)
Dose	dose	unit/hectare	. M . .	2.78 (1.69)	1.19 (2.52)	1.60 (1.66)
Wheat	wheat	0=No/1=Yes	. M . .	0.58 (0.49)	0.90 (0.31)	0.83 (0.38)
Toxicity	tox	(1/6)	. M . .	3.17 (0.90)	2.79 (1.34)	3.03 (0.97)

Dim. indicates the level of variations: M for product; N for series; T for time.
The column "SD" indicates Standard Deviations.

Table 2: Number of Observations per Category of Pesticides

Type	Herbicides	Insecticides	Fungicides	Total
Chemical class	21	6	12	39
Product	59	49	43	151
Serie	191	309	175	675

Table 3: Degree of Unbalancedness

		Dim.	Herbicides	Insecticides	Fungicides	Total
	Chemical class	C	0.199	0.062	0.292	0.151
Nests	Product	M	0.376	0.236	0.296	0.295
	Serie	N	0.839	0.843	0.810	0.830

Regulatory mentions are very useful to describe pesticide characteristics. FJ also argued that priority is given to larger markets in term of area. In 2006, tender wheat represented 43% of the French cultivated area, and generates 44% of pesticide use (Butault *et al.*, 2010). Our sample reveals whatever the category of pesticide most of products are marketed for wheat which corresponds to first field crop cultivated in France. Registration for wheat concerns 58% of herbicides, and more than 83% for the two others. Moreover, pesticides are often marketed for more than one crop. The sample illustrates herbicides that can be used on average on 2.47 crops, or 5.16 crops for insecticides (namely *Nb crops*). The heterogeneity among the different categories of pesticides illustrates the fact that products are more recent in the fungicides market than for the other categories of pesticides. The regulatory mentions enable to know the levels of toxicity and eco-toxicity of each product. However, with more than 40 mentions it is difficult to introduce each level individually. The General Tax on Polluting Inputs (TGAP)[12] classification is used to construct seven categories summarizing toxicity and eco-toxicity mentions (namely, *Tox*). The smaller category indicates the safer products (TGAP_a with a the level in TGAP classification). This classification is used as proxy for environmental indicators and to measure the potential risk generated by the use of pesticides. The relation among pesticide application rates and its potency is accounted through the variable *Dose* which average, for field crops the homologated quantity of application. The a.i. gives to pesticides their pesticidal effects; we introduce the number of a.i. into each pesticide (*Nb a.i.*). Last, the spectrum of pesticide registration is introduced with the variable *Spect* which is the number of crop for which firms have the registrations.

Finally, Series of prices are differentiated by their sales conditions. First, the type of pesticide (kilogram or liter) enables to control for the type of concentration of each product.The size of the packaging is introduced through the size of the box (*Pound*), with the intuition that with higher packages prices should be smaller. The variable *Pay 30* indicates payment within 30 days. It enables to control potential discount for cash payment situations. However, this variable is not sufficient to analyze quantity discounts which are based on the total sale of the crop year.

5 Estimation results and discussion

The dependent variable is the log of the price of the pesticide expressed in euros per hectare at the regulated average quantity of application[13] per hectare at homologated quantity of application (Beach and Carlson). We expect to confirm the results of previous researches that the "*productive characteristics generally are positively associated with price, while hazardous characteristics are negatively associated with price*" (FJ, p. 646).

The explanatory variables used in the hedonic price functions concerns the technical characteristics of pesticides and the labeling mentions imposed by regulation. Tables 4 ,

[12]The TGAP is paid by retailers of pesticides based on the total quantity of toxic pesticide a.i. they sold.

[13]To enable flexibility among different crops (e.g. corn, cotton, sorghum and soybeans) FJ applied a Box-Cox transformation both to the dependent variable and continuous covariates. If all attributes are observed, linear and quadratic functions of Box-Cox transformed variables provide the most exact estimates, however, when certain "*variables are omitted or replaced by proxies, it is the simpler forms [...] that do the best*"(Cropper, Deck and McConnell, 1988, p. 674). Hence, we consider log-linear specification to estimate the implicit prices of each characteristic with an unbalanced dataset.

5 and 6 report the parameter estimates for the hedonic functions concerning respectively herbicides, insecticides and fungicides. Variances are computed following section 3. The second column of this table reports the dimensions of the independent variables. M denotes that the variations are made at pesticide level. N denotes that the variable change is made at the level of series of prices. T denotes that the variable changes with time.

The three next columns reports the estimations results from a single nested error component structure model, with the subscript S[14]. For these estimations, the series of prices are only nested by products. The last 3 columns report the double nested error component structure estimation results, with the subscript D. Here, the inner group is made by series of prices. The middle group is made by pesticides. The upper group is defined by the chemical class of each pesticide . This enables to consider the intra-class correlation of the regressors (Moulton, 1986). The column WK presents estimations results of Wansbeek and Kapteyn-type estimator, the column SA presents Swamy Arora-type estimator, and the last column presents estimations results of the Maximum Likelihood estimator developed by Anwteiler (2001).

We first inspect the relative gain in efficiency of a double nested error component structure. Then we comment the implicit values of each pesticide characteristics based on the preferred results. Antweiler and Baltagi et al.underline the importance of unbalancedness and variance ratio to conclude on the efficiency of estimation results. The estimation of single nested models reports high variance ratios for the top level. This suggests that the estimation results should be biased (namely Moulton biais). The intuition presented before is to propose ANOVA estimators for the situations where maximization routines do not enable to estimate the double nested error component model *via* ML procedure[15], in our context optimization routines failed for the fungicide category. Moreover, by controlling the unobserved heterogeneity due to the level of variation of the different covariates, we expect to find smaller variances when same level of variation is used to computed the variances of the same nest. First, we find that the variances from the double model are always smaller than for the single models. This result is much more relevant for the variables varying at N dimensions: SA_D and WK_D variances are close or smaller than ML_D. For the other dimensions, we always find that ML results are smaller than WK and SA. We can now focus our comments on the estimation results provided by the double nested error component model.

We now discuss the estimated coefficients and their conformity with agricultural economics as well as agronomic literature. First, at the level of the series of price, the packaging size coefficients are significant at the 5% level[16] for insecticides and fungicides, the increase of the size of the box by 1% reduce the prices of 0.06% for fungicides (this result is valid whatever the estimator), or by 0.06% for insecticides (column SA_D), *ceteris paribus*. The later payments reports negative and significant coefficients for insecticides whereas they are positive for fungicides. This can be explained by the fact that, at the end of the cultural crops, discounts can be granted by retailers based on the total amount of pesticides they purchase. These coefficients are highly related to pesticide pressure and the total amount of sales.

[14]see Baltagi et al.(2001).

[15]All the estimations are made with SAS 9.3 software, using proc iml, and maximization routines. We would like to thank Professor Werner Antweiler who gave us the SAS code for estimating the single nested error component model *via* ML.

[16]This level is retained in this section.

Table 4: Estimation Results for Herbicides

Dep.Var. log(P)	Dim.	Single Nested Error components			Double Nested Error components		
		WK_S Est. (*Std.Err.*)	SA_S Est. (*Std.Err.*)	ML_S Est. (*Std.Err.*)	WK_D Est. (*Std.Err.*)	SA_D Est. (*Std.Err.*)	ML_D Est. (*Std.Err.*)
Intercept		3.503‡ (0.047)	3.498‡ (0.047)	3.201‡ (0.289)	3.484‡ (0.089)	3.414‡ (0.048)	3.562‡ (0.152)
Patent	. M . T	0.026‡ (0.009)	0.026‡ (0.009)	0.026† (0.013)	0.026‡ (0.010)	0.024† (0.010)	0.030† (0.014)
log(*Age*)	. M . T	-0.111‡ (0.035)	-0.108‡ (0.035)	-0.111‡ (0.042)	-0.105‡ (0.035)	-0.119‡ (0.035)	-0.103† (0.042)
log(*Age*)^2	. M . T	0.046‡ (0.008)	0.045‡ (0.008)	0.046‡ (0.011)	0.044‡ (0.009)	0.045‡ (0.008)	0.039‡ (0.011)
Wheat	. M . .	0.026 (0.019)	0.028 (0.019)	-0.008 (0.250)	0.022 (0.035)	0.026 (0.027)	-0.000 (0.082)
log(Dose)	. M . .	0.320‡ (0.006)	0.320‡ (0.006)	0.312‡ (0.054)	0.380‡ (0.007)	0.334‡ (0.007)	0.397‡ (0.031)
Tox	. M . .	0.102‡ (0.004)	0.101‡ (0.004)	0.094* (0.056)	0.093‡ (0.005)	0.096‡ (0.005)	0.137‡ (0.024)
log(Nb crops)	. M . .	-0.230‡ (0.010)	-0.231‡ (0.010)	-0.242 (0.167)	-0.193‡ (0.021)	-0.208‡ (0.016)	-0.220‡ (0.073)
log(Nb a.i.)	. M . .	-0.019 (0.014)	-0.020 (0.014)	-0.039 (0.155)	0.038† (0.017)	-0.053‡ (0.016)	-0.142† (0.070)
log(Spect.)	. M . .	-0.000 (0.010)	0.001 (0.010)	0.149 (0.121)	-0.013 (0.013)	0.061‡ (0.011)	0.007 (0.050)
log(Pound)	. . N .	-0.029‡ (0.005)	-0.029‡ (0.005)	-0.030* (0.016)	-0.030‡ (0.005)	-0.037‡ (0.005)	-0.110† (0.045)
Concentr.$_{\text{kg}=1}$	. . N .	-0.042‡ (0.014)	-0.040‡ (0.014)	-0.042 (0.053)	-0.040‡ (0.015)	-0.069‡ (0.014)	0.086 (0.142)
30 d. pay	. . N .	-0.008 (0.007)	-0.008 (0.007)	-0.008 (0.023)	-0.007 (0.007)	0.007 (0.007)	-0.015 (0.049)
Year$_{>2001}$	. . . T	0.008 (0.006)	0.008 (0.006)	0.008 (0.009)	0.008 (0.007)	0.012* (0.006)	0.020† (0.010)
$\hat{\sigma}^2_\xi$		0.007	0.007	0.007	0.007	0.007	0.006
$\hat{\sigma}^2_\nu$		0.008	0.007	0.008	0.005	0.007	0.029
$\hat{\sigma}^2_\mu$		0.191	0.179	0.167	0.121	0.025	0.079
$\hat{\sigma}^2_\alpha$					0.051	0.000	
log(L)		.	.	1325.468	.	.	1396.648

Std. Error beside coefficients.Level of significance : ‡=1% ; †=5% ; *=10%.

Table 5: Estimation Results for Insecticides

Dep.Var. log(P)	Dim.	Single Nested Error components			Double Nested Error components		
		WK_S Est. (*Std.Err.*)	SA_S Est. (*Std.Err.*)	ML_S Est. (*Std.Err.*)	WK_D Est. (*Std.Err.*)	SA_D Est. (*Std.Err.*)	ML_D Est. (*Std.Err.*)
Intercept		3.284‡ (0.024)	3.282‡ (0.024)	3.301‡ (0.209)	3.301‡ (0.304)	3.180‡ (0.031)	2.929‡ (0.090)
Patent	. M . T	0.027† (0.010)	0.027† (0.010)	0.029† (0.014)	0.027† (0.010)	0.025† (0.010)	0.020 (0.023)
log(*Age*)	. M . T	0.026 (0.016)	0.025 (0.016)	0.026 (0.021)	0.026 (0.016)	0.024 (0.016)	0.006 (0.021)
log(*Age*)^2	. M . T	-0.004 (0.004)	-0.004 (0.004)	-0.004 (0.006)	-0.004 (0.004)	-0.003 (0.004)	-0.004 (0.006)
Wheat	. M . .	0.477‡ (0.049)	0.467‡ (0.049)	0.184 (0.910)	0.405‡ (0.049)	0.266‡ (0.049)	0.325 (0.403)
log(Dose)	. M . .	0.374‡ (0.003)	0.375‡ (0.003)	0.385‡ (0.066)	0.234‡ (0.004)	0.388‡ (0.004)	0.480‡ (0.027)
Tox	. M . .	-0.058‡ (0.002)	-0.059‡ (0.002)	-0.068 (0.051)	-0.062‡ (0.003)	-0.061‡ (0.003)	-0.019 (0.017)
log(Nb crops)	. M . .	-0.515‡ (0.032)	-0.507‡ (0.032)	-0.314 (0.568)	-0.335‡ (0.033)	-0.306‡ (0.033)	-0.218 (0.243)
log(Nb a.i.)	. M . .	0.204‡ (0.012)	0.203‡ (0.012)	0.192 (0.241)	-0.520‡ (0.020)	0.168‡ (0.019)	0.507‡ (0.065)
log(Spect.)	. M . .	0.011 (0.011)	0.012 (0.011)	-0.008 (0.030)	0.011 (0.012)	0.024† (0.012)	0.004 (0.023)
log(Pound)	. . N .	-0.042‡ (0.003)	-0.043‡ (0.003)	-0.047† (0.020)	-0.046‡ (0.003)	-0.057‡ (0.003)	-0.149‡ (0.024)
Concentr.$_{\text{kg}=1}$	. . N .	-0.069‡ (0.008)	-0.070‡ (0.008)	-0.078 (0.065)	-0.079‡ (0.008)	-0.113‡ (0.008)	-0.037 (0.075)
30 d. pay	. . N .	-0.063‡ (0.004)	-0.063‡ (0.004)	-0.061* (0.036)	-0.058‡ (0.004)	-0.057‡ (0.004)	-0.065 (0.045)
Year$_{>2001}$	. . . T	-0.006* (0.003)	-0.006* (0.003)	-0.006 (0.006)	-0.006* (0.003)	-0.006* (0.003)	-0.003 (0.005)
$\hat{\sigma}^2_\xi$		0.004	0.004	0.004	0.004	0.004	0.003
$\hat{\sigma}^2_\nu$		0.055	0.054	0.052	0.045	0.052	0.064
$\hat{\sigma}^2_\mu$		0.526	0.445	0.167	0.107	0.044	0.608
$\hat{\sigma}^2_\alpha$					0.367	0.001	0.005
log(L)				2080.956			2732.594

Std. Error beside coefficients.Level of significance : ‡=1% ; †=5% ; *=10%.

Table 6: Estimation Results for Fungicides

Dep.Var. log(P)	Dim.	Single Nested Error components			Double Nested Error components	
		WK_S Est. (*Std.Err.*)	SA_S Est. (*Std.Err.*)	ML_S Est. (*Std.Err.*)	WK_D Est. (*Std.Err.*)	SA_D Est. (*Std.Err.*)
Intercept		3.787‡ (0.040)	3.795‡ (0.040)	3.936‡ (0.495)	3.712‡ (0.103)	3.944‡ (0.056)
Patent	. M . T	-0.030* (0.016)	-0.030* (0.016)	-0.031 (0.021)	-0.030* (0.017)	-0.029* (0.016)
log(*Age*)	. M . T	-0.012 (0.026)	-0.012 (0.026)	-0.014 (0.032)	-0.015 (0.027)	-0.013 (0.026)
log(*Age*)^2	. M . T	-0.004 (0.007)	-0.004 (0.007)	-0.004 (0.009)	-0.003 (0.007)	-0.005 (0.007)
Wheat	. M . .	-1.176‡ (0.028)	-1.176‡ (0.028)	-1.238‡ (0.349)	-1.077‡ (0.061)	-1.140‡ (0.038)
log(Dose)	. M . .	0.008 (0.011)	0.005 (0.011)	-0.030 (0.195)	0.106‡ (0.020)	-0.021 (0.016)
Tox	. M . .	0.071‡ (0.005)	0.071‡ (0.005)	0.072 (0.057)	0.051 ‡ (0.006)	0.068‡ (0.005)
log(Nb crops)	. M . .	0.591‡ (0.015)	0.590‡ (0.015)	0.622‡ (0.203)	0.582 ‡ (0.023)	0.580‡ (0.020)
log(Nb a.i.)	. M . .	0.281‡ (0.019)	0.280‡ (0.019)	0.300 (0.216)	0.171‡ (0.025)	0.212‡ (0.022)
log(Spect.)	. M . .	0.015 (0.011)	0.012 (0.011)	-0.049 (0.193)	0.062† (0.025)	-0.033† (0.016)
log(Pound)	. . N .	-0.058‡ (0.005)	-0.058‡ (0.005)	-0.059‡ (0.019)	-0.061‡ (0.005)	-0.063‡ (0.005)
Concentr.$_{\text{kg}=1}$	. . N .	-0.157‡ (0.012)	-0.157‡ (0.012)	-0.160‡ (0.055)	-0.162‡ (0.013)	-0.143‡ (0.013)
30 d. pay	. . N .	0.021‡ (0.008)	0.022‡ (0.008)	0.016 (0.029)	0.020‡ (0.008)	0.038‡ (0.008)
Year$_{>2001}$	. . . T	0.015† (0.007)	0.015† (0.007)	0.014 (0.010)	0.014* (0.007)	0.018† (0.007)
$\hat{\sigma}^2_\xi$		0.007	0.007	0.007	0.007 ()	0.007
$\hat{\sigma}^2_\nu$		0.017	0.017	0.012	0.012	0.014
$\hat{\sigma}^2_\mu$		0.102	0.092	0.171	0.056	0.022
$\hat{\sigma}^2_\alpha$					0.034	0.001
log(L)					1139.602	

Std. Error beside coefficients.Level of significance : ‡=1% ; †=5% ; *=10%.

Concerning the pesticide characteristics, we focus on each category of pesticide separately. First, concerning herbicides (Table 4), a raise of the homologation rate increase the prices by more than 0.3% (whatever the estimation method). The toxicity influences significantly pesticide prices. The toxicity (variable Tox) has a positive and significant impact on prices for herbicides and fungicides.[17] In the agronomic literature, toxicity is highly related to efficacy of products, with the idea that because of the ongoing commitment to reduce pesticide quantities, farmers intended to reduce the quantities by choosing pesticides with higher performance which can be more toxic. The most recent pesticides are cheaper than older. Actually, the effect on prices becomes positive after three year of marketing. Finally, $\text{Year}_{>2000}$ has no significant impact on herbicide prices. For insecticides this year correspond is associated to a 0.6% decrease of pesticide prices (column SA_D, and column ML_D). Finally, the prices of fungicides also decreased significantly by 2% after 2000. This result suggest that prices are lower for 2001-2006 compared to 1996-2000, which is the period post-TGAP. But this result should be interpreted with cautions, because our specification does not introduce more details on firms supply or quantities sold by retailers. This latter information is required to compute the amount of TGAP paid by retailers.

At series level, the coefficients of concentration dummies are significant at the 5% level[18] for two of the three categories. This semi-elasticity indicates that herbicides sold in powder form (e.g. unity in kg) are 7% cheaper than those sold as liquid form, resp. they are 11% cheaper for insecticides. Concentration has no significant impact on fungicide prices. This results can be explained by the fact that powders should be mixed with adjuvant before application. The coefficients of packaging size are significant for insecticides and fungicides, a 1% increase in the size of the box reduces the price by 0.06% for fungicides, and by 0.06% for insecticides, *ceteris paribus*. The payments after 30 days report negative and significant coefficients of insecticides. This suggests that retailers offer discounts, at the end of the cultural crops, based on the total amount of pesticides they purchased. Payments after 30 days coefficient are positive and significant for fungicides suggesting that payment conditions are highly related to pesticide pressure and the total amount of sales at the farmer level. However, this result do not allow to measure the magnitude of quantity discounts because we cannot observe the total sales per product over of the crop year.

At pesticide level, the innovativeness of products is illustrated by Age and Pat. The most recent pesticides are cheaper than the older ones. By introducing Age^2, we may capture the nonlinear effect of this variable on prices.[19]. The effect on prices becomes positive after three year of marketing. Patented herbicides and insecticides are more expensive than generic ones. On the contrary patented fungicides are 3% cheaper than generic ones. This can be explained by the high level of fungicides patented a.i. which is higher compared to the two others. The a.i. in the pesticide dictates its pesticidal effects; therefore, we introduce the number of a.i. into each pesticide (*# a.i.*). This variable decreases herbicide prices of 5%, and increases insecticide and fungicide prices of 17% and 21%. The scope of pesticide registration is proxied by the variable *#crop* variable,

[17] We also tested a non linear effect through a squared Tox. Tox^2 were non-significant for each category. Then, we estimated the model with Tox levels (equivalent to TGAP levels). Results for insecticide confirms that with higher levels of toxicity products are significantly cheaper. However, this solution generates multi-colinerarity implying to aggregate categories on two categories. To eliminate this limit, we introduce linearly the six categories.

[18] This is the level used this article.

[19] They are assumed to be explained by the loss of efficacy due to development of resistance of pests.

which is a proxied for the scope of pesticide registration decreases over time. This result is in line with FJ's findings. Market size is proxied by a dummy for pesticides allowed for application to wheat, FJ also argues that priority is given to larger - in term of area - markets. Insecticides marketed for wheat are 26% more expensive than those which are not. The empirical result is stronger for fungicides. Concerning the recommended rate, its increase raises herbicide prices of more than 0.3%. If seems reasonable to assume that farmers choose a pesticide product based on the cost of application per hectare, they make a trade-off which depends on the level of infestation by choosing the quantities of application. Toxicity levels interact with the quantity of application.[20] The toxicity (tox) influences significantly pesticide prices. The toxicity has a positive and significant impact on the price of herbicides and fungicides. In the agronomic literature, toxicity is heavily related to the technical performance of the product. The ongoing commitment to reduce pesticide use means that farmers will try to reduce the quantities applied by choosing pesticides with higher performance, which are often more toxic. This could suggest that the average level of toxicity of insecticides is higher compared to other categories.

Finally, to measure the impact of the TGAP, the variable $\text{Year}_{>2001}$ is used as a regressor. It has no significant impact on herbicide prices. For insecticides, it is associated with a 1% decrease in the prices, *ceteris paribus*. For fungicides, it decreases significantly the prices by 2%, which implies that prices will be lower in 2001-2006 compared to 1996-2000, the post-TGAP period. This result should be interpreted with caution, because our specification does not include other details related to firm supply or quantities sold by retailers. This information is required to compute the amount of TGAP paid by retailers. However, at product level our results suggest that TGAP decreases pesticide prices.

At chemical family level, the chemical family nomenclature takes account of the fact that the prices of some pesticides shifted due the introduction of new chemical families.[21] Most product characteristics are time invariant, and the estimation results remain valid only if the unobserved product characteristics are uncorrelated with the price of the pesticide. This assumption is reasonable here since the introduction of regulatory mentions supports the assumption that the error term is not correlated with the covariates.

Our results are partially in tunes with FJ's article who shows that the "*productive characteristics generally are positively associated with price, while hazardous characteristics are negatively associated with price*" (FJ, p. 646). For insecticides, productive characteristics are conformingly positive ($dose$, $crop$,ai), while hazardous characteristic (tox) is negative. However, these results are not found for the other categories. The difference between results of herbicides/insecticides and fungicides can be explained by the chemical action of these products. Particularly, fungicides target more heterogeneous organisms, this has an important impact on the development of pesticide resistance. A small dose of application for a specific disease is sufficient whereas the quantity of application could be an important variable for herbicides and insecticides.[22]

[20] Recall that in this article we use the retailer prices to construct price indices which are corrected fro quality change. Thus the data do not represent farmers' pesticide choices.

[21] We tried to introduce dummies for the a.i. in each pesticide. For the estimations of the single nested model, it increased the variances, especially for the variables for pesticide characteristics (variables changing within the M dimension). For the double nested model, it captures all the unobserved heterogeneity due to the chemical family. Hence, these results are not reported.

[22] Diseases solved with herbicides and insecticides are related to diploid organisms, the organism eradicated by fungicide applications are more heterogeneous and do not only concern diploid organisms.

6 Conclusion

The article used a hedonic framework to evaluate the implicit marginal price of pesticide characteristics. The specificity of our data enables to nest the observed prices by closeness in order to control for the unobservable heterogeneity of products. Based on the assumption that some intra-class correlation exist we estimated a nested error component model. We mainly find that pesticide prices slightly increased at the moment of the TGAP. In this analysis we used a hedonic framework to evaluate the implicit marginal prices of pesticides. The specificity of our data allowed us to nest observed prices by closeness, in order to control for unobservable product heterogeneity. Based on the assumption that some intra-class correlation exists we estimated a double nested error component model to an unbalanced panel. The proposed ANOVA performed well for estimation of the coefficients and reduced variances for the double nested GLS estimates. The decrease of prices in 2001, which is the TGAP introduction date, suggests that pesticide turnover and innovativeness is more important than regulation changes.

With this framework it can be shown that the main difficulty is related to the degree of unbalancedness, and the specific structure of each nest. Indeed, the ratios among $\sigma_\epsilon/\sqrt{\lambda_p}$ illustrates the weight of each dimension relative to within regression. More precisely, if this ratio is small, it illustrates that efficiency gains with respect to within regression are small. In the opposite, when these ratios are large, the gains in efficiency are important with respect to within estimates.

The model retained for this analysis require the assumption that the error term is not correlated with the covariates, by selecting regulatory mentions, this assumptions is reasonable. Further researcher would introduce the pesticide efficacy into a demand framework to measure the farmers willingness to pay for technical characteristics, such as toxicity or efficacy. The frameworks which analyses the market equilibrium may be a good alternative to evaluate the impact of the regulation changes on firms strategy. In other words the idea is to measure how regulation change affects the market segmentation by matching the supply side with a demand analysis.

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A Additional informations on the Data

IPAMPA means "agricultural means of production purchasing price index". This index is made to track trends in the prices of goods and services used by farmers for their farm operation. These prices are taken from the retailers of agricultural inputs.

E-Phy reports regulatory mentions imposed for each pesticide. It contains the specific quantity of application with respect to each crop for the specific disease. Besides, it reports information on the registrants firms, the date of registration and/or canceling, the level of toxicity of each product and the safety precautions for farmers.

The Herbicides, Insecticides and Fungicides Resistance Action Committees published a uniform classification by pesticide category: Herbicide Resistance Classification (HRAC), Insecticide Resistance Classification (IRAC), and Fungicide Resistance Classification (FRAC).

Table 7: Chemical Classes

Cat.	Group	Chemical families
Herb.	A	Inhibition of acetyl CoA carboxylase (ACCase) (e.g. Aryloxyphenoxy-propionate 'FOPs', Cyclohexanedione 'DIMs', Phenylpyrazoline 'DEN')
	B	Inhibition of acetolactate synthase ALS (acetohydroxyacid synthase AHAS) (e.g. Imidazolinone, Pyrimidinyl(thio)benzoate, Sulfonylaminocarbonyl-triazolinone, Sulfonylurea, Triazolopyrimidine)
	C	Inhibition of photosynthesis at photosystem II (e.g. Amide, Benzothiadiazinone, Nitrile, Phenyl-carbamate, Triazine, Triazolinone, Uracil,Urea)
	E	Inhibition of protoporphyrinogen oxidase (PPO) (e.g. Diphenylether, N-phenylphthalimide, Oxadiazole, Oxazolidinedione, Phenylpyrazole, Pyrimidindione, Thiadiazole, Triazolinone)
	F	Bleaching: Inhibition of carotenoid biosynthesis; Inhibition of 4-hydroxyphenyl-pyruvate-dioxygenase (4-HPPD) (e.g. Diphenylether, Isoxazole, Isoxazolidinone, Pyrazole, Pyridazinone, Pyridinecarboxamide, Triazole, Triketone, Urea)
	G	Inhibition of EPSP synthase (e.g. glycine)
	K	Microtubule assembly inhibition; Inhibition of mitosis / microtubule organisation; Inhibition of VLCFAs (Inhibition of cell division) (e.g. Acetamide, Benzamide, Benzoic acid, Carbamate, Chloroacetamide, Dinitroaniline, Oxyacetamide, Phosphoroamidate, Pyridine, Tetrazolinone)
	L	Inhibition of cell wall (cellulose) synthesis (e.g. Benzamide, Nitrile, Quinoline carboxylic acid, Triazolocarboxamide)
	N	Inhibition of lipid synthesis - not ACCase inhibition (e.g. Benzofuran, Chloro-Carbonic-acid, Phosphorodithioate, Thiocarbamate)
	O	Action like indole acetic acid (synthetic auxins) (e.g. Benzoic acid, Phenoxy-carboxylic-acid, Pyridine carboxylic acid, Quinoline carboxylic acid)
	No	Not classified
Ins.	1	Acetylcholine esterase inhibitor (e.g. Carbamates, Organophosphates)
	2	GABA-gated chloride channel antagonists (e.g. Cyclodiene organochlorines, Phenylpyrazoles (Fiproles))
	3	Sodium channel modulators (e.g. DDT, Methoxychlor,Pyrethroids, Pyrethrins)
	15	Inhibitors of chitin biosynthesis, type 0
Fng.	A	Nucleic acids synthesis (e.g. acylalanines , butyrolactones, carboxylic acids , hydroxy-(2-amino-) pyrimidines, isothiazolones, isoxazoles, oxazolidinones)
	B	Mitosis and cell division (e.g. acylpicolides, benzimidazoles, N-phenyl carbamates, phenylureas, thiophanates, toluamides)
	C	Respiration (e.g. 2,6-dinitro-anilines, benzamides, benzyl-carbamates, cyano-imidazole, dihydrodioxazines, dinitrophenyl crotonates, furan carboxamides, imidazolinones , methoxyacrylates, methoxycarbamates, oxathiin carboxamides, oxazolidinediones, oximino acetates, oximinoacetamides, pyrazole carboxamides, pyridine carboxamides, pyrimidinamines, pyrimidinonehydrazones, sulfamoyltriazole, thiazole carboxamides, thiophenecarboxamides, tri phenyl tin compounds)
	D	Amino acids and protein synthesis (e.g. anilinopyrimidines, enopyranuronic acid antibiotic, glucopyranosyl antibiotic, hexopyranosyl antibiotic, tetracycline antibiotic)
	E	Signal transduction (e.g. dicarboximides, phenylpyrroles, quinolines)
	G	Sterol biosynthesis in membranes (e.g. allylamines, hydroxyanilides, imidazoles, morpholines, piperazines, pyridines, pyrimidines, spiroketalamines, thiocarbamates, triazoles)
	M	Multi-site contact activity (e.g. chloronitriles (phthalonitriles), dithiocarbamates and relatives, guanidines, inorganic, phthalimides, quinones (anthraquinones), sulfamides, triazines)

Table 8 gives an example the structure of our data. It illustrates why we embedded the *Series* of prices within pesticide, and pesticides within chemical families.

B Homologation of pesticides

In Europe, since 1991, the directive 91/414/EEC homogenized the placing of plant protection products (i.e. pesticides) within all the European countries. It sets up a dual system

Table 8: An example to illustrate the structure of the data

Category	Chemical	Pesticide	Serie	Pound	Pay 30
Herbicides	A	Pesticide Product I	Serie 1	5	0
Herbicides	A	Pesticide Product I	Serie 2	1	1
Herbicides	A	Pesticide Product I	Serie 3	5	1
Herbicides	C/F	Pesticide Product II	Serie 4	5	0
Herbicides	C/F	Pesticide Product II	Serie 5	10	0
Herbicides	C/F	Pesticide Product II	Serie 6	20	0
Herbicides	C/F	Pesticide Product II	Serie 7	10	1

Pound indicates the size of the box.
Pay 30 indicates payment within 30 days.
More details on these data are presented in section **??**.

of authorization that successively analyzes the a.i. and pesticides.[23] The first step is relative to the registration of a.i. It is made by the EC and States Members depending on their acceptability for human health and environment. This decision is based on a previous peer review evaluation of the a.i. made by the European Food Safety Authority (EFSA). The registered a.i. are included into the Annex I of the Council Directive 91/414/EEC. The second step concerns the evaluation and registration of pesticides. It is made at State Member's level. In France, this evaluation is based on the advices of both the French Agency for Food and the Environmental and Occupational Health & Safety) (ANSES). Registered pesticides are published by the Ministry in charge of Agriculture[24] and are available on the french open-data. Moreover, this directive incorporates into registration process criteria such as acceptability for human health and environment of pesticide products. Hence, it imposed to re-evaluate each active ingredient registered before 1993. As a result, in 2003, 26% of the 1000 marketed a.i. were registered, this involved a ban on around four hundred pesticides. Since recently, the directive 91/414/EEC has been replaced by Regulation 1107/2009 which reinforces toxicity and eco-toxicity requirements to improve the protection of pesticide users, the environment and human health. Besides, the dangerousness of pesticides products requires precautions of use. Hence, for each registered pesticide, the regulation specifies the crop, the pest and the maximal rates by pest and crop it can be used on. The registration process also define for each pesticide safety precautions, toxicity and eco-toxicity mentions.

[23]Remember that the chemical action of one pesticide is given by one or multiple a.i. it includes.
[24]More detailed explanations of the registration process can be found in Hartnell, 1996.