Choices of wine consumption: measure of interaction terms and attributes

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Abstract

Interpreting interaction terms in econometric modelling is fussy. Even if logit or probit models are the most used modelling consumers' choice, they omit interaction effects among explanatory variables in the choice process. These blended effects are however declared in the modifications of consumption decision. The difficulty is to interpret coefficients associated to these effects (interaction variables). To solve this problem, we propose a decision rule enforceable whatever the nature of the estimators. We build a convenient decision rule. We carry out an application of this decision rule to the choices of the wine consumers confronted with increasingly sophisticated products.

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1 Introduction

The growing imperfection of markets and the profusion of new products constantly question the theory of the consumer. Since Lancaster (1966), economic theory admits that similar goods can be sold on the same market. Thus, the multiplicity of characteristics (attributes) of the products led the Economist to always look for suitable into revealing consumer preferences and their evolution methods. One way to take into account these related phenomena is to introduce interaction terms in econometric models. But interaction effects are very seldom treated in econometrics. The explanation of a phenomenon is however sensitive to this type of information (Asher & Popkin, 1984). In the consumer theory, for example, decisions are made at the end of an arbitration which is often badly perceived by the standard econometric models. Interpreting decisions of consumers' choice requires taking into account psychological factors which are not always perceptible in the step of econometric estimation. This complexity is notably reported by McFadden (2001) when he relates a history of econometric modellings in that context :

'The characterization of alternatives in the [multinomial logit] model in terms of their "hedonic" attributes was natural for this problem, and followed the psychometric tradition of describing alternatives in terms of physical stimuli'(p.354).

He specifies a little further that :

'[...] most applications of the standard model leave out dependence on experience, and much of the power of this model lies in its ability to explain most patterns of economic behaviour without having to account for experience or perceptions' (p.356).

Nonlinear models like logit or probit are the most used modelling consumers' choice because they allow discrimination among decisions. Nevertheless, a weakness of these models, and of econometric models in their standard use, is to omit interaction effects among explanatory variables in the choice process. These blended effects are however declared by the modifications of consumption decision when an individual must arbitrate between several goods combining several attributes but various ways. The supply of consumption goods is today ever more heterogeneous, even complex, insofar as a same good can associate various characteristics of single goods. In most cases, the combination of attributes is not perceived as purely additive. The association of attributes singly enhancive is only exceptionally perceived like the exact addition of the utility provided by each attribute taken separately. Restoring this process of consumers' choice requires the introduction of interaction effects in econometric models, that they are linear or not. The way to introduce these interactions is to add combinations of attributes to individual explanatory variables. These combinations are introduced by the product of couples of variables. The model is increased in these interaction effects, and these effects are estimated as all the others variables coefficients. The difficulty is to interpret coefficients associated to these interaction variables. Unlike the natural[2] explanatory variables whose coefficients signify elasticities (in linear models) or variations in relation to a reference (in nonlinear models), estimate coefficients of combinations of variables are much more discerning. In linear models the t-test gives straight significance of such a coefficient. Aï & Norton (2003) proved that statistical significance in nonlinear models cannot be tested with just a t-test : they are conditioned by independent variables. In this case, we must take into account *non unit* modifications of the utility introduced by the natural variables combination.

In this paper, we discuss the significance of interaction coefficients and suggest a decision rule able to arbitrate among several values of these coefficients at the end of the estimation process, in linear and nonlinear models. In a second section, we develop definition and implications of interaction terms according to models used, linear and non linear. In a third section, we explicit the decision rule useful to interpret interaction terms estimate. In a fourth section, we carry out an application of this rule of decision on a segment of the French wine consumption market, using the price as a developer of complex characteristics of consumers choices even if the "blended product" is just virtual. We conclude about usefulness and performance of this decision rule distinguishing processes of consumers' choice when they are confronted with complex goods.

2 Defining and interpreting interaction terms

Theoretical bases of econometric modelling[3] advocate to describe a phenomenon (the explained variable) starting from variables (explanatory) independent between them. This modelling exercise is carried in a context *ceteris paribus* : the information contained in the selected explanatory variables must provide the possible best estimate of the phenomenon one have to explain. The standard model is:

$$Y = \alpha + \sum_{i=1}^{n} \beta_i X_i + \varepsilon \tag{1}$$

where

- Y a phenomenon to explain,
- α a constant,

[2] The term "natural" is related to non blended variables.
[3] We make reference to the first probabilistic econometric works of Haavelmo (1940, 1944).

- X_i explanatory variables,
- β_i estimate coefficients,
- ε estimate error, representing all the information not take into account by the model.

The performance of modeling is thus closely related to the informative capacity of the explanatory variables. However, most of the time the econometrician is out this framework and must be satisfied with a rough estimate, appreciated notably by the value of the coefficient of determination. One is entitled to wonder whether, whereas the most relevant variables were selected, there would not be an information residual in interaction terms between these variables. Bowles (1970) indicates the absence of theoretical bases as the main difficulty. He emphasizes the relevance of interaction terms:

'[...] The crucial deficiency is not in the lack of the data but the absence of a theory of learning to guide us in establishing a model for our estimation. One consequence of this lack of theory has been the tendency of researchers to ignore interaction effects of inputs'(1970, p.13).

Interaction terms inform about complementary relations among explanatory variables. One distinguishes straightforward effects (explanatory variables coefficients) and blended effects (interaction terms) relative to combinations. The phenomenon is better explained and the estimate residual,ε, is reduced. Asher and Popkin (1984) reveal that omission of interaction effects can leads to wrong results. They prove that introducting interaction effects increases the understanding of this discrepancy, while their omission maintains odd discrepencies.

The impact of the estimation of interaction terms is pregnant especially for consumers' choice models. When the consumer must express a choice face to several goods offering similar attributes, how appraising his decision-making processes? The knowledge about interaction effects can be a response.

Introducing interaction terms depends on some explanatory variables or on another effect[3][4]. In the quantitative case, the model is:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \qquad (2)$$

The model including interaction between two variables X_1 and X_2 is:

[4]Interaction terms do not introduced collinearity between variables. The formula for a collinearity relationship is: $\alpha_1 X_1 + \alpha_2 X_2$ while the interaction variable is noted: $(\alpha_1 X_1)(\alpha_2 X_2)$. It is based on the weighted product of the explanatory variables. See, for example, Friedrich (1982).

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + \varepsilon \tag{3}$$

In the linear model, marginal effects are :

$$\frac{\partial Y}{\partial X_1} = \beta_1 + \beta_{12} X_2 \tag{4}$$

$$\frac{\partial Y}{\partial X_2} = \beta_2 + \beta_{12} X_1 \tag{5}$$

and the interaction marginal effect is:

$$\frac{\partial^2 Y}{\partial X_1 \partial X_2} = \frac{\partial^2 Y}{\partial X_2 \partial X_1} = \beta_{12} \tag{6}$$

For simplicity, we note:

$$\delta_1 = \beta_1 + \beta_{12} X_2$$
$$\delta_2 = \beta_2 + \beta_{12} X_1$$

In the non linear model, because the form of the distribution function is respectively:

$$Logit: \qquad F(W) = \frac{e^w}{1+e^w} = \frac{1}{1+e^{-w}}$$

$$Probit: \qquad F(W) = \int_{-\infty}^{w} \frac{1}{\sqrt{2\pi}} \overset{\frac{-t^2}{2}}{e}\, dt$$

So marginal effects are (for logit model):

$$\frac{\partial Y}{\partial X_1} = (\beta_1 + \beta_{12} X_2) \frac{e^{(\beta_1+\beta_{12}X_2)}}{1+e^{(\beta_1+\beta_{12}X_2)^2}} = \delta_1 \frac{e^{\delta_1}}{1+e^{\delta_1}{}^2} \tag{7}$$

$$\frac{\partial Y}{\partial X_2} = (\beta_2 + \beta_{12} X_1) \frac{e^{(\beta_2+\beta_{12}X_1)}}{1+e^{(\beta_2+\beta_{12}X_1)^2}} = \underset{2}{\delta} \frac{e^{\delta_2}}{1+e^{\delta_2}{}^2} \tag{8}$$

and the interaction marginal effect, from (6'), is:

$$\frac{\partial^2 Y}{\partial X_1 \partial X_2} = \frac{\partial^2 Y}{\partial X_2 \partial X_1} = (\beta_1 + \beta_{12} X_2)(\beta_2 + \beta_{12} X_1)\, e^{(\beta_1+\beta_{12}X_2)(\beta_2+\beta_{12}X_1)}$$
$$\frac{1 - e^{(\beta_1+\beta_{12}X_2)(\beta_2+\beta_{12}X_1)}}{1 + e^{(\beta_1+\beta_{12}X_2)(\beta_2+\beta_{12}X_1)}} + \frac{\beta_{12} e^{(\beta_1+\beta_{12}X_2)(\beta_2+\beta_{12}X_1)}}{\left[1 + e^{(\beta_1+\beta_{12}X_2)(\beta_2+\beta_{12}X_1)}\right]^2}$$

Or,

$$\frac{\partial^2 Y}{\partial X_1 \partial X_2} = \frac{\partial^2 Y}{\partial X_2 \partial X_1} = \delta_1\, \delta_2\, e^{\delta_1\, \delta_2}\, \frac{1-e^{\delta_1\, \delta_2}}{1+e^{\delta_1\, \delta_2}} + \frac{e^{\delta_1\, \delta_2}}{[1+e^{\delta_1\, \delta_2}]^2}$$

For a straightforward use, it is enough to write:

$$\delta_1\,\delta_2 = \delta_{12}$$

So,

$$\tfrac{\partial^2 Y}{\partial X_1 \partial X_2} = \tfrac{\partial^2 Y}{\partial X_2 \partial X_1} = \delta_{12}\, e^{\delta_{12}}\, \tfrac{1-e^{\delta_{12}}}{1+e^{\delta_{12}}} + \tfrac{e^{\delta_{12}}}{[1+e^{\delta_{12}}]^2}$$

Thereafter, we develop only the linear model (arguments can be transposable to nonlinear models from equations (7), (8) et (6')). Nevertheless, we observe that in the nonlinear case the interaction term is wider than the estimate coefficient β_{12}produced by the estimate, but must be recomputed using equation (6'), as explained in Aï & Norton (2003).

3 Decision rule

The estimation of the interaction term in the linear case is directly performed at the time of the estimation of the model. Its significance is given by a t-test. However, the interpretation of this interaction coefficient is not so easy than those of the natural explanatory variables. Because β_{12} conveys a residual blended effect between explanatory variables, we must distinguish four possible cases :

- The combination contributes nothing else : variables are independent,
- The combination overvalues attributes,
- The combination leads to an undervaluation of attributes,
- The combination leads to disutility.

Arbitration between these cases differs according to the sign of β_1 and β_2:

Adaptation to nonlinear models: this decision rule also fits over nonlinear models if one respects formulations of equations (7), (8) et (6') adapted from Aï & Norton (2003). For a straightforward use of the decision rule, we write:

$$(\beta_1 + \beta_{12} X_2) \frac{e^{(\beta_1+\beta_{12}X_2)}}{1 + e^{(\beta_1+\beta_{12}X_2)^2}} = \psi_1 \tag{9}$$

$$(\beta_2 + \beta_{12} X_1) \frac{e^{(\beta_2+\beta_{12}X_1)}}{1 + e^{(\beta_2+\beta_{12}X_1)^2}} = \psi_2 \tag{10}$$

$$\begin{aligned}&(\beta 1 + \beta_{12}X_2)(\beta_2 + \beta_{12}X_1) e^{(\beta_1+\beta_{12}X_2)(\beta_2+\beta_{12}X_1)} \\ &\tfrac{1-e^{(\beta_1+\beta_{12}X_2)(\beta_2+\beta_{12}X_1)}}{1+e^{(\beta_1+\beta_{12}X_2)(\beta_2+\beta_{12}X_1)}} + \tfrac{\beta_{12} e^{(\beta_1+\beta_{12}X_2)(\beta_2+\beta_{12}X_1)}}{[1+e^{(\beta_1+\beta_{12}X_2)(\beta_2+\beta_{12}X_1)}]^2} = \psi_{12}\end{aligned} \tag{11}$$

and replace $(\beta_1, \beta_2, \beta_{12})$ by $(\psi_1, \psi_2, \psi_{12})$.

Table 1: The decision rule

	β_1 and $\beta_2 > 0$	β_1 and $\beta_2 < 0$	$\beta_1 > 0$ and $\beta_2 < 0$ with $\lvert\beta_1\rvert > \lvert\beta_2\rvert$
Independance	$\beta_{12} = 0$		
Overvaluation	$\beta_{12} > 0$ $\beta_1 + \beta_2 + \beta_{12} > \beta_1 + \beta_2$	$\beta_{12} \in]\beta_1 + \beta_2; 0] \cup]0; +\infty]$	$\beta_{12} > \beta_1$
Undervaluation	$\beta_{12} < 0$ with $0 < \beta_1 + \beta_2 + \beta_{12} < \beta_1 + \beta_2$	$\beta_{12} \in]\beta_1; \beta_2]$ with $\lvert\beta_1\rvert > \lvert\beta_2\rvert$	$\beta_{12} \in]\beta_2; 0] \cup]0; \beta_1]$
Disutility	$\beta_{12} < 0$ with $\beta_1 + \beta_2 + \beta_{12} < 0$	$\beta_{12} \in]-\infty; \beta_1 + \beta_2]$	$\beta_{12} < \beta_2$

4 Empirical example: the case of French wine market

The database used is a census of all first ‘mise en marché’. This database is available by ONIVINS, and it includes all of ’contracts’ table wine and wine country, signed since the season 1987/88. These contracts are administrative documents, signed at the conclusion of transactions. These are standards documents that contain all the same information.

Completeness is guaranteed by the compulsory nature of the questionnaire. The contract is composed of three parts:

The first one describes contractors characteristics: buyer and seller location, name and administrative informations such as corporate name.

The second one describes products: quantity, quality, color, price of degree/hl; but also: nature of wine - table wine, wine country; the destination of the product, the crop year.

The third one defines the contract financial terms: if there was deposit, a date of payment.

Even if the database gives informations on partners, anonymity must be guaranteed. The first part is so limited to general information. We know neither name nor localisation at municipal level.

In a contract, we can have several different products exchanged. All characteristics relative to those products are defined. For each one, we have price, quantity... All products are distinguished and that’s why we work with the unity “product”.

We estimate a linear model based on characteristics of French wine as:

- color: red = 1, others = 0,
- degree,
- type: table wine = 0, country wine =1

The dependent variable, Y, is the price of the hectolitre degree, expressed in euros.

The results are:

Table 2: Results: model without / with interaction

Variable	Without IT	With IT
color	-0.299**	0.327 **
degree	0.296**	0.305**
type	1.096**	1.602**
color*degree		-0.036 **
color*type		-0.764 **
Intercept	0.326**	$0.115^{\dagger}$
N	660599	
R^2	0.28	0.30

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

We can observe that introducing interaction terms increases the quality of the model, based on the R^2 value.

Using the decision rule, we can conclude to the under valuation for both of the combinations:

- **Color and degree**

We observe that β_1 and β_2 are positives but β_{12} is negative:

$\beta_1 =$ 0.3272809 ; β_2= 0.3053606 ; β_{12}= -0.0359309

$\beta_1 + \beta_2 =$ 0.63264089 and $\beta_1 + \beta_2 + \beta_{12}$= 0.5967099 $\Rightarrow \beta_1 + \beta_2 + \beta_{12} < \beta_1 + \beta_2$

So, we are in the case of *undervaluation*.

- **Color and type**

We observe that β_1 and β_2 are positives but β_{12} is negative :

$\beta_1 =$ 0.3272809 ; β_2= 1.602212 ; β_{12}= -0.7639122

$\beta_1+\beta_2 =$ 1.924929 and $\beta_1+\beta_2+\beta_{12}$= 1.1655807 $\Rightarrow \beta_1+\beta_2+\beta_{12} < \beta_1+\beta_2$

So, we are in the case of *undervaluation* too.

In both cases, we conclude that the combination of attributes does not increase the utility of the *wine* product. Consumers do not pay much for a red wine with more degrees (combination color / degree) – which is often considered as "bad" wine – that for red country wine (combination color / type) – which is not usually considered as a good product. A good red wine must be an AOC, while the worst is a red table wine in the consumers practices. This is why the estimate result validates undervaluation and not disutility. These combinations reveal an undervaluation of consumers' preferences within the French wine market.

5 Conclusion

In this paper, we have demonstrated how using interaction terms in Econometrics can help improve the understanding of consumers' choices facing to more and more complex goods. Estimate of these terms in the regression model brings in precision and can parent another form of willingness to pay, the contingent valuation and the experimental economics margin. Actually, in these two usual methods, developed information is always based on a virtual since the relevant market does not exist and where the answers are biased a psychological degree that these analyses do not confine.

Observing Aï & Norton advices, we have built a decision rule for interaction terms. The arbitration between these combined effects is often omitted in the exercises of applied econometrics because it is complex. This decision rule increases not only the comprehension of consumers' preferences but also makes it possible to qualify their behaviors. One of its advantages is to be very simple of use: once the model estimated, it is enough to control the sign of the coefficients and to calculate their sum; then, we apply the decision rule as presented in table 1 to qualify the contribution of interaction terms. Another advantage is that this decision rule applies as well to the linear models with the nonlinear models.

The originality of this work is to try to build mathematically new prices for new goods (virtual) that can step be measured by existing methods. Baseline information is recorded on a real market, significantly reducing the degree of uncertainty as to the behaviour of consumers, hence the interest to use this information to build virtual products through attribute combinations. The case of French market of wine is informative: by using our decision rule, we estimated the utility of different types of wine, different goods of the French market of wine. We provided a pattern of the psychological factors that impact on wine goods; for example, one of the conclusions is that the combination color / degree doesn't increase the price consumers are willing to pay. But other combinations may be tested, they already exist or not. We see a certain interest for producers of wine wishing to create new products. The application of this very simple decision rule may provide a non-negligible information on the willingness to pay of consumers depending on virtual products.

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