Do taste and quality perception influence consumer preferences for wood? An econometric model with latent variables

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November 2009

Abstract:

The aim of our article is to understand consumer preferences for wood and competitive materials. Assuming that a wood product is composed of various attributes, we consider that consumers' choices are not guided by observed characteristics but, instead, by the quality perception consumers have of these attributes. An econometric model integrating this factor by means of latent variables allows us to analyze the influence of individual characteristics and information (external sources and/or experience) on product quality perception. We also include consumers' attitudes in the model by supposing that the importance consumers place on attributes accurately describes their tastes. Data on material choices (wood vs. vinyl) for window frames validate our assumptions.

Keywords: quality perception, information, taste, latent variable model, wood.

JEL Classification: C25, D12, L15

1 Introduction

Benefits derived from wood is a key factor in the competition between wood and non-wood products. However, these benefits are not necessarily directly observable by consumers when they decide to purchase a product. Indeed consumers might possess different knowledge and possess different information sources. As a consequence their perception of benefits derived from the product varies. The aim of our article is to understand in what extent demand for wood products is determined by perception, experience and information on wood characteristics. To do so, we build an econometric model of purchase decision that captures the impact of information acquisition on consumers preferences.

A consumer's decision to purchase an article depends on his/her product preferences. Generally, a product is considered to be composed of several attributes (Lancaster, 1966). In Lancaster's approach, consumers attach importance to attributes rather than the product itself. However, the quality level of each product attribute is supposed to be identical across all consumers, as well as known by all consumers. Lancaster argues that the utility derived from a product is equal to the sum of utilities derived from all the product's attributes.

Our analysis is inspired by McFadden (1986) who integrated psychological factors into consumer choice decisions. We consider that consumer preferences for a product are determined by two "non usual" factors. First, we assume that consumers can be differentiated by the importance they place on product attributes in their purchase decision. We refer to these observed variables as attribute weights or tastes. Tastes reflect individual needs and values, and explain consumer heterogeneity. Second, the quality level of each attribute is an endogenous and non-observed variable. We assume that each consumer forms a quality perception for each attribute and might judge the quality level of attributes differently for differentiated products. As noted by Ben-Akiva et al. (2002, p.448), “Perceptions are the individual’s beliefs or estimates of the levels of attributes of the alternatives”. Along this article, we will speak of quality perception as the estimated quality level by consumers on product attributes.

A consumer’s quality perception is highly influenced by the information he or she possesses, and the way information influences the quality perception depends on the type of product attribute considered. For experience attributes (Nelson, 1974), previous purchase and/or consumption might be enough to evaluate the real level of quality whereas for credence attributes other types of information could be more successful. In reality, consumers can access various sources of information, such as advertising, information disclosure by consumers groups, direct contact with professionals, or product purchase.

An important literature focuses on consumer preferences and competition between wood and non-wood products (or species) with an application to structural framing materials (Eastin et al., 2001; Garth et al., 2004; Shook et al., 2007), furniture markets (Forbes et al., 2001a, 2001b; Wu and Vlosky, 2000; Olah et al., 2003), and floor covering (Jonsson, 2005, 2006). These studies base their approach on the Lancaster’s model of product attributes. Among these studies, Shook et al. (2007) use discrete choice modeling to analyze the substitution between North-American softwood timber species, in the context of trade disputes between the U.S. and Canada. Jonsson (2006) uses Customer Satisfaction Modeling and latent variables to assess customer needs in the context of floor covering. However, both papers do not take into account that consumers have biased knowledge and information on product characteristics.

Environmental considerations become more and more important in public policy making. For example, in France the government aims to increase the wood share in the French construction sector by 25 percent (in value terms). Wood use in production has a certain global advantage as it reduces environmental damages (renewal resource, carbon dioxide sequestration, etc.) in comparison to other materials such as plastic or steal. So far, various policies to encourage the use of wood have been implemented, such as mandatory increase in the share of wood-material in public procurements, architect training programs to use wood, consumer information via TV commercials and advertisements in newspapers. The aim of our work is to set up a framework to analyze the purchase decision with respect to knowledge, experience and information on product characteristics. From a policy point of view the framework could help to implement targeted information policies or educational programs.

Our data concern hypothetical purchase choices for specific materials (vinyl and wood) in the French window market. We assume that consumers do not necessarily place the same values on these window materials. A window is composed of various attributes, such as acoustic and thermal insulation, product life, and environmental characteristics. Since most window attributes are not observable before purchase, consumers possess imperfect information and assess the quality of materials based on their information sources and experience. The assessment of the quality of each attribute depends on the material, and thus influences the global quality perception for each material. These perceived qualities are introduced into the model as latent variables. Our methodology is general and can be applied to any situation with discrete choice behavior where products are characterized by several attributes for which quality is not directly observable and where indicators exist, that is, observable variables related to information and product experience that might determine quality perception.

This paper is organized as follows. First, we present the assumptions of our model for latent variables (quality perceptions) and discuss the modifications made with respect to the existing literature. Second, the econometric methodology is described. A two-step estimation procedure is adopted: we first estimate the latent variable model, and then the predicted latent variables are introduced into a discrete choice model. Third, data on material choices in the French window market are used to show that endogenous quality levels of product attributes provide a meaningful explanation of the choice decision of consumers. Finally, we conclude that consumers have different quality perceptions of materials depending on the information they possess on product attributes and we discuss the importance of information campaigns to modify purchase decisions.

2 Attributes and quality perception in product choice

The purpose of this paper is to construct an econometric model that explains consumers' purchase decisions by simultaneously integrating perceived product quality (latent variables) and tastes (observable variables). This methodology allows to better understand consumer preferences for quality supposing that individual beliefs (on quality) are based on private information and experience.

In the economic literature on transportation, latent preferences have been introduced into mode choice models (Ben-Akiva et al., 2002). For instance, Johansson et al. (2006) argue that people have different attitudes towards environmental considerations, safety, comfort, convenience and flexibility, and that this has an important impact on the consumer's choice of transportation. The introduction of attitudinal and behavioral indicator variables makes it possible to construct a more precise choice model. Marketing studies attempt to establish the link between perceived value and consumer behavior. Indeed, the perception of product quality depends, in part, on the messages and information transmitted to consumers. Depending on the amount and quality of information, consumers might react differently in terms of consumption behavior. Swait and Sweeney (2000) showed that the utility of buying a specific product is conditional on the type of consumer. They proposed segmenting consumer behavior into groups possessing specific behavior characteristics. Ben-Akiva et al. (2002) proposed a general methodology for including latent variables such as attitudes and perceptions in choice models. The methodology integrates a discrete choice model and a latent variable model, each one consisting of structural and measurement equations. The basic assumption in their methodology is that observable explanatory variables simultaneously explain utility and latent variables.

We adopted a similar model but also integrated substantial modifications. The set up of our model is outlined in Figure 1. Observed variables are represented in rectangles, whereas unobservable (or latent) variables are represented in ellipses. Solid arrows represent structural equations which correspond to cause-and-effect relationships. The relationships between observable indicators and latent variables are represented by dashed arrows.

[Figure 1 here]

We can see that all observed explanatory variables do not affect the same latent endogenous variables. In particular, variables related to information possessed by consumers, which we call V^1, only explain quality perception of products Z^* and not utility U^* directly, contrary to Ben-Akiva et al. (2002). Quality perception is a determinant of consumer utility and based on quality indicators I. As with classical choice models, utility is also explained by individual characteristic variables referred to as V^2 and V^3 in Figure 1 (see Section 4 for a description of variables). Therefore, consumer preferences, which simultaneously depend on tastes for different attributes and product quality perception, determine consumer product choices.

Moreover, we suppose in our model that consumer heterogeneity is observable, contrary to the framework of Ben-Akiva et al. (2002), and more generally to models that focus only on consumer tastes through latent classes (for a review of the literature, see Greene 2001). The observed variable is the weight consumers give to attributes in their purchase decision, referred to as W in Figure 1. We assume that the weight that consumers give to attributes accurately describes their tastes. The assumption refers to location or differentiation models (Hotelling, 1929; Mussa and Rosen, 1979) where consumers are differentiated by their preferences for product quality generally represented by their revenue, taste or travel distance.

In our study, we want to focus on preferences for product characteristics and exclude the product price from their demand decision. Thus, in our survey, respondents were requested to make a product choice considering that products are sold at identical prices. Technically, product choices depend on the difference between perceived utility. In the case where prices are assumed to be identical, product price is no longer an explanatory variable for the product choice.[1] We should notice that, in reality, for a same standard window frame, prices vary considerably as they are sold with different services. However, the price interval for wooden and plastic window frames do largely overlap. The consumer's choice is then only based on the technical properties of products, and price need not to be considered in our econometric set up. This assumption allows us to concentrate mainly on non-directly observable product attributes for which consumers might have different quality perceptions. The model aims to link the consumer's knowledge about product attributes with his or her quality perception and tries to see in what way information campaigns could orientate the consumer's choices.

3 Econometric methodology

The integrated model described in the previous section is composed of two parts: a standard discrete choice model and a latent variable model that is defined to carry out the treatment and the prediction of latent perception variables. The latent variable model (or structural equation model, SEM) consists of structural latent variable equations and measurement equations. The discrete choice model is composed of a structural equation and a decision rule equation.

3.1 The latent variable model

The latent variable model has been popularized by the LISREL program – Linear Structural Relationship (Jöreskog 1979; Jöreskog and Sörbom 1982). The latent variables are modeled by specifying a structural model and a measurement model. In general, the structural latent variable equations specify the relationship between endogenous and exogenous latent variables. However, it is also possible, as in our analysis, to include exogenous observed variables as part of these structural equations. The measurement equations specify the relationship between the measured indicators and the latent variables.[2]

Assuming a linear specification, the structural latent variable equations written in matrix form are:

$$Z^* = V^1\beta + \epsilon_Z, \tag{1}$$

where Z^* is a vector of latent (or non observed) variables of quality perception and beliefs. V^1 is a vector of (observed) explanatory variables related to the information held by the consumer, β is the matrix of unknown parameters to be estimated, and ϵ_Z is the error vector i.i.d. $(0, \Sigma_Z)$. As mentioned above, unlike the study of Ben-Akiva et al. (2002), V^1 are specific regressors of

Z^*.

The set of measurement equations is defined as follows:

$$I = Z^* \gamma + \epsilon_I, \tag{2}$$

where I is a vector of measured indicators of perceived quality, γ is the matrix of unknown parameters to be estimated, and ϵ_I is the measurement error vector i.i.d. $(0, \Sigma_I)$.

Our latent variable model is detailed in Appendix A.2.

3.2 The discrete choice model

The decision rule consists of a stated choice depending on the latent utility U^*:

$$y = \begin{cases} 1 & \text{if} \quad U^* = U_{wood} - U_{vinyl} \geq 0 \\ 0 & \text{otherwise,} \end{cases} \tag{3}$$

where $y = 1$ if the respondent chooses wood as the material for his/her windows, and $y = 0$ if he/she prefers vinyl. U^* is the latent utility difference between utility for wood (U_{wood}) and utility for vinyl (U_{vinyl}).

As in many empirical studies, the structural utility function is assumed to be linear:

$$U^* = X\alpha_X + Z^*\alpha_Z + W\alpha_W + \epsilon_U. \tag{4}$$

Utility depends on observed explanatory variables (X), including socio-demographic variables (V^2) and behavioral variables related to housing (V^3) in our analysis. However, utility also depends on latent variables of quality perception (Z^*) and taste factors (W). W is a vector of (observed) weights allocated to the commodity characteristics, and encompasses consumer tastes and attitudes. The introduction of such variables is the other important difference with respect to the model of Ben-Akiva et al. (2002). α_X, α_Z, α_W are the parameter vectors associated with these variables. Assuming that the distribution of the error term ϵ_U is standard normal, we estimate a Probit model that represents the respondent's choice of material:

$$P(y = 1) = \Phi(X\alpha_X + Z^*\alpha_Z + W\alpha_W), \quad (5)$$

where $\Phi(.)$ is the standard normal cumulative distribution function.

3.3 Estimation method

As in the case of Johansson et al. (2006), we chose to estimate the interest parameters in two steps. First, the latent variable model, equations (1) and (2), and the associated parameters are estimated. This particularity allows us to compute the predicted values of latent variables (perception variables). The framework for modeling and estimation of the variable latent model is based on the LISREL program. This is a hybrid technique that encompasses aspects of confirmatory factor analysis, path analysis and regression. The estimation of our model is described in Appendix A.2. Second, we transfer the predicted perception variables into the choice model, equations (3) and (4), and the resulting model is then estimated, conditional on the perception variables (as well as other explanatory variables V^2 and V^3, and taste factors W).

We decided to adopt a two-step method and to specifically analyze the latent variable model for several reasons. First, SEM and associated programs are powerful tools that make it possible to take into account interactions, correlated independent variables and error terms, measurement errors, multiple latent variables each measured by multiple indicators. Second, a two-step method allows a good adjustment of the latent variable model. Finally, it allows us to specifically study the reliability of indicators for latent perception and to better understand how information influences quality perception for materials, which is the focus of our paper.

The two-step estimation procedure that consists in transferring the fitted latent variables into the utility function may pose two problems. First, as noted in Ben-Akiva et al. (2002), the fitted latent variables may introduce measurement error in an explanatory variable of the second-step regression. If the measurement error is uncorrelated with the observed (fitted) measure of the latent variable but correlated with the latent variable itself, then the two-step estimation produces consistent estimators of all regression parameters (Wooldridge, 2002). This is the usual assumption of applied econometricians when dealing with generated regressors (Pagan, 1984). In the opposite case (correlation with the fitted latent variable), this results in inconsistent estimates of the parameters. However, if the variance of the latent variable's random error is small, then a sufficiently large sample size may reduce the measurement error and result in acceptable parameter estimates. We might suppose that generated regressors do not pose problems of inconsistency as usually done. However, we will still check in the empirical application that the variance of the error for the latent variable is sufficiently small.

Second, the presence of a generated regressor generally produces invalid standard errors and test statistics because these latter ignore the sampling variation in the estimated parameter associated with the generated regressor (Wooldridge, 2002). Two alternative solutions are commonly used in this case : deriving the asymptotic distribution of the two-step estimator for an equation with a generated regressors or using bootstrap standard errors. We will use this latter solution.

4 Application: Choice of materials (wood vs. vinyl) in the French window frame market

4.1 Data

All the data used here are from a specific survey on consumer tastes and beliefs about windows. The survey was conducted by a marketing agency[3] in November 2003, and concerned a set of 968 consumers representative of the French population drawn from a stratified sample frame. 940 participants remained after eliminating individuals with missing data. The survey was done by phone. Respondents were informed that the survey aimed to better understand consumer behavior towards window purchase and was used for scientific (and non commercial) purposes. No other information concerning windows were given.

The survey included six types of data:

- knowledge that individuals possess about attributes and their quality (variables referred to as V^1). Knowledge was supposed either to be obtained through experience. Experience was derived from the window material (wood, vinyl, aluminum, etc.) in their place of residence, window age, how they would classify the insulation (e.g., thermal, acoustic) and brightness of their home. Or knowledge is also supposed to be dependent on private external information sources. Respondents were asked whether they felt informed about the windows and about materials or whether they had been informed on windows recently.

- Socio-demographic characteristics of individuals (variables referred to as V^2): age, gender, socio-professional group (SPG), family composition.

- Lodging characteristics of individuals (variables referred to as V^3): type of housing (e.g., house, apartment), building style of their housing (classic, modern, typical), importance (with a five-point Likert scale) attached to the home.

- Consumer tastes for product attributes (weight W): Table 2 describes the importance consumers attribute to window attributes into their product choice. We considered several attributes of a window: thermal insulation, acoustic insulation, maintenance, product life, aesthetics, environmental properties, fire resistance and safety. The choice of the attributes was based on interviews with architects and confirmed by scientific studies (Eastin et al., 2004).

- Quality perception of product attributes (quality indicators I), which was analyzed for all attributes and for each material (wood and vinyl). Table 1 describes consumers' perception for window attributes according to the material (wood or vinyl).

- Stated choice y based on the question: "Suppose that wooden windows and vinyl windows are sold at the same price, which material would you choose?"

Table A.6 in Appendix A.1 presents summary statistics and a description of variables V^1, V^2, V^3 and y. All answers concerning judgments are rated on a 1 to 5 scale (Likert scale) where 1 corresponds to a low appreciation and 5 to a high one, and 3 indicates indifference.

[Table 1 here]

Table 1 shows that consumers value differently window characteristics for wood and vinyl. In general, vinyl windows are perceived to have a (very) high thermal and acoustic insulation. Vinyl windows are considered to be easier to maintain than wooden windows. On the opposite, wooden windows are perceived to be highly aesthetic and environmental-friendly. Respondents seemed to underestimate the thermal and acoustic value of wood. Thus, beliefs about technical properties of wood are sometimes false, which is less frequently the case for vinyl. One of the explanations for this result could be the experience of respondents with rather old (not necessarily well maintained) wooden windows which, in most cases, are not double glazed. The basic assumption of our model on equal prices (i.e., respondents were supposed to consider the vinyl window price to be equal to the wooden window price) seems to be adequate. Consumers value wooden and vinyl windows similarly. Moreover in both cases, the price is not a good indicator of the quality of a window (only significantly different from zero for the vinyl windows), see Table 3. We will come back to this assumption in the estimation of the choice model.

Table 2 also gives precious information. First of all, respondents did not consider price to be the most important criteria in a window purchase. Second, environmental considerations are least important in consumers purchase decisions. Characteristics that are perceived to be very good for vinyl windows, such as thermal and acoustic insulation or maintenance, are the most important factors when buying a window.

[Table 2 here]

4.2 Results

4.2.1 The latent variable model

The latent variable model consists of a structural model and a measurement model. Both models are simultaneously estimated by a LISREL-type structural equation modeling program.[4] The first part of the latent variable model is composed of two latent variables Z_1^* (quality perception of wood) and Z_2^* (quality perception of vinyl) explained by variables V^1 (see in the upper part of Table 3 for variables retained in the empirical application). The second part of the latent variable model deals with the measurement equations (see the lower part of Table 3). Ten quality indicators are used to predict latent perceived quality variables. A χ^2 statistic built on the discrepancy function gives a good indication of the model fit. For our model, the test statistic is equal to 2081.75 with 319 degrees of freedom. Its p-value is less than 0.0001. The goodness of fit index (GFI) is close to 1 (with a value of 0.8416). Moreover, the root mean square error of approximation (RMSEA) is equal to 0.0767. These measures indicate that the model fits the data well.

[Table 3 here]

Estimation results of latent variable equations One objective of this paper was to better understand how quality beliefs are formed and, more precisely, if knowledge on windows and materials (obtained either through experience or by external information sources) changes quality beliefs. In the upper part of Table 3, we report the estimation results for the two latent variables, quality perception of wood and quality perception of vinyl.[5] These results allows us to know which factors (proxies of information) positively or negatively influence the quality perception for both materials.

First, recent information received by individuals on windows and conveyed by way of advertising or by store advisors for instance, has a negative impact on their perception of wood.[6] Second, the degree of information respondents feel to possess both about windows and materials has a significant impact on the perceived quality of window materials. On the one hand, the more that individuals feel to be informed about windows, the greater the quality perception of wood. On the other hand, the coefficient associated with the information on materials is significantly positive for the perceived quality of vinyl.

Third, another way that consumers acquire information is through experience. In the survey, we collected data on the type of windows (i.e., type of material) in their lodging as well as their perception of brightness and performance of insulation in their house. We created variables by crossing both questions in order to simulate experience and perception on materials. Estimation results show a significant impact of these variables on perceived quality. So a combination of the material of the windows in their home with the observed level of insulation and brightness in their home, influences respondents' opinions on the quality perception of materials. For instance, good or very good thermal and acoustic insulation associated with wooden windows at home improves the perceived quality of wood and decreased the perception of vinyl. In the same way, poor brightness associated with wooden windows increase the perception of vinyl, whereas this has no impact on the perception of wood. Also, Do-It-Yourselfers (DIY) who might have a higher probability to manipulate materials than non-DIY, have a better opinion of wooden windows, whereas this has no effect on the perception of vinyl.

Finally, we have checked the accuracy of the predicted latent perception variables before injecting them in the choice model. Indeed, as indicated in the description of the estimation method, the two-step procedure may result in inconsistency of parameters due to the introduction of measurement errors by using fitted latent variables as regressors. However, the estimated variances of the latent variable random errors are small (0.42 and 0.53, respectively, for perceived wood quality and perceived vinyl quality). Thus, we may expect that an individual's true value of the latent variable is not too far off from its expected value.

Estimation results of measurement equations The measurement model allows us to kwow which indicator variables are the best predictors for the (latent) quality perception and contribute to the construction of the latent preferences. Hence, results concerning the measurement equations indicate the level of reliability and validity of the indicators of the quality perception (in the lower part of Table 3).

The estimated factor loadings in the measurement equations are all positive and significantly different from zero at the 1% level of significance, excepted for the price indicators. The results confirm that the question of the global quality of windows is the best indicator of perceived quality among all indicators, with R^2 equal to 0.61 and 0.71, respectively, for perceived wood and vinyl quality. Moreover, thermal insulation seems to be the second best indicator (0.56 and 0.73, respectively, for wood and vinyl), followed by acoustic insulation, maintenance and product life. Fire resistance, safety and environmental considerations are weak indicators for the perception of window quality. Finally, the dependence between quality perception and price indicators is low: Correlation coefficients between the price indicator and the latent variable (quality perception) turned out to be very small, 0.0017 and 0.0193, respectively, for wood and vinyl. This confirms that consumers did not integrate price into their judgment of materials.

4.2.2 The choice model

In the discrete choice model, we estimated the probability of choosing wood ($y = 1$) rather than vinyl ($y = 0$) as material for windows. We must remember that respondents were requested to make a product choice considering that products are sold at identical prices. Several tests already showed that respondents had taken into account this recommendation. To eliminate any ambiguity, we included the price indicators for wooden and vinyl windows into the choice model. None of the variables are significantly different from zero. So we may conclude that respondents have correctly answered the questionnaire and focuse on other explanatory variables to analyze consumer preferences. Our model includes, along with "usual" explanatory variables, the predicted latent variables (i.e., predicted quality perceptions of wood and vinyl) coming from the latent variable model, and taste (or attitudes) on the basis of attribute weight. Table 5 presents the results of the choice model estimation.

Before analyzing parameter estimates in Table 5, we made several specification tests on our model. We had to make sure that the integrated model described in Figure 1 is an appropriate specification for explaining the role of information in the choice decision. In particular, a latent variable model was combined with the choice model in order to take non-observed perception variables into account that could influence consumer choice. Moreover, our model supposes that the preferences and tastes are different between consumers, and that the weights consumers put on attributes (assumed to represent the tastes of consumers) are observed factors that affect their utility. We report the results of likelihood ratio (LR) tests on these assumptions in Table 4.

[Table 4 here]

We first tested a model without attribute weights. There are nine restrictions such that coefficients associated with the weights for the nine defined attributes of a window (including price) are equal to zero. This model is not accepted at the 1% level, revealing the importance of tastes in the choice decision. Second, the hypothesis that the two parameters of the predicted latent variables are jointly equal to zero is also rejected at the 1% level. This result confirms that the integration of the latent variable model is necessary and that the quality perception variables provide a meaningful explanation of the choice decision of consumers. We also tested for the null hypothesis that both coefficients associated with weights and coefficients associated with latent variables are equal to zero. The test statistic is also greater than the critical value implying the rejection of this hypothesis. Finally, we carry out the standard LR test for the global goodness-of-fit testing the null hypothesis that all coefficients excepted the contant term are zero. This hypothesis is also highly rejected. The integrated model appears to be the most accurate specification.[7]

[Table 5 here]

Several conclusions can be drawn from the estimates in Table 5. First, as seen by the results of previous tests, quality perception is important in consumers' purchase decision. Indeed, estimated parameters associated with each of two latent variables, quality perception of wood and quality perception of vinyl, are highly significantly different from zero (at the 1% level). As expected, a higher quality perception of wood leads to a greater probability of choosing this material for windows. In the same way, a lower quality perception of vinyl also implies a choice of wood rather than vinyl.

Second, tastes have a significant effect on the material choice for three of the nine characteristics of a window: thermal insulation, aesthetics and maintenance. For these indicators, quality beliefs differ considerably between wooden windows and vinyl windows (see Table 1). Thermal insulation has a negative effect on the choice for wooden windows. Respondents perceived wood to be less performing for thermal insulation than vinyl (see Table 1). Furthermore, we can see in the lower part of Table 3 that the thermal insulation property highly influences the quality perception of either wooden or vinyl windows. Moreover, if aesthetics is important or very important factor in the window choice, wooden windows will be preferred over vinyl ones. Indeed, people generally believe that wooden windows are more attractive than vinyl windows (see Table 1). Vinyl windows are generally considered to be easier to maintain than wooden windows. As a result, when people attach importance to maintenance, they will choose vinyl windows rather than wooden windows. It should be observed that both the parameters of aesthetics and maintenance indicators are significantly different from zero at the 1% level, while the one of thermal insulation is significantly different at the 5% level. Individuals do not attach same importance to window characteristics. Tastes for window characteristics however could be altered by educational programs. For instance, civic education on environmental responsibilities could raise tastes for environmental considerations and could modify consumer purchase choice in favor of wood.

Third, other variables such as lodging characteristics or socio-economic factors also influences the choice of window material. For example, consumers living in standard or modern houses will opt less easily for wooden windows than consumers of traditional (typical) livings. Vinyl is more frequently chosen by owners rather than tenants. Older people seem to have a higher probability to purchase wooden windows than younger people. An explication of this result might be the fact that they have more spare-time to maintain. The region a person lives in is also an explaining factor but not the socio-professional group (SPG). However, a high income level for the consumer explains the choice of wood rather than vinyl. A family with children will have a slight preference for wood, whereas this preference is definitely evident for singles. Surprisingly, ecologically-minded consumers tend to prefer vinyl windows rather than wooden windows, maybe because they think that harvesting and thus wood as a material is harmful for forests.

Our results show that quality beliefs that consumers possess about windows and materials highly influence their consumption choice. In the case of windows, quality perception is determined by the consumer's level of knowledge, based on either (external) information or experience. The choice model shows that the consumption decision is highly dependent on consumer quality perception. This means that information campaigns might be an efficient tool for increasing the market share of wood: Either by informing people on real performances of wood (for example, wood possesses the same thermal and acoustic performance as vinyl), or by trying to change tastes, i.e. purchase criteria (for example, by educating the citizen on the importance of the sustainability of materials used in house construction).

5 Conclusion and perspectives

We set up an econometric model where the quality level of product attributes is an endogenous variable and depends on the information level of consumers, in the case of window choice. We showed that the introduction of quality perceptions and tastes for different attributes significantly improves the results of a "classical" discrete choice model. This result is not very surprising since several attributes of windows are not observable before purchase. The situation of imperfect information in purchase decisions means that consumers do not assess the objective quality level of attributes in the same way. Therefore, depending on the information they possess on attributes, they form different quality perceptions.

The quality perception of attributes is a determining factor in the purchase decision, especially for the attributes for which consumers have high preferences. This means that if producers can favorably influence the consumer's perception, demand might increase. For example, a better perception of thermal insulation (which is not observable before purchase) positively influences global quality perception and could thus highly influence purchase decisions. Thus, if wood producers could persuade people that wooden windows insulate as effectively as vinyl ones –or even better– (by doing better marketing of their products), consumers might switch their consumption towards wooden windows. With the model we aimed to show that consumer preferences are heterogeneous and based on imperfect information. Indeed, consumers do not necessarily possess correct information on properties of products. The perception consumers have on these properties is a very important factor in their purchase decision. Consequently, we might think that information campaigns can easily modify consumer purchase choices. A logic extension should be to test whether information provision positively (or negatively) influences consumer preferences.

In our application to windows, we use stated choice data because data on observed choices were much more difficult to collect on the window market. It could be useful to apply this approach to observed choices and stated preferences (taste indicators and quality perception of products). Studying consumer beliefs about product quality could also be possible with experimental data. More sophisticated analyses of the impact of different kinds of information available (e.g., general information before going into the store, information available in the store on the product) could also enrich the analysis and provide interesting insights for policy-making.

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A Appendix

A.1 Descriptive Statistics

[Table A.6 here]

A.2 Estimation of the latent variable model

The latent variable model is a structural equation model composed of two structural equations (A.1) and (A.2), corresponding to the two materials and two sets of measurement equations (A.3) and (A.4), expressing relationships among latent variables Z^* and manifest variables or indicators I. The complete system can be written as follows:

$$Z_1^* = \beta_1 V^1 + \epsilon_{Z_1} \tag{A.1}$$

$$Z_2^* = \beta_2 V^1 + \epsilon_{Z_2} \tag{A.2}$$

$$I_1 = \gamma_1 Z_1^* + \epsilon_{I_1} \tag{A.3}$$

$$I_2 = \gamma_2 Z_2^* + \epsilon_{I_2}, \tag{A.4}$$

where V^1 is a (8×1) vector of explanatory variables, β_1 and β_2 are the associated (1×8) vectors of parameters to be estimated, and ϵ_{Z_1} and ϵ_{Z_2} are i.i.d $(0, \Sigma_{Z_1})$ and $(0, \Sigma_{Z_2})$, respectively. I_1 and I_2 are (10×1) vectors of indicators (see Table 1 for definitions), γ_1 and γ_2 are the (10×1) vectors of unknown parameters to be estimated,[8] and ϵ_{I_1} and ϵ_{I_2} are the measurement errors respectively i.i.d $(0, \Sigma_{I_1})$ and $(0, \Sigma_{I_2})$. The covariance of the error terms in the structural latent equations and in the measurement equations are equal to zero.

Structural equation modeling is a multivariate technique using covariance structure analysis. We call θ the parameter vector to be estimated, which includes β_1, β_2, γ_1, γ_2 and the variances of matrix Σ_{Z_1}, Σ_{Z_2}, Σ_{I_1} and Σ_{I_2}. The parameter vector θ is estimated iteratively by an algorithm that minimizes the difference between the sample covariance matrix S and the estimated covariance matrix of estimated parameters $\widehat{\Sigma}(\hat{\theta})$.

Maximum likelihood estimation (MLE) is the most common method used to estimate structural parameters of this model. Multivariate normal distribution and continuous variables are some of the key assumptions of MLE. However, the manifest variables are often not continuous (dichotomous or polytomous variables). This is the case in our model. In particular, the measured indicators and some observed variables are based on a five-point Likert scale (ordinal variables). In this case, the assumption of multivariate normality of data does not hold. The parameter estimates of the latent variable model are still convergent, but the estimated standard errors are underestimated and the fit measures based on χ^2 values are not good.

In practice, when the number of Likert categories is 4 or higher and skew and kurtosis are within normal limits, use of MLE may be justified. However, as reported by Zhang and Browne (2006), another approach can be to estimate tetrachoric and polychoric correlations,[9] respectively, from the dichotomous and ordinal variables, and to use generalized least squares (GLS) where the weight matrix is the inverse of the matrix of tetrachoric/polychoric correlations (instead of Pearson correlations, Muthén, 1984). When the model is correctly specified, GLS gives asymptotically valid test statistics and standard error estimates (Browne, 1984). The discrepancy function to minimize is written as $F = F(S, \Sigma(\theta))$. For GLS, this function is:

$$F_{GLS} = \frac{1}{2} tr(W^{-1}(S - \Sigma)^2),$$

where W is the weight matrix and tr indicates the trace of a matrix.

Notes

[1] In the empirical application, different tests were carried out to make sure that the assumption was verified, i.e. that consumers did not integrate price into their judgements. In the questionnaire, respondents were asked to give a price appreciation, for wooden as well as plastic window frames. First, we showed that the price estimation was a bad indicator for product quality. Second, respondents did not judge differently the price levels of wooden and plastic frames. Finally, price indicators were not significant explanatory variables in the global choice model.

[2] In structural equation modeling, non-observed variables are called latent variables and observed variables are called manifest variables.

[3] ED Institut, marketing studies institute, www.edinstitut.com.

[4] We used the CALIS procedure (Covariance Analysis of Linear Structural Equations) from the SAS system for Windows (version 9.1) to estimate parameters and test the appropriateness of the linear structural equation model using covariance structure analysis. Since we had a set of linear structural equations to describe our model, we used the LINEQS statement. In particular, it is possible to specify variances and covariances in the model, to choose between different estimation methods and to enter correlation matrices instead of raw data. We constructed tetrachoric/polychoric correlation matrices using the FREQ procedure of SAS.

[5] In order to have the best predictions of the latent variables (i.e., minimizing the variance of their random error), we only retained statistically significant factors.

[6] Respondents were asked if they had received recently information (either through ads or in stores) on windows.

[7] Significant gains with respect to simpler models can also be measured in terms of correctly predicted observations and pseudo R^2. For the integrated model, 67% of observations are correctly predicted by the model, and R^2 is equal to 0.18. Without latent variables, 63% of observations are correctly predicted by the model, and R^2 falls to 0.13. If weights and latent variables are not included in the model, the percentage of correctly predicted observations is 60%, and the pseudo R^2 is 0.08.

[8] For each material and thus for each vector of indicators I_1 and I_2, the parameter associated with the indicator called "global quality" is set to 1.

[9] Tetrachoric and polychoric correlations extrapolate what the categorical variable distributions would be if continuous, adding tails to the distribution. As such, it is an estimate based on the assumption of an underlying continuous bivariate normal distribution.

Figure 1: Integrated choice and latent variable model

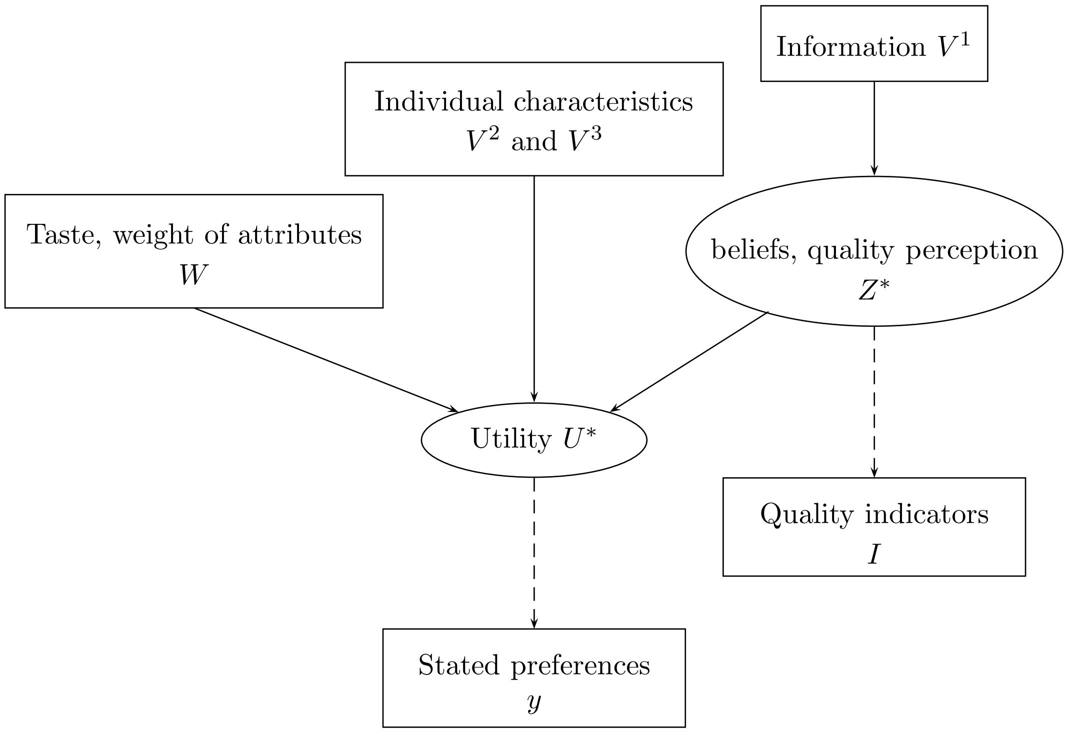

Table 1: Quality perception of product attributes for wood and vinyl (indicators I)

Appreciation (Lickert scale)	Very low (=1)	Low (=2)	Indifferent (=3)	High (=4)	Very high (=5)	Mean	Std.
Question: What do you think about this attribute for the wooden (vinyl) window?							
Wood							
I_{11} Global quality	4.04%	15.5%	2.55%	50.2%	27.7%	3.82	1.12
I_{12} Thermal insulation	3.72%	17.8%	9.57%	39.3%	29.7%	3.73	1.17
I_{13} Acoustic insulation	4.04%	18.7%	14.0%	38.1%	25.1%	3.61	1.17
I_{14} Maintenance	17.7%	53.8%	2.45%	18.8%	7.23%	2.44	1.19
I_{15} Product life	3.62%	25.4%	8.62%	35.9%	26.4%	3.56	1.23
I_{16} Aesthetics	1.06%	3.09%	1.28%	21.2%	73.4%	4.63	0.76
I_{17} Environment	5.74%	17.0%	14.9%	32.6%	29.8%	3.64	1.23
I_{18} Fire resistance	35.5%	39.7%	7.66%	13.4%	3.72%	2.10	1.14
I_{19} Safety	15.1%	36.1%	12.3%	26.9%	9.57%	2.80	1.26
I_{1p} Price	5.43%	16.3%	42.0%	28.5%	7.77%	3.17	0.97
Vinyl							
I_{21} Global quality	2.66%	7.02%	7.77%	40.4%	42.1%	4.12	1.00
I_{22} Thermal insulation	1.70%	5.21%	12.1%	38.1%	42.9%	4.15	0.94
I_{23} Acoustic insulation	1.49%	5.00%	18.0%	38.3%	37.2%	4.05	0.94
I_{24} Maintenance	1.06%	2.87%	6.17%	28.9%	61.0%	4.46	0.82
I_{25} Product life	1.17%	6.60%	18.2%	34.6%	39.5%	4.05	0.97
I_{26} Aesthetics	5.85%	18.4%	5.11%	44.9%	25.7%	3.66	1.20
I_{27} Environment	7.02%	27.9%	24.0%	29.9%	11.2%	3.10	1.14
I_{28} Fire resistance	21.2%	35.6%	16.9%	21.7%	4.57%	2.53	1.18
I_{29} Safety	11.4%	25.0%	17.2%	35.4%	11.0%	3.10	1.22
I_{2p} Price	3.30%	16.4%	41.3%	30.5%	8.52%	3.25	0.94

Notes: $N = 940$.

Table 2: Taste for product attributes (weight W)

(Lickert scale)	Not important (=1)	Few important (=2)	Indifferent (=3)	Rather important (=4)	Very important (=5)	Mean	Std.
Question: When you choose a window, how important is this attribute?							
Thermal insulation	0.64%	1.38%	0.32%	11.0%	86.7%	4.82	0.56
Acoustic insulation	1.28%	5.43%	0.85%	15.1%	77.3%	4.62	0.86
Product life	0.53%	3.94%	1.49%	21.0%	73.1%	4.62	0.75
Aesthetics	0.32%	7.23%	0.43%	27.1%	64.9%	4.49	0.86
Fire resistance	5.00%	12.8%	2.45%	23.3%	56.5%	4.14	1.24
Maintenance	1.17%	5.96%	0.64%	23.0%	69.3%	4.53	0.87
Environment	3.72%	11.4%	4.04%	31.5%	49.4%	4.11	1.15
Safety	2.77%	6.38%	1.91%	20.6%	68.3%	4.45	1.00
Price	1.17%	4.57%	3.40%	24.7%	66.2%	4.50	0.86

Notes: $N = 940$.

Table 3: Estimation results of the latent variable model

	Z_1^* (Wood)		Z_2^* (Vinyl)		
Latent variable equations (two equations, one per column)	Coef.	t-stat	Coef.	t-stat	
(Explanatory) Variables V^1					
Received information (recently)	−0.1190	−1.83			
Informed about windows (feeling)	0.0927	4.37			
Informed about materials (feeling)			0.0798	4.05	
Do-it-yourselfers	0.0569	3.51			
Very good thermal insulation × Home wooden windows	0.9322	13.50	−0.7467	−10.79	
Good acoustic insulation × Home wooden windows	0.4728	6.76	−0.7488	−9.81	
Poor Brightness × Home wooden windows			0.3621	3.05	
Purchase of windows × Home wooden windows	0.9154	5.92	0.7054	4.61	
R^2	0.38		0.20		
Measurement equations (two times ten equations, one per row)	Coef.	t-stat	Coef.	t-stat	R^2
(Explained) Indicators I					
I_{11} Global quality	1.0000	–			0.60
I_{12} Thermal insulation	0.9293	19.75			0.56
I_{13} Acoustic insulation	0.8434	18.92			0.47
I_{14} Maintenance	0.7378	15.82			0.32
I_{15} Product life	0.9699	20.15			0.55
I_{16} Aesthetics	0.5278	18.31			0.43
I_{17} Environment	0.5291	10.50			0.15
I_{18} Fire	0.4198	9.30			0.18
I_{19} Safety	0.5409	12.84			0.35
I_{1p} Price	0.0390	1.02			0.00
I_{21} Global quality			1.0000	–	0.71
I_{22} Thermal insulation			0.9187	27.29	0.72
I_{23} Acoustic insulation			0.8401	22.87	0.61
I_{24} Maintenance			0.6566	21.26	0.48
I_{25} Product life			0.6532	17.75	0.34
I_{26} Aesthetics			0.8150	18.62	0.37
I_{27} Environment			0.4788	10.69	0.17
I_{28} Fire			0.3174	7.12	0.09
I_{29} Safety			0.4868	12.39	0.27
I_{2p} Price			0.1427	3.79	0.02

Fit function=2.2170

Goodness-of-fit statistics	$\chi^2(319)$	GFI	RMSEA
	2081.75 (¡0.0001)	0.8416	0.0767

Notes: $N = 940$. GFI=Goodness of fit index, RMSEA=Root mean square error approximation.

Table 4: Specification tests

Null hypothesis	$\ln Lr$	LR statistics	Critical value	Decision
Model without weights of attributes W H_0 : coef. related to W null	-554.71	52.20	$\chi^2_{0.01}(9) = 21.67$	Reject H_0
Model without quality perception Z^* H_0 : coef. related to $\hat{Z}^*_1$ and $\hat{Z}^*_2$ null	-562.04	66.85	$\chi^2_{0.01}(2) = 9.21$	Reject H_0
Model without Z^* and W H_0 : coef. related to W, $\hat{Z}^*_1$ and $\hat{Z}^*_2$ null	-592.21	127.20	$\chi^2_{0.01}(11) = 24.72$	Reject H_0
Model with only the constant term H_0 : all coef. excepted the constant term null	-643.08	169.97	$\chi^2_{0.01}(34) = 56.06$	Reject H_0

Notes: $N = 940$. For the unrestricted (complete) model, $\ln Lu = -528.61$.

Table 5: Estimation results of the choice model

Variable	Estimated Coef.	Bootstrap Std. err.
Constant	1.7702***	0.6738
I_{1p}	−0.0651	0.0494
I_{2p}	−0.0413	0.0535
Age	0.1700***	0.0478
Not ecologically sensitive[a]	−0.3326	0.2718
Not very ecologically sensitive[a]	−0.2458	0.1760
Rather ecologically sensitive[a]	−0.2832***	0.1091
High income level[a]	0.7434***	0.2599
Gives little importance to home[a]	−1.0187*	0.6119
Gives big importance to home[a]	−0.2676***	0.1029
SPG1	0.2668	0.2021
SPG3	0.0859	0.1435
SPG4	−0.1166	0.1560
Reg1	−0.2225	0.1613
Reg2	−0.3333**	0.1417
Reg3	−0.2294*	0.1394
Reg4	−0.1837	0.1766
Single	0.3844**	0.1450
Family	0.1728	0.1098
Woman	0.0741	0.0970
Owner	−0.4208***	0.1182
Modern	−0.3059**	0.1369
Classic	−0.2935**	0.1170
Rooms	0.0347*	0.0206
Quality perception of wood	0.5268***	0.1728
Quality perception of vinyl	−0.7616***	0.1271
Acoustic insulation	0.0136	0.0639
Thermal insulation	−0.2091**	0.1020
Product life	−0.0300	0.0688
Aesthetics	0.1985***	0.0652
Fire resistance	−0.0208	0.0466
Maintenance	−0.3165***	0.0683
Environment	0.0294	0.0506
Safety	−0.0243	0.0574
Price	−0.0249	0.0628
Log-likelihood $\ln l$	-528.61	
McFadden's Pseudo R^2	0.1780	
Correctly predicted	67%	

Notes: Number of observations $N = 940$. Number of bootstrap replications = 941. ***: significant at 1%, **: at 5%, *: at 10%.
[a] Variables Ecological sensitivity, Finances and Home (defined in Table A.6) initially built on a 1-5 scale have been tranformed into dummies.

Table A.6: Descriptive statistics

Variable	Description	Mean	Std.	Min	Max
Stated Choice y	=1 if wood is chosen	0.4330	0.4958	0.00	1.00
Variables V^1					
Home thermal insulation	Assessment of insulation	3.8553	1.3393	1.00	5.00
Home acoustic insulation	Assessment of insulation	3.8298	1.3514	1.00	5.00
Home brightness	Assessment of brightness	4.4319	0.9337	1.00	5.00
Home wooden windows	=1 if windows in wood	0.5372	0.4989	0.00	1.00
Home vinyl windows	=1 if windows in vinyl	0.3128	0.4639	0.00	1.00
Change of windows	=1 if recent change	0.0649	0.2465	0.00	1.00
Received information	=1 if recent information	0.2543	0.4357	0.00	1.00
Informed about windows	Assessment of information	3.0787	1.3152	1.00	5.00
Informed about materials	Assessment of information	2.8819	1.3288	1.00	5.00
Do-it-yourselfer	Do-it-yourself rate	3.3202	1.5007	1.00	5.00
Purchase of windows	=1 if recent purchase	0.0840	0.2776	0.00	1.00
Variables V^2					
Home	Importance to home	4.5489	0.7170	1.00	5.00
Apartment	=1 if apartment	0.3160	0.4651	0.00	1.00
Rooms	Number of rooms	5.2883	3.1098	0.00	73.0
Owner	=1 if owner (0 if tenant)	0.6660	0.4719	0.00	1.00
Modern	=1 if modern building	0.2287	0.4202	0.00	1.00
Classic	=1 if classic building	0.5298	0.4994	0.00	1.00
Typical	=1 if typical building	0.2298	0.4209	0.00	1.00
Variables V^3					
Age	Class of ages	3.2755	1.2068	1.00	5.00
Woman	=1 if woman	0.5840	0.4931	0.00	1.00
Single	=1 if single	0.1564	0.3634	0.00	1.00
Single parent	=1 if single-parent family	0.0372	0.1894	0.00	1.00
Couple	=1 if couple	0.2915	0.4547	0.00	1.00
Family	=1 if couple with kids	0.4957	0.5002	0.00	1.00
Ecological sensitivity	Ecologically-sensitive	3.9734	1.0495	1.00	5.00
Finances	Assessment of own finances	3.0021	1.1611	1.00	5.00
SPG1	Farmer, craftsman, merchant	0.0596	0.2368	0.00	1.00
SPG2	Executive, liberal profession	0.1074	0.3098	0.00	1.00
SPG3	Intermediate profession	0.1447	0.3520	0.00	1.00
SPG4	Employee	0.1106	0.3139	0.00	1.00
SPG5	Manual laborer, service personnel	0.1787	0.3833	0.00	1.00
SPG6	Unemployed, retired	0.3989	0.4899	0.00	1.00
City size	City size	2.8777	1.4221	1.00	5.00
Reg1	Paris region	0.1660	0.3722	0.00	1.00
Reg2	Western region	0.2245	0.4175	0.00	1.00
Reg3	North-Eastern region	0.2426	0.4289	0.00	1.00
Reg4	South-Western region	0.1213	0.3266	0.00	1.00
Reg5	South-Eastern region	0.2457	0.4308	0.00	1.00

Notes: Number of observations $N = 940$.