Distance decay in the willingness to pay for wine: disentangling local and organic attributes

Supplemental Material

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Figure S1: Location of participants in the study area.
The nothern vineyards of the *Côte de Nuits* (Burgundy) are located at the south-west of *Dijon*, with a relative proximity: about 4.5 kilometers between the city center and the closest vineyard. We differentiate the vineyards from the *commune* of *Marsannay-la-Côte* that contains the vineyards from the geographical indication of *Marsannay*. Vineyard plot locations come from Corine Land Cover in 2006. We also show the location of participants' dwellings and the INRA experimental station where the experiment take place. The north-south highway (N274, named *Voie Georges Pompidou* on the map) allows peoples living close to vineyards to be at 10 minutes by car from the experimental station. This limits the selection bias that can potentially arise from oversampling participants living close to vineyards.

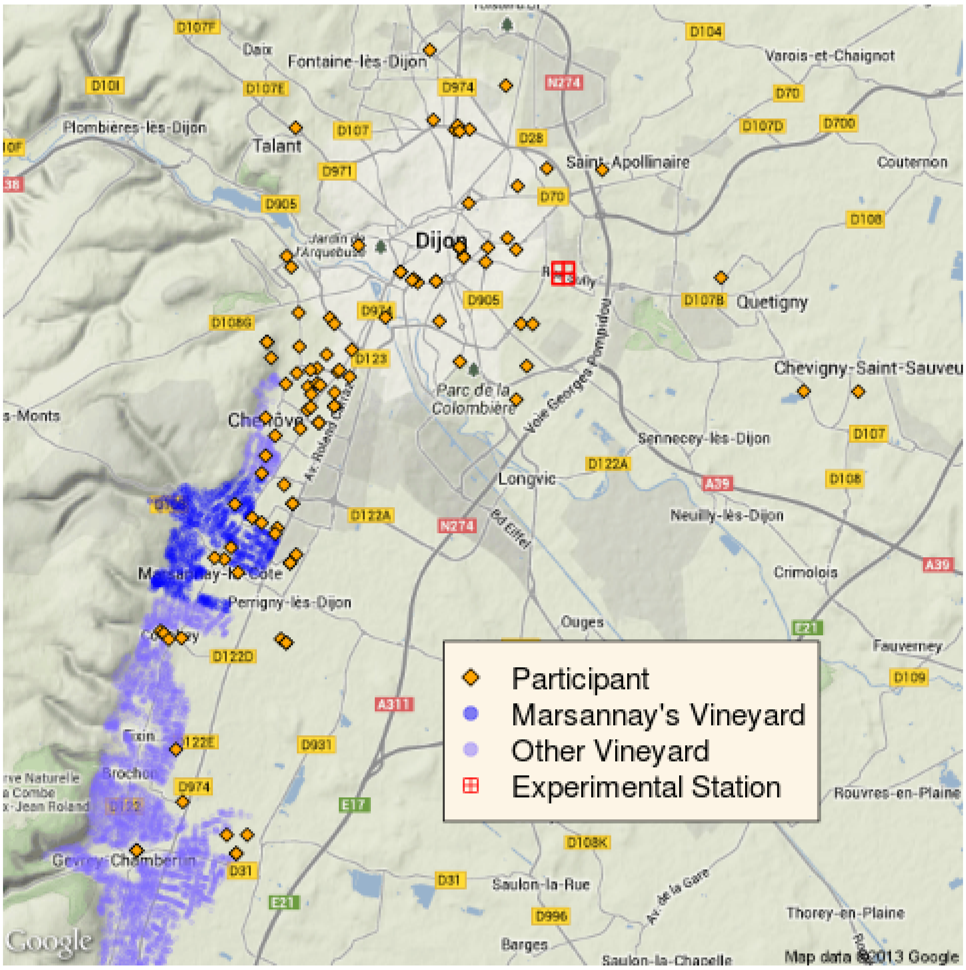


Figure S2: The four bottles of wine sequentially proposed to the participants.

From the left to the right, there are the *Marsannay* from *Domaine Molin* (local organic), the *Vacqueyras* from *Domaine Carobelle* (non-local organic), the *Vacqueyras* from *Domaine Mas du Bouquet* (non-local non-organic), the *Marsannay* from *Domaine Kohut* (local non-organic). All these wines come from *propriétaires-récoltants*, which means that the same farm entity cultivates the vineyard and makes the wine. The names of the owners are written on each label and each wines are of the 2010 vintage, which is available for sale at the moment of the experiment.

Figure S3: Relations between frequency of purchasing Burgundy wines and distances to vineyards.
To evaluate the potential presence of a familiarity effect correlated with the distances between participants' dwellings and local GI, we plotted the distances between participants and wineyards with their answers to question about frequencies of local wines purchasing. The value 1 counts for exclusively, 2 for regularly, and 3 for rarely. In terms of computed distances 1 and 2, not any significantly correlation appears, indicating that people living close to vineyards do not purchase more frequently local wines. Nevertheless, the results from Perceived distances reveal that people purchasing more frequently Burgundy wines perceived themselves as living closer to vineyards.

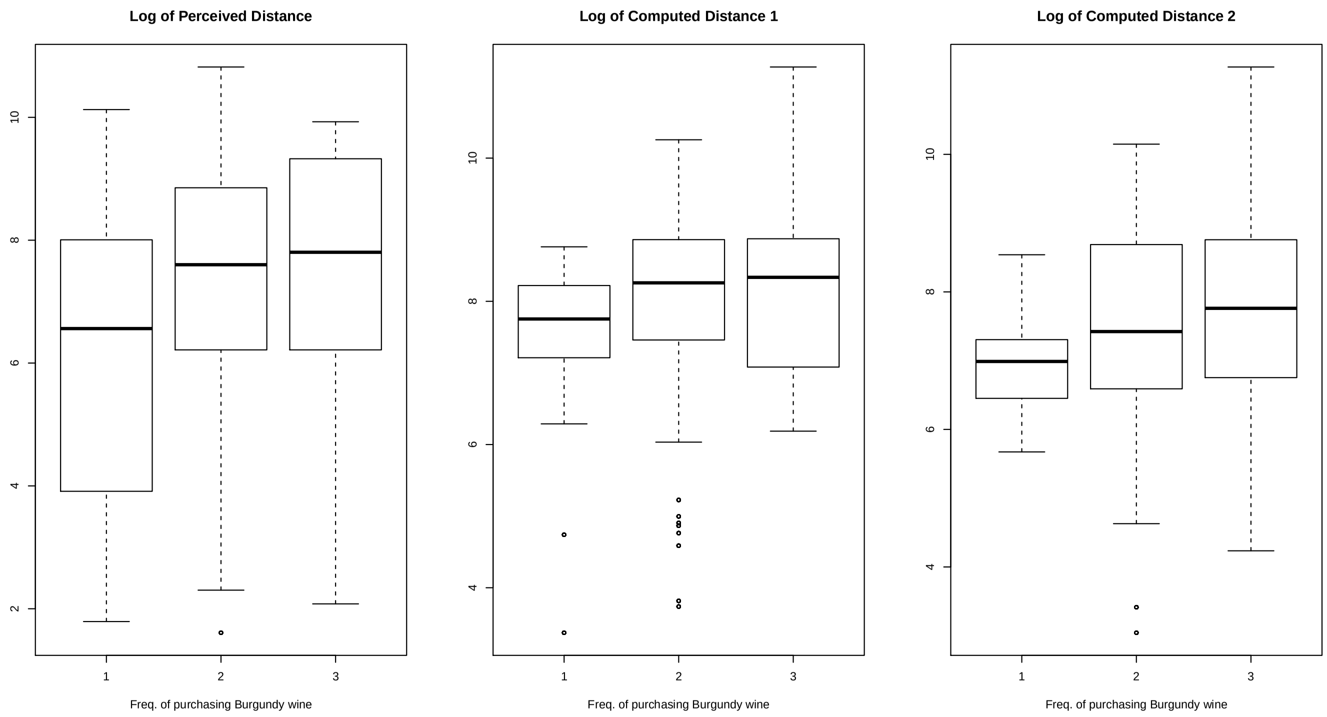


Figure S4: Time-line to elicit WTP according to different information levels.

Information # 1: Only the bottles of wine are made available to participants:
No information revealed

Information # 2: Information on general organic agriculture definition:
"Unlike regular agriculture, organic farming is a production method that is characterized by the absence of use of synthetic chemistry. Thus, wines from organic viticulture are obtained without the use of chemicals or fertilizers or synthetic pesticides. Organic farming led farmers to select more environmentally friendly practices."

Information # 3: Information on GHG emissions from regular agriculture:
"In France, agriculture is responsible for 20% of emissions of greenhouse gases while transport and industry account for 26% and 18% of these emissions (source: INSEE). Chemical fertilizers used in conventional agriculture is a source of emission of greenhouse gases responsible for global warming. Organic farming led farmers to select practices that emit less greenhouse gas emissions."

Information # 4: Information on the effects of pesticides on health:
"The cultivation of the vine in France represents 14% of pesticides used for only 3.7% of the agricultural area (source: INRA). A study of the association Future Generations published in February 2013 revealed the presence of pesticide residues in hair of wine employees and people living close to vineyards. A study by the IVS revealed in April 2013 that the French have a rate of pesticides higher than the European average body."

Information # 5: Information on the effects of pesticides on water bill:
"The communes of Burgundy are supplied with drinking water from different wells catchments. Tap water is variously affected by pesticide contamination related to agriculture and regular wine production. Raw water of Dijon presents below the health standard levels and therefore are not subject to any treatment against pesticides. In contrast, the raw water of some wine producing communes at the south of Dijon have higher levels of pesticides. Treatment against pesticides is performed on the collection points. In an evaluation in 2010 on Chenôve and Marsannay-la-Côte, the processing cost of pesticides is estimated at 5% of the water bill, or €10/year for the average annual household consumption (120m^3)."

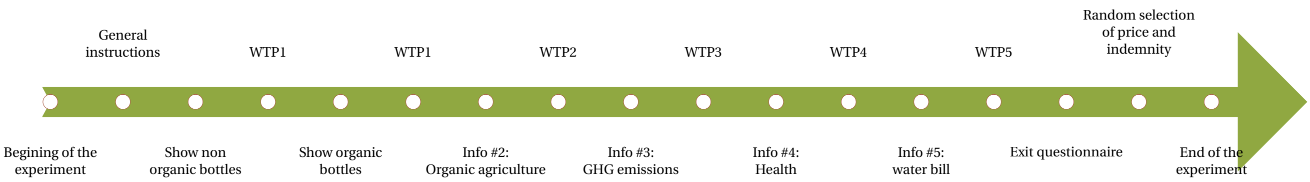


Figure S5: Correlations between available distances from vineyards

During the experiment, the following question was asked:

"How far do you think the distance (as the crow flies) between your residence and the nearest vineyard plot is?"

This question allowed us to obtain what we call the "perceived" distance from the closest vineyard. We also asked the postal address of participants to obtain the locations of their principal dwellings (as it is used by Figure S1 of this Supplemental Material) and to compute two other distances: "Computed Distance 1" from the closest vineyard (the light blue area in Figure S1), and "Computed Distance 2" from the closest vineyard from the GI *Marsannay* (the purple area in Figure S1).

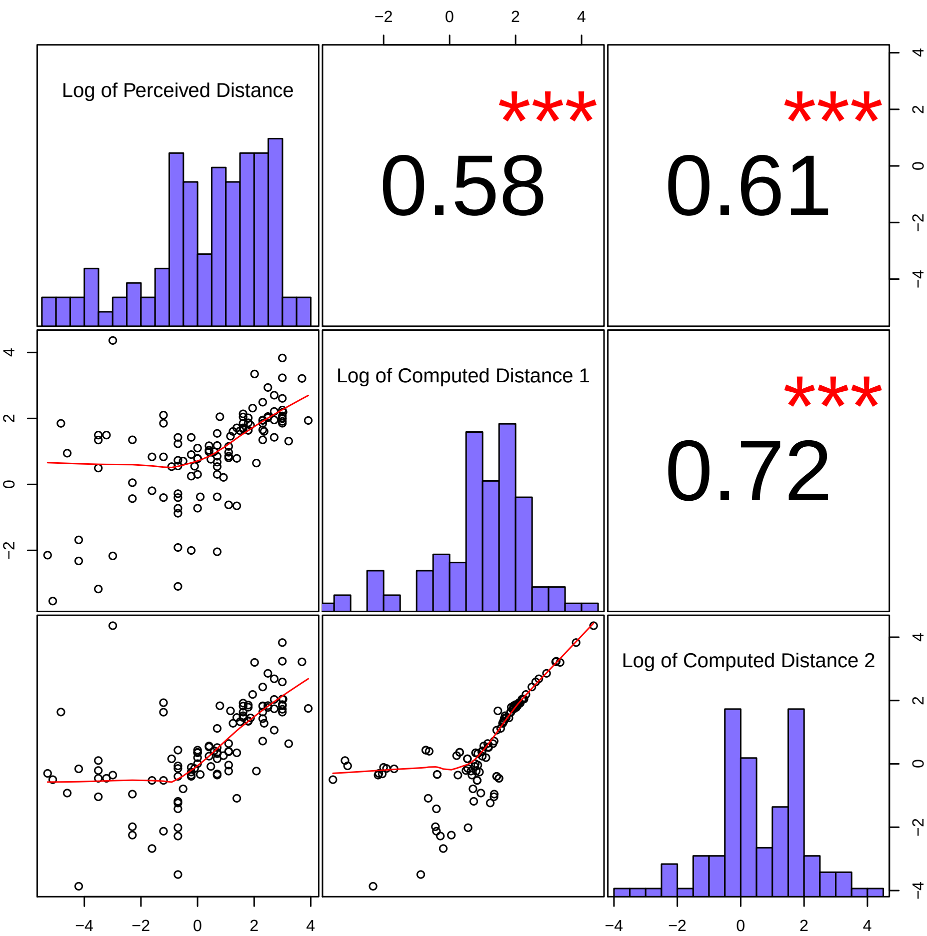
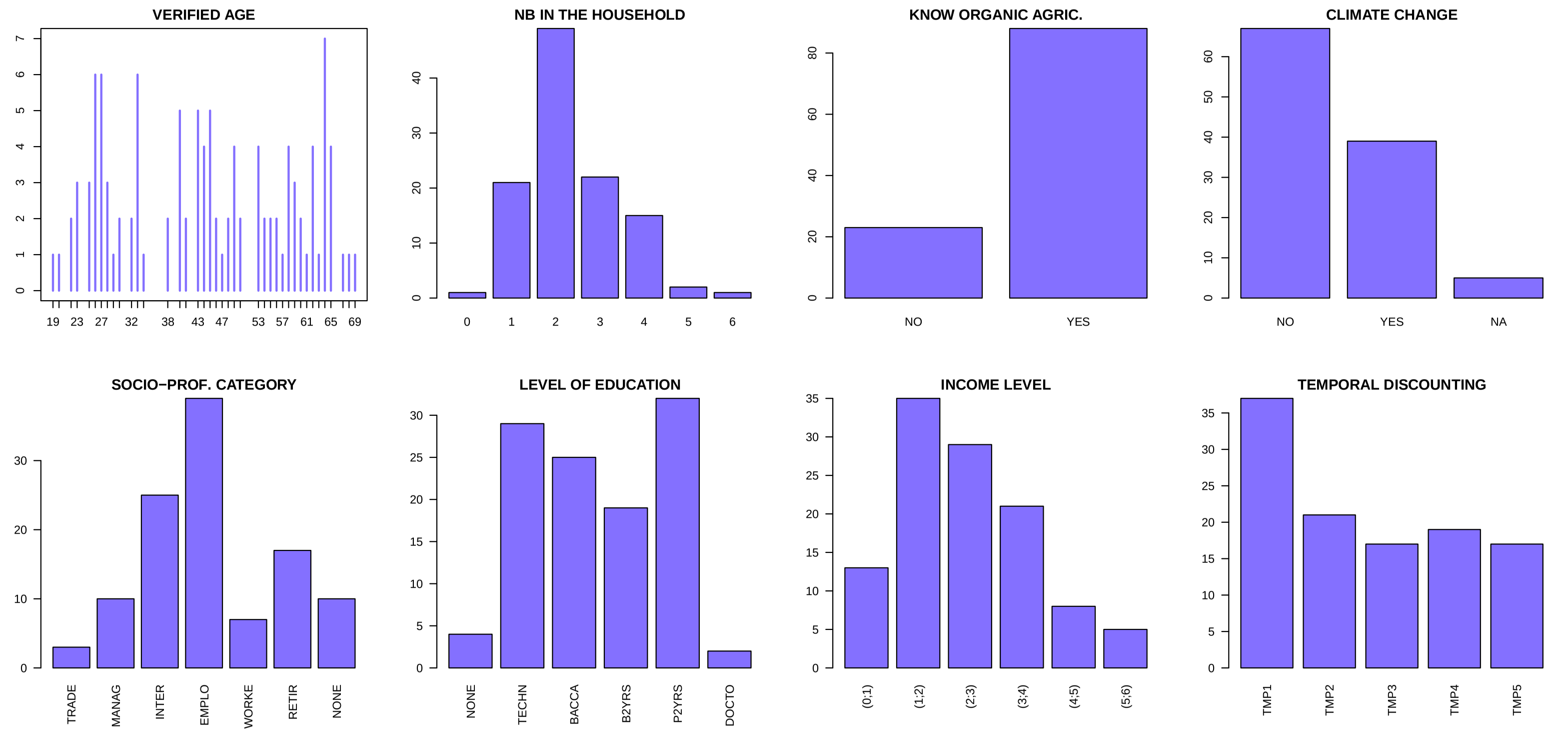


Figure S6: Distributions of control variables

We show here the sample distributions of participants' ages, the number of people in the households, the participants knowing organic agriculture, the participants knowing the detrimental effect of non-organic agriculture on climate change, the socio-professional categories, the levels of education, the levels of income and a measure of temporal discounting. This latter variable is computed from 4 questions.
1. Do you prefer €1000 today or €1100 in one year? 2. Do you prefer €1000 today or €1100 in two years?
3. Do you prefer €1000 today or €1300 in three years? 4. Do you prefer €1000 today or €1300 in three years?
The answers are aggregated as follows, TMP1 counts for people that always respond 1000, TMP2 for those that repond 1100 at the 1., TMP3 for those that respond 1100 at the 2., TMP4 for those that respond 1300 at the 3. and TMP5 for those that repond 1300 at the 4.



1 Empirical Model

1.1 Sample Structure

Our collected sample consists of $i = 1, \ldots, N$ participants of whom we asked their WTP for $k = 1, \ldots, K$ wines for different levels of information $j = 1, \ldots, J$. We have $N = 111$, $K = 4$ and $J = 5$, resulting in a pooled sample of 2,220 observations. The econometric strategy aims to identify the effects on WTP of the wine and information dummies (perfectly balanced among participants) and individual characteristics X_i such as the distance to the closest vineyard, the income class or the controls.

$$\text{WTP}_{ijk} = \alpha + X_i\beta + \eta_k + \theta_j + \varepsilon_{ijk} \tag{1}$$

The vector of β coefficients measures the respective effects of individual characteristics on WTPs, η and θ are the respective premiums attached to each wine k and the level of information j. α is a constant that ensures that the residuals ε_{ijk} are centered. We are also interested in modeling organic premiums, which for both for local and non-local wines is the difference between WTP for organic and regular: global premiums are $WTP_{ij}(k = \text{O-NL}) - WTP_{ij}(k = \text{NO-NL})$ and the local premiums are $WTP_{ij}(k = \text{O-L}) - WTP_{ij}(k = \text{NO-L})$. In this latter case, the wine dimension K is dropped (as the corresponding fixed effects) to obtain a pooled sample of 555 observations. The general pooled structure of the data can be simplified by setting $L = N \times K \times J$.

$$\text{WTP}_\ell = Z_\ell\lambda + \varepsilon_\ell, \; \ell = 1, \ldots, L. \tag{2}$$

From these pooled data, the assumptions of independently, identically and asymptotically Gaussian residuals ε_ℓ would be very strong. The most obvious gaps from the classical framework are the deviation from normal distribution, heteroskedasticity and error correlations within individuals. The deviation from normal distribution could be due to the small sample size and the presence of some influential observations resulting from misunderstandings in participants' interpretation of the questions, unexpected reactions to lab conditions, or some degree of unwillingness to respond seriously. Deviation from homoskedasticity and independence might be due to unobserved characteristics or unobserved differentiated responses (i.e., coefficient heterogeneity) of participants. This could induce some (positive) correlations between the residuals for the same individual for different wines and at different levels of information.

Our estimation strategy deals with two specific econometric issues usually observed in experimental data. They are:

1. Small number of participants ($N = 111$) with some influential outliers.
2. Correlated non-spherical residuals, because sequential WTPs are pooled.

To deal with the first issue, we propose an M-robust estimator which takes account of outliers and avoids reducing the sample size by their removal (a common practice in the literature). In relation to the second issue, most papers in the literature in experimental economics papers use panel data methods. We chose to take into account the correlated non-spherical residuals employing clustered standard errors which is comparable to the random-effects method but imposes fewer constraints on the structure of the variance-covariance matrix (Wooldridge, 2003).

1.2 Robust M-regressions

We limit the adverse effects of potentially fat-tailed residuals by underweighting the influential outliers (Belsley et al., 1980). As an alternative to the common practice of dropping individuals with high absolute error values (for small samples an undesirable practice, which does not preserves the cylinder structure of the sample and can exclude some potentially important insights), M-estimation is a general method of outlier-robust regression method which preserves sample size (Rousseeuw and Leroy, 1987; Venables and Ripley, 2002). The general M-estimator minimizes in λ the objective function:

$$\sum_{\ell=1}^{L} \kappa(\varepsilon_\ell) = \sum_{\ell=1}^{L} \kappa(\text{WTP}_\ell - Z_\ell \lambda) \tag{3}$$

where the function κ is exogenously specified. It must be positive, symmetric, increasing with the absolute value of the residuals, and null for zero residuals: $\kappa(0) = 0$. It is clear that the ordinary least square (OLS) estimator is a particular case with $\kappa(\varepsilon) = \varepsilon^2/2$. By noting $\widehat{\omega}_\ell$ the derivative of the function $\kappa(\cdot)$ evaluated at $\widehat{\varepsilon}_\ell$ and divided by $\widehat{\varepsilon}_\ell$, the first order conditions from the minimization of Equation 3 is similar to a weighted least-square problem.

$$\sum_{\ell=1}^{L} \widehat{\omega}_\ell (\text{WTP}_\ell - Z_\ell \lambda) Z_\ell = 0 \tag{4}$$

This first-order normalized derivative $\widehat{\omega}_\ell$ is simply the corresponding weighting scheme. However, the weight function depends upon the residuals, the residuals depend upon the estimated coefficients, and the estimated coefficients depend upon the weight function. So, an iterative solution (*iteratively reweighted least-squares*, IRLS) is required. The algorithm used to recover the coefficients is:

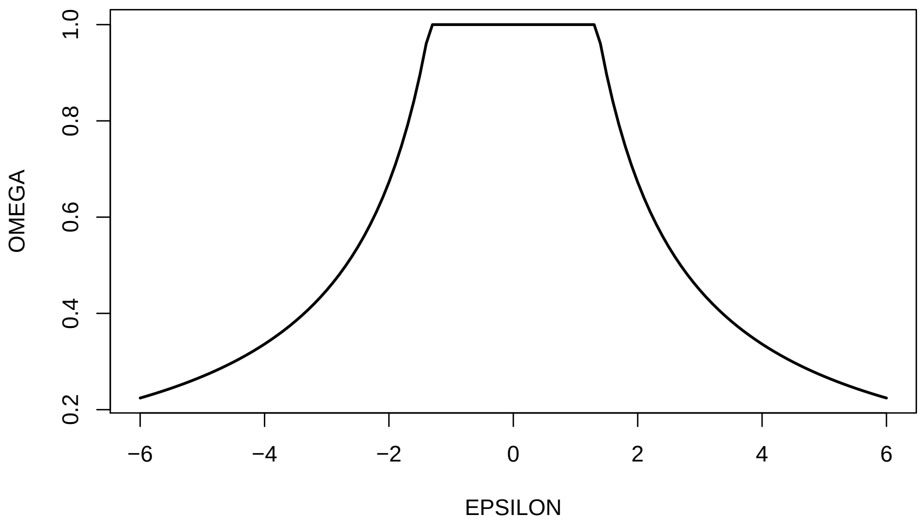
1. Determine the initial estimates $\widehat{\lambda}^0$ from the uniformly weighted least-squares;
2. Calculate the residuals $\widehat{\varepsilon}^0_\ell$ and associated weights $\widehat{\omega}^0_\ell = \omega(\widehat{\varepsilon}^0_\ell)$;
3. Solve for weighted least squares estimates using these weights.

Steps 2 and 3 are repeated until the estimated coefficients converge, i.e., become relatively constant between steps (we use a tolerance of .0001). According to the default **R** function `rlm` (Venables and Ripley, 2002), we choose a Huber's weighting scheme. This has the advantage that it corresponds to a convex optimization problem and gives a unique solution (up to collinearity). The Huber objective function increases without a bound as the residual departs from 0 and the weights for the Huber function decline when $|\widehat{\varepsilon}_\ell| > R$. Mathematically, the Huber weight function is:

$$\omega(\varepsilon) = \begin{cases} 1 & \text{for } |\varepsilon| \leqslant R \\ R/|\varepsilon| & \text{for } |\varepsilon| > R \end{cases} \tag{5}$$

The value R is called a "tuning" constant, from which the weights attributed to an observation begin to decline. This constant is generally dependent on the estimated standard deviation of the residuals $\widehat{\sigma}_{\varepsilon}$, we use the default value from (Venables and Ripley, 2002): $R = 1.345 \times \widehat{\sigma}_{\varepsilon}$. The bisquare weighting scheme is another frequently-used possibility but can have multiple local minimums, so we use it only as a robustness check. The following Figure S7 presents the shape of the Huber's weighting function with an unitary variance of the residuals. It is clear that WTP in accordance with the Gaussian assumption on the residuals has a weight of 1, as in standard OLS.

Figure S7: Huber weigthing function for $R = 1.345$



1.3 Clustered Standard Errors

In addition to the M-regression development, (Huber, 1967) was among the first people to acknowledge the need for standard error correction when some deviations of the NID assumption appear on residuals. His seminal work led to the sandwich class of Heteroscedastic and Autocorrelation Consistent (HAC) asymptotic matrix of variance-covariance. From this general framework, the cluster correction of residuals, now common in econometrics (see (Wooldridge, 2003) for a survey), is of particular importance for data from experimental economics. Here, we are principally interested in individual (i.e., participant) clusters because the other sample dimensions (wine type and information) are modeled as dummy variable fixed effects in eq. (1) which controls for much unobserved heterogeneity.

So, the asymptotic results that we need to obtain the HAC matrix are based on the number of clusters that grow to infinity ($N \rightarrow \infty$) for a given number of within cluster observations, the standard and most straightforward case according to (Wooldridge, 2003). We note $\widetilde{Z}_{\ell} \equiv Z_{\ell}\sqrt{\omega_{\ell}}$ the weighted explanatory row vector and allow the variance-covariance matrix of errors to have an arbitrary form, including within-individual correlation and heteroskedasticity according to what is observed in the data. According to the cluster literature, the weighted HAC variance-covariance matrix of coefficient can be consistently estimated by:

$$\widetilde{\mathbb{V}}(\widehat{\gamma}) = \left(\sum_{i=1}^{N} \widetilde{Z}_i^\top \widetilde{Z}_i \right)^{-1} \left(\sum_{i=1}^{N} \widetilde{Z}_i^\top \widehat{\varepsilon}_i \widehat{\varepsilon}_i^\top \widetilde{Z}_i \right) \left(\sum_{i=1}^{N} \widetilde{Z}_i^\top \widetilde{Z}_i \right)^{-1} \quad (6)$$

where $\widetilde{Z}_i$ and $\widehat{\varepsilon}_i$ are the within-cluster averages of their equivalent in pooled data: $\widetilde{Z}_\ell$ and $\widehat{\varepsilon}_\ell$. Cluster analysis is more general than mixed (or hierarchical) models because it does not impose equicorrelation within clusters (Newey and West, 1987). However, the cluster approach considers that the values of the parameters are well estimated by the last step of the IRLS, which seems appropriate in our case. The correction refers only to the standard errors associated with the coefficients. The **R** function written to compute the robust HAC matrix from weighted least squares, is available from the authors upon request.

Table S1: Pooled Willingness-To-Pay 4 Wines with 5 levels of Information

We report the coefficients associated to the secondary control variables of models (4), (5) and (6), reported in the Table 4 of the main paper. **VAGE** counts for the age of the participants, **NBENF** the number of children, **SOCIO** for the socio-professional category (merchant is the reference category, then manager, intermediate professions, employee, worker, retired and other), **ACHVIN** for the frequency of wine purchasing (weekly is the reference category, 2 for two or three times per month, 3 for one per month, 4 for more rarely, and nobody answers never), **BOURVIN** for the frequency of local wine purchasing (exclusively is the reference category, 2 for regularly, 3 for rarely, and nobody answers never), **BIOVIN** for the frequency of organic wine purchasing (with the same coding as the local wine, 4 counts for never), and **SEXE** is the sex of the participant, man is the reference modality, 2 is for woman.

	(4)	(5)	(6)
VAGE	−0.041 (0.027)	−0.037 (0.026)	−0.040 (0.027)
NBENF	−1.088*** (0.331)	−1.081*** (0.319)	−1.077*** (0.327)
SOCIOMANAG	−3.887* (2.246)	−4.550* (2.369)	−4.030* (2.427)
SOCIOINTER	−1.691 (1.930)	−2.108 (2.055)	−1.721 (2.097)
SOCIOEMPLO	−2.377 (1.962)	−2.753 (2.101)	−2.430 (2.149)
SOCIOWORKE	−2.720 (2.152)	−3.144 (2.359)	−2.772 (2.364)
SOCIORETIR	−0.167 (1.871)	−0.550 (1.997)	−0.138 (2.016)
SOCIONONE	−3.487 (2.229)	−3.665 (2.331)	−3.577 (2.399)
factor(ACHVIN)2	−0.489 (0.682)	−0.190 (0.648)	−0.321 (0.694)
factor(ACHVIN)3	−1.971*** (0.633)	−1.583** (0.653)	−1.666** (0.712)
factor(BOURVIN)2	0.400 (0.766)	0.396 (0.794)	0.386 (0.756)
factor(BOURVIN)3	0.471 (0.935)	0.340 (0.942)	0.357 (0.902)
factor(BIOVIN)2	8.652*** (1.562)	8.503*** (1.430)	8.668*** (1.482)
factor(BIOVIN)3	8.658*** (1.559)	8.601*** (1.419)	8.620*** (1.432)
factor(BIOVIN)4	7.081*** (1.534)	6.804*** (1.388)	6.947*** (1.392)
factor(SEXE)2	1.280** (0.581)	1.337** (0.576)	1.231** (0.575)
Constant	3.486 (3.288)	1.320 (3.195)	2.664 (3.193)
Observations	2,220	2,220	2,220
R^2	0.267	0.277	0.268
Adjusted R^2	0.254	0.265	0.256

Note: *p<0.1; **p<0.05; ***p<0.01

Last steps of IRLS to limit the influence of outliers. Standard Errors are clustered by individuals.

Table S2: Pooled Global Organic Premiums with 5 levels of Information

We report the coefficients associated to the secondary control variables of models (4), (5) and (6), reported in the Table 4 of the main paper. **VAGE** counts for the age of the participants, **NBENF** the number of children, **SOCIO** for the socio-professional category (merchant is the reference category, then manager, intermediate professions, employee, worker, retired and other), **ACHVIN** for the frequency of wine purchasing (weekly is the reference category, 2 for two or three times per month, 3 for one per month, 4 for more rarely, and nobody answers never), **BOURVIN** for the frequency of local wine purchasing (exclusively is the reference category, 2 for regularly, 3 for rarely, and nobody answers never), **BIOVIN** for the frequency of organic wine purchasing (with the same coding as the local wine, 4 counts for never), and **SEXE** is the sex of the participant, man is the reference modality, 2 is for woman.

	(4)	(5)	(6)
VAGE	0.001 (0.009)	0.003 (0.010)	0.001 (0.010)
NBENF	−0.141 (0.107)	−0.133 (0.120)	−0.141 (0.110)
SOCIOMANAG	0.254 (0.641)	0.281 (0.700)	0.100 (0.663)
SOCIOINTER	−0.684 (0.557)	−0.758 (0.520)	−0.843* (0.449)
SOCIOEMPLO	−0.545 (0.541)	−0.629 (0.495)	−0.689 (0.439)
SOCIOWORKE	−0.250 (0.580)	−0.290 (0.535)	−0.423 (0.484)
SOCIORETIR	−0.176 (0.555)	−0.435 (0.493)	−0.522 (0.429)
SOCIONONE	−0.848 (0.572)	−0.881 (0.554)	−0.876* (0.497)
factor(ACHVIN)2	−0.252 (0.260)	−0.276 (0.269)	−0.289 (0.268)
factor(ACHVIN)3	−0.943*** (0.238)	−0.894*** (0.250)	−1.004*** (0.279)
factor(BOURVIN)2	0.364 (0.257)	0.209 (0.267)	0.249 (0.266)
factor(BOURVIN)3	0.675** (0.320)	0.563 (0.357)	0.638* (0.356)
factor(BIOVIN)2	0.006 (0.607)	1.018* (0.546)	0.712 (0.556)
factor(BIOVIN)3	0.415 (0.591)	1.247** (0.539)	1.058* (0.543)
factor(BIOVIN)4	0.325 (0.537)	1.185** (0.512)	0.987** (0.487)
factor(SEXE)2	0.752*** (0.202)	0.584*** (0.214)	0.646*** (0.210)
Constant	2.142** (0.864)	1.531* (0.921)	1.807* (1.010)
Observations	555	555	555
R^2	0.169	0.132	0.132
Adjusted R^2	0.121	0.082	0.082

Note: *p<0.1; **p<0.05; ***p<0.01
Last steps of IRLS to limit the influence of outliers. Standard Errors are clustered by individuals.

Table S3: Pooled Local Organic Premiums with 5 levels of Information
We report the coefficients associated to the secondary control variables of models (4), (5) and (6), reported in the Table 4 of the main paper. **VAGE** counts for the age of the participants, **NBENF** for the number of children, **SOCIO** for the socio-professional category (merchant is the reference category, then manager, intermediate professions, employee, worker, retired and other), **ACHVIN** for the frequency of wine purchasing (weekly is the reference category, 2 for two or three times per month, 3 for one per month, 4 for more rarely, and nobody answers never), **BOURVIN** for the frequency of local wine purchasing (exclusively is the reference category, 2 for regularly, 3 for rarely, and nobody answers never), **BIOVIN** for the frequency of organic wine purchasing (with the same coding as the local wine, 4 counts for never), and **SEXE** is the sex of the participant, man is the reference modality, 2 is for woman.

	(4)	(5)	(6)
VAGE	-0.028^{***} (0.009)	-0.026^{***} (0.009)	-0.027^{***} (0.009)
NBENF	-0.266^{**} (0.108)	-0.292^{**} (0.125)	-0.296^{**} (0.117)
SOCIOMANAG	-1.842^{***} (0.553)	-2.026^{***} (0.612)	-2.095^{***} (0.602)
SOCIOINTER	-1.960^{***} (0.512)	-2.304^{***} (0.483)	-2.328^{***} (0.459)
SOCIOEMPLO	-1.818^{***} (0.486)	-2.165^{***} (0.447)	-2.173^{***} (0.428)
SOCIOWORKE	-1.543^{***} (0.520)	-1.786^{***} (0.525)	-1.854^{***} (0.485)
SOCIORETIR	-1.209^{**} (0.496)	-1.572^{***} (0.418)	-1.610^{***} (0.398)
SOCIONONE	-2.642^{***} (0.559)	-2.866^{***} (0.542)	-2.844^{***} (0.519)
factor(ACHVIN)2	-0.127 (0.257)	-0.126 (0.258)	-0.137 (0.261)
factor(ACHVIN)3	-0.640^{**} (0.253)	-0.607^{**} (0.260)	-0.678^{**} (0.295)
factor(BOURVIN)2	-0.449 (0.318)	-0.603^{*} (0.343)	-0.585^{*} (0.326)
factor(BOURVIN)3	0.123 (0.364)	0.057 (0.398)	0.088 (0.381)
factor(BIOVIN)2	0.106 (0.609)	1.177^{**} (0.577)	1.005^{*} (0.579)
factor(BIOVIN)3	0.624 (0.555)	1.628^{***} (0.546)	1.510^{***} (0.537)
factor(BIOVIN)4	0.428 (0.513)	1.424^{***} (0.535)	1.304^{**} (0.515)
factor(SEXE)2	0.515^{**} (0.210)	0.524^{**} (0.206)	0.557^{***} (0.203)
Constant	5.652^{***} (0.823)	4.322^{***} (0.968)	4.505^{***} (1.032)
Observations	555	555	555
R^2	0.192	0.169	0.169
Adjusted R^2	0.146	0.121	0.121

Note: *p<0.1; **p<0.05; ***p<0.01
Last steps of IRLS to limit the influence of outliers. Standard Errors are clustered by individuals.

Table S4: Results from regressions about organic premiums with control variables
The table presents the regressions for both local and global premiums, with interactions between distances and information levels. These results have to be interpreted with care: the effect of information should be read for a given distance from vineyard. The coefficients in rows 4 to 7 are the value of information for someone at null distance from a vineyard; the effect is greater than shown in the main text.

Endogenous variables:	Global Organic Premiums			Local Organic Premiums		
	(1)	(2)	(3)	(4)	(5)	(6)
Perceived Distance	−0.126**			−0.155**		
	(0.052)			(0.063)		
Computed Distance 1		−0.068			−0.039	
		(0.070)			(0.084)	
Computed Distance 2			−0.095			−0.021
			(0.078)			(0.093)
INFO2: General	0.199	0.702**	0.705**	0.058	0.308	0.616**
	(0.194)	(0.345)	(0.336)	(0.244)	(0.403)	(0.304)
INFO3: Greenhouse	0.818***	1.443***	1.233***	0.783**	1.190**	1.032***
	(0.242)	(0.424)	(0.400)	(0.341)	(0.488)	(0.390)
INFO4: Health	1.699***	1.704***	1.999***	1.590***	1.559***	2.179***
	(0.361)	(0.508)	(0.491)	(0.428)	(0.517)	(0.592)
INFO5: Water Bill	1.504***	1.665***	1.581***	1.572***	1.479***	1.864***
	(0.340)	(0.528)	(0.516)	(0.448)	(0.550)	(0.614)
lDDC:INFO2: General	0.006			0.028		
	(0.025)			(0.031)		
lDDC:INFO3: Greenhouse	−0.039			−0.035		
	(0.032)			(0.043)		
lDDC:INFO4: Health	−0.130***			−0.112**		
	(0.045)			(0.054)		
lDDC:INFO5: Water Bill	−0.097**			−0.099*		
	(0.044)			(0.057)		
lVDC:INFO2: General		−0.062			−0.006	
		(0.044)			(0.051)	
lVDC:INFO3: Greenhouse		−0.122**			−0.088	
		(0.055)			(0.062)	
lVDC:INFO4: Health		−0.128*			−0.106	
		(0.066)			(0.067)	
lVDC:INFO5: Water Bill		−0.116*			−0.084	
		(0.070)			(0.072)	
lVDM:INFO2: General			−0.059			−0.046
			(0.041)			(0.038)
lVDM:INFO3: Greenhouse			−0.090*			−0.065
			(0.050)			(0.048)
lVDM:INFO4: Health			−0.159***			−0.180**
			(0.061)			(0.074)
lVDM:INFO5: Water Bill			−0.100			−0.129*
			(0.065)			(0.077)
Constant	1.771**	0.926	1.304	5.277***	3.901***	3.847***
	(0.839)	(0.948)	(1.034)	(0.877)	(1.050)	(1.145)
Observations	555	555	555	555	555	555
R^2	0.172	0.157	0.159	0.195	0.170	0.171
Adjusted R^2	0.118	0.102	0.104	0.142	0.115	0.117

Notes: *p<0.1; **p<0.05; ***p<0.01
Weights are computed from the last step of IRLS M-regression. Standard Errors clustered by individuals.

2 Mathematical details for policy simulations

2.1 Configuration # A: Per-Unit Tax on Non-Organic Wines

To simulate the tax scenario, we consider a situation where consumers are aware of logos without additional information. Beyond what is coveyed by the logo, consumers have no additional precise knowledge about the process of production, which corresponds to information # 1. Public intervention here consists of imposition of a per-unit tax on the regular products. Hence $WTP_{i1}(k)$, $k \in \mathbb{K}$, are considered by the regulator to determine the welfare impact of the tax τ. We also tested the combination of a per-unit tax on the regular wine product and a subsidy on the organic wine. However, this scenario does not improve welfare because the subsidy is relatively costly and does not lead to many changes by participants. As before, consumer i can choose between five purchasing outcomes: the non-local non-organic wine at price $P(\text{NL-NO}) + \tau$, the local non-organic wine at price $P(\text{L-NO}) + \tau$, the non-local organic wine at price $P(\text{NL-O})$, the local organic wine at price $P(\text{O-L})$ or none of those. The consumer's purchasing decision is still made based on her surplus maximization, which leads to:

$$\mathbf{CS}_i^\tau = \max\{0, \text{WTP}_{i1}(k) - P^\tau(k); k \in \mathbb{K}\} \tag{7}$$

where $P^\tau \equiv P$ for organic wines and $P^\tau \equiv P + \tau$ for non-organic ones. Equation 7 differs from following Equation 12 because of the tax τ and because of different WTP linked to different contexts of information as elicited in rounds # 1 and # 5.

The absence of complete information about the pesticide problems related to wine leads to a non-internalized damage. This non-internalized damage is slightly different from the cost of ignorance suggested by Foster and Just (1989). In their framework, consumers incur a cost of ignorance from consuming a contaminated product that could cause detrimental health effects without knowledge of the adverse information. This biases the purchasing decision in round # 1. In the situation of complete information (round # 5), some consumers stop buying the product they previously bought. The non-internalized damage or benefit linked to the production of the wine $k \in \mathbb{K}$ is $\mathbb{1}[k,i] \times \left(\text{WTP}_{i5}(k) - \text{WTP}_{i1}(k)\right)$, where $\mathbb{1}[k,i]$ is an indicator variable that takes the value 1 if the wine k is purchased by the consumer i, namely if $\text{WTP}_{i1}(k) - P^\tau(k) > \max\{0, \text{WTP}_{i1}(k') - P^\tau(k'); k' \neq k\}$. If the product is not purchased, $\mathbb{1}[k,i] = 0$.

By using (7), the complete surplus integrating the non-internalized damage and benefit is defined by:

$$\mathbf{C}_i(\tau) = \mathbf{CS}_i^\tau + \sum_{k \in \mathbb{K}} \mathbb{1}[k,i] \times \left(\text{WTP}_{i5}(k) - \text{WTP}_{i1}(k)\right) \tag{8}$$

This complete surplus integrates the non-internalized damage or benefit represented by WTP differences following the revealed information. With this complete surplus, the regulator also considers the possible tax income coming from each participant. The tax is paid only by consumers purchasing the non-organic wines with $\mathbb{1}[\text{NL-NO}, i] = 1$ or $\mathbb{1}[\text{L-NO}, i] = 1$ leading to a possible income $\tau \times \mathbb{1}[\text{NL-NO}, i]$ or $\tau \times \mathbb{1}[\text{L-NO}, i]$ received by the regulator. By taking into account the complete surplus integrating the non-internalized damage and the estimated tax income, the per-unit welfare related to a participant i is as follows:

$$\begin{aligned}\mathbf{W}_i(\tau) &= \max\{0, WTP_{i1}(k) - P^{\tau}(k); \forall k \in \mathbb{K}\} \\ &+ \sum_{k\in\mathbb{K}} \mathbb{1}[k,i] \times \big(\mathrm{WTP}_{i5}(k) - \mathrm{WTP}_{i1}(k)\big) + \tau(\mathbb{1}[\text{NL-NO}, i] + \mathbb{1}[\text{L-NO}, i]).\end{aligned} \tag{9}$$

The optimal tax τ^* is given by *tatônnement*, maximizing the sum of welfare $\sum_i^N \mathbf{W}_i(\tau^*)$ over the $N = 111$ participants.

2.2 Configuration # B: Standard Imposing Organic Practices

Public intervention here consists of banning the non-organic producing process. There is an improvement regarding the production process for all wines, but there is a reduction in the diversity of products. Producers with non-organic products will turn to the organic process and we assume that consumers will have the same WTP for these "new" products becoming organic as the corresponding WTP for the organic products elicited in the lab. The markets will have two *Vacqueyras* organic wines and two *Marsannay* organic wines. Because of a Bertrand competition, the price will be the same for each wine inside each GI. Consumer i can choose between three purchasing outcomes: the two organic bottles of non-local wines at price $P(\text{NL-O})$, the two organic bottles of local wines at price $P(\text{L-O})$ or neither of those. The consumer's purchasing decision is based on her surplus maximization, which is equal to:

$$\mathbf{CS}_i^S = \max\{0, \mathrm{WTP}_{i1}(\text{NL-O}) - P(\text{NL-O}), \mathrm{WTP}_{i1}(\text{L-O}) - P(\text{L-O})\} \tag{10}$$

The non-internalized benefit linked to the organic product for $k' \in \mathbb{K}' \equiv \{\text{NL-O}, \text{L-O}\}$ is $\mathbb{1}[k', i] \times (\mathrm{WTP}_{i5}(k') - WTP_{i1}(k'))$, where $\mathbb{1}[k', i]$ is an indicator variable taking the value 1 if the organic wine k' is purchased by the consumer i. By using (10), the complete surplus integrating the non-internalized damage or benefit is defined by:

$$\mathbf{C}_i^S = \mathbf{CS}_i^S + \sum_{k'\in\mathbb{K}'} \mathbb{1}[k', i] \times \big(\mathrm{WTP}_{i5}(k') - \mathrm{WTP}_{i1}(k')\big) \tag{11}$$

This complete surplus integrates the non-internalized benefits represented by WTP differences following the revealed messages.

2.3 Hypothetical Configuration: Complete Information Campaign

This configuration consists of an information campaign perfectly understood by consumers and revealing complete information about both non organic and organic wines, which corresponds to the situation in round # 5. Similar to round # 5, the campaign reveals all the information of interest on all products. Application of an additional regulatory instrument (e.g. a Pigouvian tax) is useless. Consumers directly internalize all information provided by the campaign.

We assume that a consumer purchases a bottle of wine if her WTP is higher than the price observed for that bottle in the supermarket. She chooses the option generating the highest utility with a utility of non-purchase normalized to zero. Because complete information is perfectly internalized by consumers, no other tool can improve the welfare. The per-unit surplus and welfare for participant i is as follows:

$$\mathbf{W}_i^L = \max\{0, \text{WTP}_{i5}(k) - P(k); k \in \mathbb{K}\} \tag{12}$$

with $\mathbb{K} = \{\text{NL-NO}, \text{L-NO}, \text{NL-O}, \text{O-L}\}$. In many real life situations however, consumers' information is very limited, which differs significantly from the situation presented in this configuration.

2.4 Policy simulations leading to Table 6

Policy simulations compare the welfare effects of two regulatory instruments aimed at internalizing attributes valued by consumers after revelation of full information. For each configuration with a number $N = 111$ we detail the sum of welfare variations linked to one purchased bottle and defined by $\Delta W_N^{\tau} = \sum_i^N [W_i^{\tau^*} - W_i^0]$ for the tax τ^* (in column 2 of Table 6 of the main paper), $\Delta W_K^S = \sum_i^N [C_{S,i} - W_i^0]$ for the mandatory standard (in column 3 of Table 6) and $\Delta W_N^L = \sum_i^N [W_i^L - W_i^0]$ for the full information campaign (in column 4 of Table 6).

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Figure S8: Demand functions for the level 5 of information

The results for the information 1 are presented in the main text, see Figure 8