The informational content of geographical indications

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Working Paper Version 0.1 : April 13, 2019

Abstract

Geographical indications (GIs) convey information about the place of production as a proxy for the quality of agricultural products. The quality of the GI proxy depends on its underlying sources of variations, among tangible (topography, geology of land plots), intangible (reputation, influence of landowners) and idiosyncratic (random) determinants. We propose to disentangle this informational content for wine-related GIs of the *Côte d'Or* region (Burgundy, France). Thanks to their hierarchical and nested structure, GIs are shown to have a high informational content (a signal to noise ratio of about 4) which could explain their support by the wine market. We apply an original signal decomposition to actual and alternative wine classifications of the region (from history and from counterfactual simulations) to show significant improvements of GIs in the last century and potential guidelines for better designed GIs in the future.

Keywords: Certification, wine production, strategic quality disclosure, variance decomposition, ordered models.

J.E.L. Codes: C24, L15, Q13.

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1 Introduction

Using the place of production to signal the quality of agricultural products is not consensual in trade relations (Josling, 2006; USTR, 2017). It is nevertheless well recognized that distinguishing products of good quality from bad is fundamental for consumers and producers when the quality cannot be assessed before buying and selling choices are made (Akerlof, 1970; Nelson, 1970). Thus, one stumble point in the debate is the extend to which geographical indications (GIs) provide information about product quality (Winfree and McCluskey, 2005; Yu et al., 2017). We study this informational content of GIs through the econometric relationship between the natural and human characteristics of vineyards and the wine-related GIs of the *Côte d'Or* region (Burgundy, France).

Wine is an emblematic agricultural product whose quality strongly depends on the natural conditions prevailing on production sites (Jackson and Lombard, 1993; Bokulich et al., 2014; Knight et al., 2015; van Leeuwen et al., 2018). Wine is also an experience good well-suited to study the transmission of quality information between producers and consumers (Combris et al., 1997; Ali and Nauges, 2007; Ashenfelter, 2008; Storchmann, 2012). In Burgundy, the ranking of vineyards according to their quality potential for wine production has a long history that date back to the middle age, with numerous modifications that have resulted to the actual scheme (Jullien, 1816; Morelot, 1831; Lavalle, 1855; Danguy and Aubertin, 1892; Garcia, 2011; Wolikow and Jacquet, 2018). In short – more details will be given in the next section – the GIs that we study are fully based on the fine-scale location of the vineyard plots, with both a vertical and a horizontal dimension of differentiation. The vertical dimension is a quality ranking with 5 items: *Côteaux Bourguignons* < *Bourgogne Régional* < *Bourgogne Village* < *Premier Cru* < *Grand Cru*. The horizontal dimension is the name of one among the 31 *communes* (i.e., administrative municipalities) without an explicit hierarchy between them : *Beaune*, *Gevrey-Chambertin*, *Pommard*, *Fixin* for example. Such a hierarchical and nested structure is now quite usual for wine-related GIs in France (Bordeaux, Rhône Valley, see Gergaud et al., 2017) and other wine-producing countries (Germany, United States and Italy, see Storchmann, 2005; Costanigro et al., 2010, 2019).

Our main contribution is to identify the informational content of actual, past and counterfactual GI designation schemes for about 60 000 vineyard plots. The informational content of GIs is defined as their ability to describe natural characteristics of production sites, according to the property that more informative signals lead to greater variability of conditional expectations (Ganuza and Penalva, 2010). We propose to distinguish tangible, intangible and random information about production sites by decomposing the sources of variation of GIs (Bowsher and Swain, 2012). The first set of tangible information relates to the natural attributes of vineyard plots that are known to impact wine quality: topography (elevation, slope, aspect), geology (subsoil material, soil depth, soil humidity) and climate (solar radiation, longitude, latitude). The quality of vineyard plots is revealed from the vertical differentiation of GIs by an econometric model that account for this ordered structure. The second set of information relates to the human characteristics that have historically impacted the GI designation process. Through the reputation of landowners, their influence with the decision makers or their collective actions, some administrative units have had a differential treatment that could bias the quality signal conveyed by the horizontal dimension of GIs. Knowing the geographical co-variations between tangible and intangible variables and the difficulty to control for all tangible variables that impact vineyard quality (i.e., *terroir* variables), the major empirical challenge is to disentangle these two sources of variations. We propose a semiparametric approach that exploits the precise location of vineyard plots to control for the unobserved spatial heterogeneity from *terroir* through smooth functions of geographical coordinates (Wood et al., 2016). The empirical strategy is based on the structural difference between the spatial continuity of *terroir* and the discontinuity of administrative borders according to the axiom that nature makes no jumps.

Our approach is related to the literature about reputation, quality disclosure and strategic certification that provides some guidance for the question at hand (see Bagwell, 2001; Dranove and Jin, 2010 for reviews). The vineyard quality gradient that we study is based on characteristics given by the nature, contrary to models where quality is strategically chosen by producers (Shapiro, 1982; Besanko et al., 1987; Albano and Lizzeri, 2001; Jin and Leslie, 2003; Desquilbet and Monier-Dilhan, 2014). The resulting exogeneity of these variables allows the empirical identification to be more transparent and to focus our analysis on the historical process that lead to the actual GI information put on wine bottles. We argue that the long history of GIs designations allows to neglect the role of actual wine producers and their undoubtedly impact on wine quality. In effect, as generations of producers succeed each other with numerous vineyards bought and sold, the informational content of GIs is a collective reputation issued from history dependence (Tirole, 1996) and reasonably independent to actual individual reputations of producers. This long run vineyard quality relies exclusively on the unchangeable location of productions sites, which precludes spurious correlation from the assortative matching between qualities and names as in Tadelis (1999) (i.e., a GI name can not be sold without its associated vineyard natural quality).

A large body of literature about wine quality disclosure is concerned with expert reviews and the use of this information by consumers. Such ratings are shown to have mainly short run effects, both on the demand (Friberg and Grönqvist, 2012) and the price of wines (Ali et al., 2008; Dubois and Nauges, 2010). The major problems about the aggregation (Ashenfelter and Quandt, 1999) and the relevance (Cao and Stokes, 2010; Bodington, 2017) of these signals put some doubts about their own interest for consumers (Ashenfelter and Jones, 2013). Ratings by experts, judges or websites are also shown to be significantly divergent from historical GIs for Bordeaux wines (Thompson and Mutkoski, 2011) probably because of their fundamental differences. Ratings are exogenous paying year-to-year sources of information, while GIs are long run public certifications voluntarily put on bottle labels by producers. This remark adds the tedious question of the endogenous adoption of quality disclosure such as GIs that could produce unintended economic consequences (Hollander et al., 1999; Bederson et al., 2018). For wine-related GIs in Burgundy, their economic (Combris et al., 2000; Carew and Florkowski, 2010; Sáenz-Navajas et al., 2013) and historical (Meloni and Swinnen, 2018) importance is such that, to the best of our knowledge, the entirety of wine producers and sellers in the region puts the GIs as the main information message on bottle labels.

We find a high informational content of actual GIs in terms of the underlying tangible vineyard quality, with a variance of the signal 4 times higher than the variance of the noise (this corresponds to a R^2 of about 80 %). This high informational content gets along with the evidence of some signal bias due to the intangible variations of GI designations. Nevertheless, this bias has decreased since the creation of GIs in 1936 trough continuous evolution that happened. This decreasing bias of GI designation schemes from history could be an illustration of the theory developed by Benabou and Laroque (1992) about strategic information transmission. We show that some administrative units have profited from their private information about vineyard quality to manipulate the GI signal and extract rents through undeserved high rated vineyards. However, the hierarchical GI certification appears increasingly less biased, or more efficient in the sens of De and Nabar (1991): the probability that a vineyard plot gets classified at least in its category becomes higher than the probability of lower quality plots being classified in that category. We also show that a monopolistic certifying party discloses useful information in the form of rank orderings as predicted by the theory of Guerra (2001). This contrasts with models that found weak (if any) welfare gains associated to the information conveyed by a monopolistic certifying party (Shapiro, 1986; Lizzeri, 1999). These two results suggest that the high informational content of GIs and their actual economic importance in Burgundy comes from their long history and their independent management.

The following Section 2 presents in greater details the historical and regional contexts, jointly with the data used. Section 3 presents the data generating process under consideration (also called the population structural model), the signal decomposition framework and the econometric strategy. Section 4 presents the results and Section 5 concludes.

2 Data

2.1 The *Côte d'Or* region

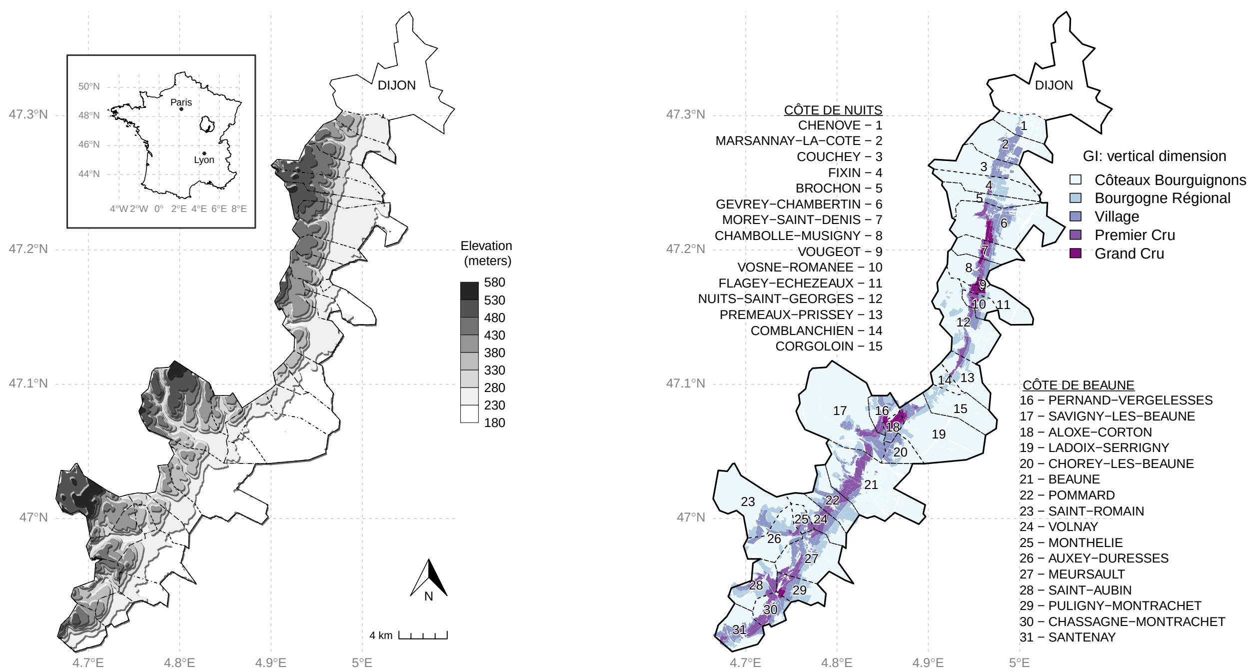
The *Côte d'Or* (literally, slope of gold) is a northeastern French administrative unit (*département*) included in the larger wine-producing region of Burgundy (Figure 1). We study a subset of the most famous vineyards of this region that was granted World Heritage Status by UNESCO in 2015 (https://whc.unesco.org/fr/list/1425). The area under consideration is a strip of about 65 km on the north-south gradient of at most 5 km from east to west, located between latitudes 46.9 and 47.3 and longitudes 4.7 and 5 (World Geodetic System 1984). The main natural attributes of vineyards in the area are illustrated by the distribution of elevation in the left panel of Figure 1. The presence of *combes* (dry valley) produces some rounded patterns with fine-scale variations of the typical topographical variables (elevation, slope and exposition) that are known to have some direct and indirect impacts on vineyard and wine quality. Firstly, elevation is expected to determine wine quality principally through its indirect correlation with temperatures and atmospheric outcomes. Temperatures during the growing season and the harvest are determinant for the grape maturity cycle, sugar content and structure of aromas. The latitude position of vineyards also contents some information about temperature variations along the north-south gradient. Secondly, slope is expected to have both a direct effect through the drainage capacity of vineyard plots and an indirect effect through the correlated soil characteristics (steeper soils are in general thinner). The longitude variable is indirectly related to precipitations, as the hill at the west provides a protective barrier that limits rains and, consequently, soil moisture. Thirdly, the exposition is expected to have a direct effect through sunshine cycles and indirect effect through its correlation with the wind, which is known to have a strong importance to dry grapes and to concentrate aromas.

2.2 Historical context

Some archaeological evidences locate the first vineyards in this region in the antiquity (Garcia, 2014). The first written evidences date from the 7th century, with abbeys archives that describe the donation of vineyards between groups of Benedictines monks whose names are still used in actual GI classifications (*Abbayes de Bèze*, *de Saint-Vivant* for instance). The origin of Burgundy's vineyard classification can be found in the work of the Cistercians monks who delineate plots of land that produced wine of distinct character (12th century, Lavalle, 1855). However, the first exhaustive spatial delineation of the region is the administrative separation of *communes* following the decree of 1789 after the french revolution. What we consider as the horizontal dimension happened before

Figure 1: **Vineyards of the *Côte d'Or*, topography (left) and geographical indications (right)**

Notes: Elevation on the left side map is decretized in 8 classes of 50 m intervals. From the east to the west, the elevation is first convex then concave, which means that highest slopes are for average elevations. GIs on the right side map are located on these highest slopes. The spatial precision of the vertical dimension of GIs is such that, best vineyards classified as *Grands Crus* are not visually well separated from just below *Premiers Crus*. The right panel also reports the names of the 31 *communes* of the area, the horinzontal dimension of GIs.



the vertical dimension of actual GIs (Garcia, 2011, p.40). The delineation of *communes* was based on the spatial distribution of churches (usually built in the 9th-12th centuries) without the goal of signaling wine or vineyard quality. The first exhaustive classification scheme about the quality of vineyards is due to Lavalle (1855), a Professor of natural and medical history from Dijon university inspired from previous writings of other scientists Jullien (1816) and Morelot (1831). He provides a ranking of vineyards in 4 levels, from the best *Tête de Cuvée* to *Première*, *Deuxième* and *Troisième Cuvées*. The interaction between the horizontal and vertical dimension is of particular matter in his work, as he write (p.162, translation from the author) "I have studied the wines of each of the *communes* of the *Côte* as if the other *communes* had not existed and the classification that I give is true only for each *commune* taken in isolation."

These two spatial delineations were merged in a map of the region in 1860 by the *Comité d'Agriculture et de Viticulture de l'Arrondissement de Beaune*, the local organization of wine producers of the time. This map contains small modifications from the initial 1789 and 1855 classifications (Wolikow and Jacquet, 2018) and was extensively used afterward as a legal basis to regulate wine trade in the region. It opens an avenue for court trials, collective actions and lobbying about the right to use the names of both dimensions that are not yet called GIs to label the wines. As it is well documented by Jacquet (2009), the capacity of producers and owners to negotiate or influence the judgments and the delineations was determinate by the *commune* to which they belong, in particular regarding their reputation. The author shows that there was an unequal treatment between *communes* in terms of the vertical differentiation of vineyards, whereas the separation between advantaged and disadvantaged *communes* is not well established as "the reputation of the wine-growing *communes* of Burgundy is not an objectively measurable phenomenon" (p.189 of Jacquet, 2009, translation from the author). In 1936, a French national institute was created (INAO) to legally manage what become the GIs of all wine regions of the country on a harmonized basis. In Burgundy, the first official GIs are principally based on the map of 1860, jointly with the jurisprudence which has taken place since then. Some important modifications are implemented during the 20th century with the creation of *Premiers Crus* in 1943 and the fine-scale digitalization of plot-level delineation in a Geographical Information System after 2000. The GIs are called *Appellation d'Origine Contrôlée* in France since this period and corresponds to Protected Designation of Origin for the European Union (https://ec.europa.eu/agriculture/quality/schemes_en).

2.3 Actual GI classifications

Actual GIs are a nest between a vertical quality ranking in 5 items and a horizontal differentiation scheme through the name of one among the 31 administrative municipalities (*communes*) that are shown in the right panel of Figure 1. The highest-quality vineyards are labeled *Grands Crus*, each of which has its own independent appellation title (ex: "*Clos de la Roche*" or "*Chevalier-Montrachet*"). There are 32 *Grands Crus* on the area, XX in the *Côte de Beaune* (southern part) and XX in the *Côte de Nuits* (northern part) for a total area of XX ha (XX %). It follows in the hierarchy 532 *Premiers*

Crus which have to be associated with their *commune* names on bottle labels (ex: "*Les Chaumes*" from *Vosne-Romanée* or "*La Chapelle*" from *Auxey-Duresse*). There are XX ha of *Premiers Crus* in the *Côte de Beaune* (XX %) and XX ha in the *Côte de Nuits* (XX %). The third vertical level corresponds to *Bourgogne Village* with or without the name of the administrative *commune* (ex: *Pommard Village* or *Côte de Nuits Village*). The vertical differentiation of GIs ends with *Bourgogne Régional* (XX ha, 25.9 %) and *Coteaux Bourguignons* (Xx ha, 16.3 %) that are sometimes grouped in a same *régional* level. Putting the name of the *commune* where the vineyard is located is forbidden for these GIs. The difference between these 2 lasts GIs was initially justified in terms of grape varieties (*Pinot noir* or *Chardonnay* for *Bourgogne Régional* and *Gamay noir* or *Aligoté* for *Côteaux Bourguignons*) but this distinction is less and less relevant as *Pinot noir* becomes the main variety in the region.

The picture of actual GIs is not complete without the mention of the complexities that exists between the vertical and the horizontal dimensions, which lead to strong difficulties for actual consumers to distinguish their respective information signal. It is important to note that the terms *commune* and *village* are often used as synonymous for rural areas of France, whereas the first is related to the horizontal dimension and the second for the vertical dimension. In addition, some vertical items from *Grands Crus*, *Premiers Crus* or even *Villages* dimensions can be located on two different contiguous *communes*: the *Grand Cru* "*Bonnes Mares*" is shared between the *communes* of *Chambolle-Musigny* and *Morey-Saint-Denis*, the *Fixin Premier Cru* "*Clos de la Perrière*" is shared between the *communes* of *Brochon* and *Fixin*, the *Vosnes-Romanée Village* is shared between the *communes* of *Vosnes-Romanée* and *Flagey-Echézeaux*. Moreover, at the beginning of the 20th century, 10 *communes* have chosen to add the names of their most famous *Grand Cru* to their administrative names, for example *Aloxe-Corton* or *Gevrey-Chambertin*. This complexity reaches its climax in the two administrative *communes* of *Chassagne-Montrachet* and *Puligny-Montrachet* that share the same *Grand Cru* "*Montrachet*" and have chosen to add it to their names. However, the legal obligation to mention in large font the vertical items *Grands Crus*, *Premier Crus*, *Village*, *Régional* on wine bottle labels suggests that this information is clearly identifiable to consumers.

2.4 Summary Statistics

The region under study is quite homogeneous in terms of wine varieties (*Pinot Noir* for red wines and *Chardonnay* for white wines) and in terms of the actual economic structures of wine production, with the co-existence of small producers and wine-trader (*négociants*) located in bigger *communes* of *Beaune* and *Nuits-St-Georges*. As shown by Figure 1, the balanced distribution of topographic variables between and within the *communes* is fundamental for the econometric analysis that follows. It appears from the left panel that each *commune* approximately contains the whole range of elevation, slope and exposition. The right panel shows that administrative delineations of *communes* articulate with each other on the north-south gradient, which ensures sharp climatic differences. The Table 4 of Appendix A presents some descriptive statistics about the exhaustive plot-level data on the 31 *communes* of the area. For about 60 000 vineyard plots of a small average size of 2 000 m^2 (about 0.5 acres), the elevation is distributed between 200 and 500 m with an average of 286 m. Slopes have an average of 5.73 degrees with a high standard deviation (coefficient of variation of about 100 %). The solar radiation is scaled for numerical stability in econometric estimations, it is initially distributed from 0.5 to 1.23 millions Joules with an average of 1 millions J. To add flexibility in the estimations the aspect variable is discretized in 8 dummy variables for different radians ranges, which shows that more the 50 % of vineyard plots have a south-eastern exposition with radians between 90 and 180 degrees. Our data contains both the current GIs both with the vertical dimension (named Current GI in the Table) and the horizontal dimension (not reported). Les villages sont dans les communaux, we also have geological and pedological discrete vraibles not significant for our empirical strategy see RM.

3 Models

We first present the structural model of GI designation that is assumed to be the data generating process. Secondly, we describe the decomposition of the vineyard quality signal from the GI information available to consumers. Thirdly, we discuss the empirical challenge to separate the *terroir* effects from the human influences and the specification procedure that we propose.

3.1 Structure of GIs

The variation in soil and climate (i.e., *terroir*) between vineyard sites is the basis of the GI classification system. Vineyard quality signal in the long run of history is supposed to be an unknown function $q : \mathbb{R}^{K^*} \mapsto \mathbb{R}$ of the K^* natural characteristics X^* of each vineyard plots. From this scalar quality, GIs are designated through a continuous latent variable y^* defined as the difference between the long run quality signal and an idiosyncratic random term ξ that we call the designation noise:

$$y^* = q(X^*) - \xi. \tag{1}$$

This mapping between the tangible *terroir* characteristics X^* and the objective quality represents the accumulate knowledge from informed people that have contributed to the vineyard classification on the long run of history. At this stage, we consider the latent variable as an unbiased (while not perfect) signal of the quality of vineyards with $\mathbb{E}(\xi \mid X^*) = 0$. The designation noise could be attributed to imperfect knowledge or anecdotal facts that cause random deviations around the signal. The presence of designation noise is due to the absence of a deterministic rule between vineyard natural characteristics and the GIs, hence the orthogonality of the designation noise is more a definition than an assumption. The adequacy between this quality signal and consumer preferences for the taste of wines and the related question of the value of the GI information would require economic data about wine prices or declared preferences that we do not use here. Instead, we propose to evaluate the relevance of the GI information according to this long run quality signal which is different than evaluating the relevance of the quality signal itself. The ordered structure of the vertical dimension of GIs explains our reference to vineyard and wine qualities.

The hierarchical structure of GIs is modeled through the multi-valued scalar $y \in \{1, \dots, 5\}$ that represents the vertical differentiation of GIs: *Côteaux Bourguignons* < *Bourgogne Régional*

< *Bourgogne Village* < *Premier Cru* < *Grand Cru*. The GI of a given vineyard plot is a crude measurement of the underlying latent variable through a threshold-crossing relationship:

$$y = j \quad \Leftrightarrow \quad \alpha^c_{j-1} < y^* < \alpha^c_j, \quad \text{for} \quad j = 1, \ldots, 5, \tag{2}$$

with $\alpha^c_0 = -\infty < \alpha^c_1 < \cdots < \alpha^c_5 = +\infty$ for all $c \in \{1, \ldots, 31\}$ by construction. The exponent c on the thresholds marks the *communes* in which the vineyard are located among the 31 *communes* of the area under consideration, i.e., the horizontal dimension of GIs. The variations in the thresholds between *communes* correspond to the differential treatments between administrative units that have been documented by historians and presented above. For instance, a *commune* c_1 has a preferential treatment in terms of *Premier Cru* ($j = 4$) if its corresponding thresholds are smaller than those of another given *commune* c_2: $\alpha^{c_1}_3 < \alpha^{c_2}_3$ and $\alpha^{c_1}_4 < \alpha^{c_2}_4$. This means that the quality requirements for *Premier Cru* of the *commune* c_1 are less stringent and, consequently, the average vineyard quality is smaller: $\mathbb{E}(y^* \mid y = 4, c = c_1) < \mathbb{E}(y^* \mid y = 4, c = c_2)$.[1]

Within a given *commune*, the ordered structure of GIs provides an efficient certification process according to the definition of De and Nabar (1991): the probability with which a vineyard get classified into at least its own quality category is higher than the probability with which another vineyard with lower quality levels will get classified into at least that category. For two vineyard plots 1 and 2 with differentiated natural characteristics such that $q(X^*_1) > q(X^*_2)$ and located within the same *commune* c_0, one can show that $\text{Prob}(y_1 \geqslant j) > \text{Prob}(y_2 \geqslant j)$ for all j because:

$$\text{Prob}(y_i \geqslant j) = F\left[q(X^*_i) - \alpha^{c_0}_{j-1}\right], \quad \text{for} \quad i = 1, 2. \tag{3}$$

where F is the strictly increasing cumulative distribution function of the designation noise ξ. The efficiency of the GI designation scheme is also verified in the absence of threshold variations

[1]The link with average quality from this last inequality requires the addtional assumption that $\mathbb{E}(\xi \mid X^*, c) = 0$, i.e., that the random part of the latent variable is unrelated between *communes*. We make this assumption in the rest of the paper, which has the same rationale than the orthogonality of designation noise in regard to *terroir* variables presented above and implies it by the law of iterated expectations: $\mathbb{E}(\xi \mid X^*) = \mathbb{E}[\mathbb{E}(\xi \mid X^*, c) \mid X^*] = 0$.

between *communes* (α_j^c constant among c for each j) which is equivalent to GI signal unbiasedness.

The efficiency property and the absence of bias are no longer true for vineyard plots located in different *communes*, say c_1 and c_2 to continue with the same example. The vineyard plot 2 of lesser quality has a higher probability of being classified into at least j_1 (the GI quality category of 1) if $\alpha_{j_1}^{c_2} - \alpha_{j_1}^{c_1} > q(X_1^*) - q(X_2^*)$. In this case, the preferential treatment accorded to the *commune* c_2 is a source of bias in the GI classification that contradicts the efficiency of the vertical GI differentiation.[2] In particular, the probability that another given plot 3 of the same quality that plot 1 while from another *commune* c_3 is higher in the GI classification scheme corresponds to the ordinal superiority measure defined by Agresti and Kateri (2017):

$$\gamma_{3|1}^{j_1} \equiv \text{Prob}(y_3 > y_1 \mid X_1^*) = F\left(\frac{\alpha_{j_1}^{c_3} - \alpha_{j_1}^{c_1}}{\sqrt{2}}\right). \tag{4}$$

We use the approximation that the cdf of the normalized difference between designation noises is equal to the marginal cdf (this approximation is exact in the case of a Gaussian distribution). An appealing property of this measure of ordinal superiority is that it does not depend on the conditioning tangible characteristics X_1^* of vineyard plots. This allows a direct comparison between the horizontal dimension of GIs (the *communes* c) for each vertical level j. For a given *commune* of reference (as c_1 in Equation 4), this implies $30 \times 5 = 150$ measures of ordinal superiority. Hence, we assume an additive separability between the horizontal and vertical intercepts to simplify a bit more: $\alpha_j^c = \alpha_j - \mu_c$. The ordinal superiority measure between 2 given *communes* A and B becomes $\gamma_{A|B} = F\left[(\mu_{c_B} - \mu_{c_A})/\sqrt{2}\right]$ regardless of j, which allows to divide by 5 the number of ordinal superiority statistics. These 30 statistics provide some objective measures of the differential treatments that have been applied between *communes* according to the GI vertical classification of their vineyards.

[2] $\alpha_{j_1}^{c_2} > \alpha_{j_1}^{c_1}$ is a necessary condition to have a higher probability for the vineyard plot 2.

3.2 Informational content

Our formal analysis about the informational content of GIs is based on the framework of Ganuza and Penalva (2010) about information signal ordering, in addition to the variance decomposition formulas provided by Bowsher and Swain (2012). According to the former paper, we consider GIs as an information structure, i.e., a joint distribution between the states of the world (unobserved long run vineyard qualities) and the GIs (respectively noted y and c for their vertical and horizontal dimensions). We propose to evaluate to what extend the observation of y and c from the labels of bottle allows the consumers to recover vineyard quality, with the precision criteria that a more informative signal leads to a more disperse distribution of expectations of the state of the world conditionally to the signal. Contrary to Ganuza and Penalva (2010), we measure the dispersion through conditional variance of the signals as it is allowed by the work of Bowsher and Swain (2012). This leads to 4 nested variance decomposition:

$$\textit{Total decomposition :}\ \mathbb{V}(y^*) = \mathbb{V}[q(X^*)] + \mathbb{V}[\xi] \tag{5}$$

$$\textit{Joint decomposition :}\ \mathbb{V}[q(X^*)] = \mathbb{V}\{\,\mathbb{E}[q(X^*) \mid y, c]\,\} + \mathbb{E}\{\,\mathbb{V}[q(X^*) \mid y, c]\,\} \tag{6}$$

$$\textit{Vertical decomposition :}\ \mathbb{V}\{\,\mathbb{E}[q(X^*) \mid y, c]\,\} = \mathbb{V}\{\,\mathbb{E}[q(X^*) \mid y]\,\} + \mathbb{E}\{\,\mathbb{V}[\mathbb{E}(q(X^*) \mid y, c) \mid y]\,\} \tag{7}$$

$$\textit{Horizontal decomposition :}\ \mathbb{V}\{\,\mathbb{E}[q(X^*) \mid y, c]\,\} = \mathbb{V}\{\,\mathbb{E}[q(X^*) \mid c]\,\} + \mathbb{E}\{\,\mathbb{V}[\mathbb{E}(q(X^*) \mid y, c) \mid c]\,\} \tag{8}$$

The *total decomposition* of Equation 5 comes from the law of total variance, the law of iterated expectations and the definition of designation errors by $\mathbb{E}(\xi \mid X^*) = 0$. It describes the variance of the latent GI variable as the sum of a *signal variance* and a *noise variance* defined from the data generating process. The signal to noise ratio $\mathbb{V}[q(X^*)]/\mathbb{V}[\xi]$ gives the proportion of relevant information conveyed by the continuous quality grade $q(X^*)$ in terms of the irrelevant information from the noise ξ. This decomposition represents the maximum informational content that GIs can reach for the data generating process under consideration, which corresponds to the case where the continuous quality grade (or all tangible variables X^*) are conveyed to consumers through the label of bottle.

The *joint decomposition* of Equation 6 comes from the law of total variance applied to the continuous quality grade (Bowsher and Swain, 2012). It separates the part of the signal that is conveyed jointly by the vertical and the horizontal dimensions of GIs (the *joint signal*, which is the variance of the expectation) and the part that is lost due to this simplification of the continuous quality information (the *joint noise*, which is the expectation of the variance). If the continuous quality grade $q(X^*)$ would be observable, the share of the *joint signal* in terms of the *total signal* defined previously would be the R^2 of the regression of $q(X^*)$ on the full set of dummy variables from y and c. According to the nested structure of the *total* and *joint* decomposition, we define the *joint informational content* of horizontal and vertical dimensions of GIs as $\mathbb{V}\{\,\mathbb{E}[q(X^*) \mid y, c]\,\}/(\mathbb{E}\{\,\mathbb{V}[q(X^*) \mid y, c]\,\} + \mathbb{V}[\xi])$. This statistic measures the share of the vineyard quality information that is conveyed to consumers through both y and c dimensions of GIs.

The *vertical decomposition* of Equation 7 separates the *joint signal* between the part that is conveyed through the vertical dimension of GIs (the *vertical signal*, the variance of the expectation) and the residual part that remains to the horizontal dimension (the *vertical residual*). The first term represents the variance of the quality information that can be assessed by consumers only through the vertical dimension y of GIs. Consumers may choose to favor this dimension by choice based on their experience or they can have a bounded rationality due to limited cognitive ability to understand the full structure of GIs. An important point is that in the absence of preferential treatment between *communes* in the GI designation scheme, the residual part of this decomposition (the *vertical residual*) would tend to zero. In such a case, the vertical dimension is unbiased and provide all the relevant information about vineyard quality available to consumers. The only loss in information is due to the discretization of the continuous quality grade and the *joint signal* is equal to the *vertical signal*. We also propose to define a *vertical noise* as the sum of the *vertical residual* and the *joint noise*. This corresponds to the information loss of using only the vertical dimension:

$$\textit{Vertical noise :}\ \mathbb{E}\{\,\mathbb{V}[q(X^*) \mid y]\,\} = \mathbb{E}\{\,\mathbb{V}[q(X^*) \mid y, c]\,\} + \mathbb{E}\{\,\mathbb{V}[\mathbb{E}(q(X^*) \mid y, c) \mid y] \qquad (9)$$

The last *horizontal decomposition* of Equation 8 is the symmetric of the previous one as it defines a *horizontal signal* and a *horizontal residual*. This means that the decomposition of the *joint signal* between a *vertical* and a *horizontal* part is non-unique, depending on the GI dimension that is privileged. The first *horizontal signal* measures the dispersion of the expectation of vineyard quality conditionally on the *commune* of the vineyards. This informational content is due both to the incidental spatial correlation between vineyard quality and *commune* delineations, and to the historical factors that have made GI thresholds to depend on the *communes*. In the absence of preferential treatment of certain *communes*, this signal is reliable as it indicates that some *communes* have better tangible conditions to make wines of better quality. As before, the residual part of the decomposition is the marginal gain of using the vertical dimension of GIs for consumers that rely only on the horizontal dimension. We also define the *horizontal noise* as the sum of the *joint noise* and the *horizontal residual*, it corresponds to the loss in GIs signal of using only the horizontal dimension of GIs:

$$\textit{Horizontal noise}: \mathbb{E}\{\,\mathbb{V}[q(X^*)\mid c]\,\} = \mathbb{E}\{\,\mathbb{V}[\mathbb{E}(q(X^*)\mid y, c)\mid c] + \mathbb{E}\{\,\mathbb{V}[q(X^*)\mid y, c]\,\} \tag{10}$$

3.3 Ordered Generalized Additive Model

The identification of the unknown function $q(\cdot)$ that relates tangible attributes of vineyards to the underlying long run GI quality grade is subject to 2 empirical challenges that we consider jointly: the specification of the functional form for the effect on a given tangible variable x_k and the presence of unobserved *terroir* variables that impact vineyard quality. These unobserved effects from the econometrician point of view are taken into account in GI designations by observations on the field and knowledge of people involved in GI designations. These are serious econometric concerns due to the potential confounding effects that such variables could have through their spurious correlations with *commune* delineations that group together adjacent vineyard plots. Identifying the information conveyed by GIs about tangible variables requires that all these *terroir* variables would be observable, which is unfortunately not the case and probably never will be. We propose instead to estimate an Ordered Generalized Additive Model (OGAM, Wood et al., 2016; Wood, 2017 with Kammann and Wand, 2003; Lausted Veie and Panduro, 2015 for applications) that allows to specify semiparametrically the effect of each observed tangible variables and to control for omitted *terroir* variables through a bivariate smoothing of geographical coordinates. This identification strategy is based on our definition of *terroir* as the full set of natural variables that impact long run vineyard quality. As coming from natural processes, we consider them as spatially continuous according to the axiom that nature makes no jumps, in contrast to the discontinuities introduced by *commune* administrative delineations related to intangible human determinants of GIs.

Consider that we only observe the realizations of a subset $X_i \subset X_i^*$ of the whole *terroir* variables that are taken into account in the GI designation for a given vineyard plot $i = 1, \ldots, N$. These observed tangible variables are elevation, slope, exposition solar radiation and geographical coordinates that are described to have both direct and indirect effects on vineyard quality. By noting C_i the row vector of dimension 31 with c_{ih} equals to 1 if the vineyard i is located in the *commune* h and 0 otherwise, the specification of a logistic distribution for the reduced-form errors leads to a semiparametric ordered logit model that can be estimated by maximum likelihood:

$$\text{Prob}(y_i > j \mid X_i, C_i) = \Lambda[B(X_i)^\top \beta + C_i^\top \mu - \alpha_j] \tag{11}$$

where Λ is the logistic cdf. The intangible determinants that impact GIs through varying designation thresholds – noted μ_c previously – are taken into account by the dummy variables C_i which work as *commune* fixed effects. In the absence of theoretical priors about the effects of all observed tangible variables X_i, we specify them through a series of functional transformations noted $B(\cdot)$ with an associated vector of coefficients β. From an initial set of K observed tangible variables (with $K < K^*$) the series and the vector of coefficients are of dimension $\widetilde{K} = \sum_k L_k$ where L_k is the number of transformations used to specify the effect of each variable x_k. For instance, a second-order polynomial specification for all observed tangible variables is noted $B(X_i) = [x_{1i}\ x_{1i}^2\ x_{2i}\ x_{2i}^2\ \cdots\ x_{Ki}\ x_{Ki}^2]$

with a set of $\widetilde{K} = 2 \times K$ coefficients to estimate.

Polynomial specifications are shown empirically to have a limited performance to account for the complex interactions between natural characteristics of vineyards and the continuous quality grade used in GI designations. Hence, we turn to semiparametric thin plate regression splines that have optimal smooth approximation properties according to Wood (2017). The matrix $B(X)$ is specified through additive low rank isotropic smoothers of the individual tangible variables x_k. The cost of this additional flexibility is the need to estimate jointly a smoothing parameter that controls the penalization of the superfluous wiggliness. Accordingly, the complexity of the spline transformations are determined endogenously for a given maximum basis reduction for each variable through a quadratic penalty. The minimization of the penalized deviance is done by penalized iterated weighted least square and the smoothing parameter is estimated using a separate criterion from restricted maximum likelihood framework. The computational details are given in Wood et al. (2016). The complexity of the effect of a given variable or of the whole model can be assessed through the effective degree of freedom that accounts for the endogenous penalization of any given dimension reduction (Wood, 2017, p.273). The most sensible point is the estimation of the smoothing parameter which is source of additional uncertainty, while Wood et al. (2016) provide some corrections for inference and traditional goodness of fit measures such as Akaike Information Criteria.

Goodness of fit measures provide information about predictive abilities of estimated parameters but give little guidance about the identification of the individual effects of the RHS variables that are impacted by the degree of smoothing of geographical coordinates. To determine the sufficient complexity that allow to control for unobserved spatial heterogeneity correlated with *commune* delineations, we use the surrogate residuals recently defined by Liu and Zhang (2018) in an auxiliary regression that does not take into account *commune* fixed effects. Using residuals for specification purpose has a long history in econometrics, complemented by generalized residuals for non linear outcomes (Pagan and Hall, 1983; Gourieroux et al., 1987; Chesher and Irish, 1987). Define a surrogate variable $S \mid X, y \sim \lambda\left[\, B(X)^{\top}\beta - \alpha_y \mid y \,\right]$ that follows a truncated logistic distribution conditionally on y, the observed distribution of the vertical dimension of GIs. The principle of using the observed values of y to estimate the residuals is shared by generalized residuals, the originality of the surrogate approach is to draw randomly the realizations instead of computing them analytically. This allows to estimate the full distribution of model errors instead of only their first moments and sensibly extend the potential applications in regression diagnostics (Liu and Zhang, 2018). We obtain the residuals from N random draws of the surrogate variable S_i:

$$R_i = S_i - \mathbb{E}(S_i) = S_i + \alpha_{y_i} - B(X_i)^\top \beta \tag{12}$$

and regress them on the *commune* fixed effects. This allows to test the presence of correlated residual patterns after accounting only for tangible variables in auxiliary regressions. By increasing the complexity of $B(X_i)$ through increasing spline bases dimension of the smooth functions of geographical coordinates, the joint significance of *commune* fixed effect decreases as the unobserved spatial patterns are increasingly accounted for. Failing to reject the null hypothesis of a Fisher test of joint significance of *commune* fixed effects is expected to determine that the sufficient complexity is attained by the auxiliary model. Then, we estimate jointly the effect of tangible and intangible GI determinants in a full OGAM for the given degree of spatial smoothing as in any parametric regression framework. Note that the F-tests are bootstrapped to take into account the additional uncertainty attributable to the random draws of surrogate residuals.

4 Results

4.1 Models of GI designation

The model (0) in the second column of Table 5 corresponds to a standard ordered logit model with additive quadratic effects for each topographic variables, third-order polynomials with full interactions for spatial coordinates, *commune* and exposition fixed effects. The χ^2 statistics of joint significance are equivalent to a F-test for non linear models. They indicate that all series of variables are significant at 1 % level, with an overall pseudo-R^2 of 28.8 %. The most significant series of variables is the set of 30 *commune* dummies that corresponds to the intangible determinants of GIs delineations, closely followed by the spatial coordinates. Elevation, solar radiation, exposition and slope variables follow in decreasing order of joint significance, for an overall significance of tangible variables higher than intangible variables. The quadratic effects of tangible variables are reported in Figure 3 of Appendix. Elevation and slope variables have inverted-U effects with the highest vineyard quality at about 250 meters and 15 degrees. The effect of solar radiation is linearly increasing and the southern expositions provides the higher marginal probability of a high GI classification (see the Reproducibility Material, RM, from the link at the title page of the article). Panel A of Figure 4 in Appendix shows the marginal effects of spatial coordinates on the expected vineyard quality. The third-order parametric specification with interactions produces some ellipsoidal smooth patterns with two central kernels that describes a core-periphery structure. The values of *communes* fixed effects are interpreted in the next subsection in terms of ordinal superiority.

Following models (I) to (V) in Table 5 are OGAMs with increasing complexity in the smoothing of spatial coordinates from the left to the right, as it appears from the corresponding row of effective degrees of freedom. The semiparametric structure of these models allows to keep the same degrees of freedom for exposition and *commune* dummies of respectively 7 and 31. Increasing the complexity of the spline series that transform spatial coordinates increases slightly the pseudo-R^2 to 75 % and the percent of good predictions to 90 % in the most complex OGAM (V) of the last column of the Table. Simultaneously, the joint significance of spatial coordinates increases while the significance of other explanatory variables decreases, as the spatial pattern of GIs are increasingly grasped by spatial coordinates to the detriment of other RHS variables. In addition to goodness-of-fit measures, Figure 3 of Appendix shows the interest of OGAMs relatively to the parametric model (0). Panel A shows that the high effect of elevation on the 0-300 meters range are not present in the parametric model. The same is true for high effect of slopes on the 0-5 degrees

Table 1: **Joint variable significance for ordered models of GI designations**

Variable	(0)	(I)	(II)	(III)	(IV)	(V)
Elevation	5 352.6**	5 020.2**	2 385.4**	1 677.7**	1 692.6**	1 766.8**
	[2]	[8.955]	[8.94]	[8.827]	[8.809]	[8.844]
Slope	395.63**	1 281.1**	458.16**	266.06**	225.27**	243.6**
	[2]	[8.477]	[8.485]	[8.546]	[8.389]	[8.374]
Solar Radiation	1 898.1**	2 491.6**	1 196.5**	667.29**	554.73**	557.9**
	[2]	[8.311]	[8.187]	[7.73]	[7.633]	[7.473]
Spatial Coords	13 012**	41 458**	73 705**	94 095**	103 941**	107 523**
	[15]	[98.7]	[295.2]	[483.1]	[666.7]	[844.7]
Exposition	1 221.2**	110.35**	123.16**	222.32**	153.52**	160.81**
	[7]	[7]	[7]	[7]	[7]	[7]
Commune	14 670**	6 793.2**	6 079.7**	4 594.7**	3 555**	2 894.5**
	[31]	[31]	[31]	[31]	[31]	[31]
Nb Observ.	59 901	59 901	59 901	59 901	59 901	59 901
McFadden R^2	28.87	51.05	61.85	67.9	72.1	75.16
Pc good pred.	58.74	73.95	79.94	84.23	86.93	89.15
Akaike IC	119	82.41	64.71	54.94	48.29	43.54
Surrogate F	279.44	18.93	6.77	4.12	2.49	2.17

Notes: ** accounts for joint significance at 1% from the reported Chi-square statistics, effective degrees of freedom are inside brackets. Column (0) corresponds to an ordered logit model with quadratic effects for elevation, slope and solar radiation (edf= 2) with a full interaction between 3-orders polynomials for longitude and latitude (edf= $3 + 3 + 3 \times 3 = 15$) and with respectively 7 and 31 dummy variables for exposition and *communes* fixed effects. Models (I) to (V) are OGAMs with elevation, slope and solar radiation additively specified with a maximum of 9 edf, shrinked endogenously by a quadratic penalization. Spatial coordinates are specified in an increasing order of complexity with the maximum edf of 100, 300, 500, 700 and 900. The last row reports the bootstraped Fisher statistics for the joint nullity of *communes* fixed effects on surrogate residuals from auxiliary regressions without *commune* dummies.

range. This results are particularly stringent as these ranges concentrate the majority of vineyards. In terms of spatial smooth effects reported in Figure 4 of Appendix, OGAMs produce more detailed spatial variations that the ellipsoid structure from the parametric model (0). This suggests some fine-scale variations of vineyard qualities according to spatial determinants related to *terroir*. Recall that geological and pedological no significant see RM.

4.2 Ordinal superiority of *communes*

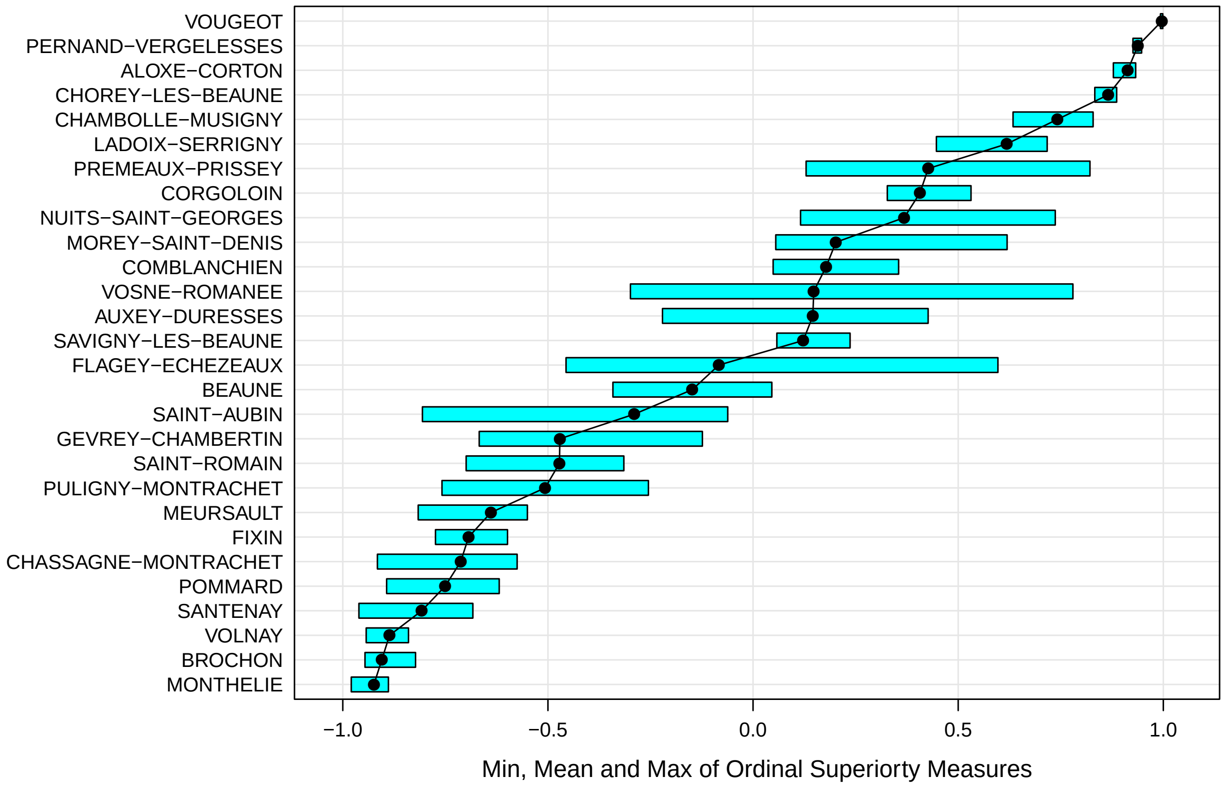
The last row of Table 5 reports the bootstrapped F-tests about the joint significance of *communes* dummies on surrogate residuals from auxiliary models. **??** in Appendix presents in more details the relevance of smoothing spatial coordinates to control for unobserved *terroir* variables. It first appears that OGAMs provide some important progress compared to the parametric model (0). Secondly, XXX effective degrees of freedom appears to be a sufficient complexity level to rule out correlated omitted spatial effects. Above this complexity level *commune* dummies stay highly significant, which indicates robust effect on GI designation schemes of still persistent intangible human-related characteristics from history. Similar vineyard plots from one side or another of administrative delineations are shown to have significantly different probabilities of being in different vertical levels of GIs. We use estimated *communes* fixed effects from the OGAM of respectively 800, 900 and 1000 maximum edf for the smoothing of spatial coordinates to measure ordinal superiority reported in Figure 2.

Ordinal superiority measures are scaled to be between -1 and 1 in a way that a negative value indicates an advantage relative to the average and a positive value indicates a disadvantage (Agresti and Kateri, 2017). *Communes* from the *Côte de Nuits* at the North appear to be more advantaged on average with 10 *communes* among the 15 most advantaged (from the top to the bottom of the Figure). The proximity to Dijon where trials take place between 1860 and 1936 is a potential explanation for this pattern. The *communes* that have a *syndicat* (a group of producers) for collective action[3] appear

[3] Jacquet (2009) (p.189, 211) reports the *communes* of *Gevrey-Chambertin*, *Ladoix-Serrigny*, *Santenay*, *Vosne-Romanée*, *Vougeot* as having experienced the first *syndicats*, whereas there have been some internal conflicts in

Figure 2: **Ordinal superiorty measures for the *communes* in actual GI designation scheme**

Notes: For a given *commune* c on the y axis, ordinal superiority measures are computed from the difference between the estimated fixed effect μ_c and the average fixed effect $\overline{\mu}$ of all *commune* according to: $\Delta_c = 2 \times \Lambda[(\mu_c - \overline{\mu})/\sqrt{2}] - 1$. The horizontal bars represent the range of measures according to different OGAMs with varying complexity for the effects of spatial coordinates, black dots represent the average of these measures. Relatively privilegied *communes* appear at the top of the Figure, whereas relatively disadvantged *communes* appear at the bottom.



to be privileged while the separation is not clear-cut. The hierarchy of advantaged and disadvantaged *communes* does not follow strictly their past or actual reputations, as some advantaged *communes* are not reputed[4] (*Pernand-Vergeless* and *Chorey-les-Beaune*) and some reputed *communes* are disadvantaged (*Pommard* and *Meursault*). Nor the raw distribution of GIs see RM.

Santenay.

[4]We do not consider *Marsannay-la-Côte*, *Chenove* or *Couchey* as advantaged *communes* because this result seems attributable to border effects typical in semiparametric approaches.

Table 2: **Signal decompositions from OGAM with spatial coordinates**

		Effective degrees of freedom for spatial smoothing				
Decomp.	Term	(99)	(295)	(483)	(667)	(845)
Total	Signal	84.81	94.71	95.90	96.76	97.57
	Noise	15.19	5.29	4.10	3.24	2.43
Joint	Signal	68.88	78.50	75.96	77.86	78.73
	Noise	15.96	16.23	19.97	18.93	18.86
Vertical	Signal	55.08	40.32	56.76	61.32	57.55
	Residual	13.80	38.19	19.19	16.54	21.18
	Noise	29.74	54.40	39.13	35.44	40.02
Horizontal	Signal	21.30	37.25	24.59	27.47	29.09
	Residual	47.60	41.27	51.39	50.40	49.65
	Noise	63.54	57.48	71.34	69.31	68.50

Notes: The effective degrees of freedom for spatial smoothing terms in parenthesis show that each decomposition corresponds to model (I) to (V) from Table 5. Decomposition terms are expressed in percent of variance of the latent variable y^* according to equations (5) to (8) in the text. For each column, the sum of vertical signal and vertical residual equals the joint signal, as the sum of horizontal signal and vertical residual. The vertical noise equals the sum of the vertical residual and the joint noise, as the horizontal noise equals the sum of horizontal residual and joint noise.

4.3 Informational content of GIs

Table 2 reports the decomposition from equations (5) to (8) with $q(X_i^*)$ predicted from OGAMs with increasing complexity order of spatial coordinates. Intangible *commune* fixed effect are set at their regional average as they are outside the signal of tangible vineyard quality. The Total signal of the first row of Table 2 is increasing with the effective degree of freedom, which is not surprising as the models are increasingly complex. As the variance of total noise is normalized in ordered models and the variance of y^* from the data generating process is constant between models, this indicates an increase in the variance of vineyard quality predicted from tangible variables. In contrast to this monotonic pattern between models, the other decomposition provide similar order of magnitude for the different terms without a monotonic relationship with the complexity of spatial effects.

Enxplain the number of the abstract

The joint signal of both vertical and horizontal dimension of GIs counts for about 77 % of the variance of the latent GI variable (the joint signal plus the total noise plus the joint noise equal 100 % for every models). The vertical signal alone counts for about 55 % of the variance and the horizontal signal for 25 %. The fourth column shows some deviations from other models while the order of magnitude are respected.

Difference betwen bias and noise: private information is not fully reliable, so that the possibility of honest mistakes makes it very difficult to establish fraud conclusively. This clearly makes a crucial difference in insiders' ability to deceive the public repeatedly, hence in the profitability of market manipulation.

4.4 Alternative GI designation schemes

Les premiers crus n'existent pas, tout comme la distinction entre ordinaire et Bourgogne.

On enlève les communes de "CHENOVE", "MARSANNAY-LA-COTE", "COUCHEY", "COMBLANCHIEN", "CORGOLOIN", "SAINT-ROMAIN" car il n'ya qu'un AOC présent là-dessus.

for old model, omitted variable test and decomposition in RM

Knowing the continuous ranking of vineyard we can evaluate the informational content of alternative GI designation schemes. Verticality in particular (administrative is strange). We consider 3 different dimensions of differentation. First from history, second by changing the latent variable and third by adding a vertical level. Details

The results show that dropping the intangible effects are the more important part to increase the informational content of the vertical dimension without impacting the horizontal part. Dropping the intangible is greater than adding a level but if we want we do not need to target the high level but the middle with more vineyard plot. Maybe it is different from the value. Then, additive cumulative gain of dropping random terms and intangible attributes.

Table 3: **Signal decompositions from alternative GI designations**

		Alternative scenarios of GI designations							
Decomp.	Term	1936	S.0	S.I	S.II	S.III	S.IV	S.V	S.VI
Total	Signal	97.60	97.60	97.60	97.60	97.60	97.60	97.60	97.60
	Noise	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40
Joint	Signal	43.30	81.10	80.70	81.20	82.80	79.20	79.60	79.00
	Noise	54.30	16.40	16.80	16.40	14.80	18.40	18.00	18.60
Vertical	Signal	17.80	70.70	59.80	70.70	73.10	58.00	58.50	57.90
	Residual	25.40	10.40	21.00	10.50	9.70	21.10	21.00	21.10
	Noise	79.70	26.80	37.80	26.80	24.50	39.50	39.00	39.70
Horizontal	Signal	29.10	29.10	29.10	29.10	29.10	29.10	29.10	29.10
	Residual	14.20	52.10	51.70	52.10	53.70	50.10	50.50	49.90
	Noise	68.50	68.50	68.50	68.50	68.50	68.50	68.50	68.50

Notes: Vineyard quality is predicted from model (V), which provides the best fit of actual GIs. The first column reports the informational content of 1936 GIs in terms of the predicted vineyard quality. Scenario S.0 is a benchmark scenario with surrogate residuals to represent actual GIs. S.I drops the random terms, S.II drops the intangible determinants through averaging *commune* fixed effects and S.III drops random terms and intangible determinants. Scenario S.IV, S.V and S.VI respectively add a vertical GI level on *Bourgogne*, *Village* and *Premier Cru*, in increasing order in the hierarchy.

5 Conclusion

An original framework disentangle, link with tangible caracteristics of plots.

In other words, the Burgundy classification cation appears to be a good indicator of Burgundy wine quality, while Bordeaux ranking appears little representative of Bordeaux wine quality. (Combris et al., 2000, p.965)

These two results suggest that the high informational content of GIs and their actual economic importance comes from their long history and their independent management.

Our results about historical and potential improvement counter the idea that "only flexibility can keep the concept of terroir alive" White et al. (2009); Ashenfelter (2017). Even conditions change, the consumer preference face to the GIs signal will change but the historical and independent certifiers. Face to cliamte change burgundy (harvest date), GIs are still very relevant markers for the value of wine and will probably continue.

How to improve the signaling of quality through GIs or to imagine alternative sources of signaling. Les AOC ne sont pas immuables et il est important de voir qu'ils se sont améliorés, gestion pyublique des AOC en question, la littértaure sur la fourniture privée. Le financement de l'INAO

Next step would be to look at consumer reaction to quality signaling (welfare implication) but difficult on GIs because of their stability. Another difficulty would be the endogenous quality from viticultural practices in reaction to good classification and associated high prices.

Value of information But also: Consumers may migrate toward higher quality (vertical sorting) of to wine whose product characteristics best meet their idiosynchratic needs (horizontal). Both can increase welfare. Numerous paper about vertical welfare imroving (DZJi10 p.952 for a review) Reputation should thus be relevant if prospective buyers believe that it predicts current quality in markets in which current quality is imperfectly observable (Shapiro, 1982, Landon and Smith 1998).

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A Appendix

Table 4: **Descriptive statistics for the variables used in the econometric analysis**

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Acreage [1000 m^2]	59,901	1.904	3.389	0.001	0.517	2.173	177.200
Elevation [1000 m]	59,901	0.286	0.056	0.210	0.241	0.318	0.505
Slope [degree]	59,901	5.730	5.465	0.000	1.542	8.683	36.970
Solar radiation [scaled]	59,901	−0.000	1.000	−9.882	−0.243	0.323	3.512
Longitude [degree]	59,901	4.838	0.104	4.665	4.740	4.956	5.004
Latitude [degree]	59,901	47.070	0.111	46.900	46.980	47.170	47.300
Current GI [*Coteaux*]	59,901	0.163	0.369	0	0	0	1
Current GI [*Régional*]	59,901	0.259	0.438	0	0	1	1
Current GI [*Village*]	59,901	0.403	0.491	0	0	1	1
Current GI [*Premier Cru*]	59,901	0.143	0.350	0	0	0	1
Current GI [*Grand Cru*]	59,901	0.032	0.176	0	0	0	1
Past GI [*Régional*]	59,901	0.567	0.495	0	0	1	1
Past GI [*Village*]	59,901	0.406	0.491	0	0	1	1
Past GI [*Grand Cru*]	59,901	0.027	0.162	0	0	0	1
Aspect [0 – 45]	59,901	0.045	0.208	0	0	0	1
Aspect [45 – 90]	59,901	0.185	0.389	0	0	0	1
Aspect [90 – 135]	59,901	0.362	0.481	0	0	1	1
Aspect [135 – 180]	59,901	0.212	0.409	0	0	0	1
Aspect [180 – 225]	59,901	0.101	0.301	0	0	0	1
Aspect [225 – 270]	59,901	0.044	0.206	0	0	0	1
Aspect [270 – 315]	59,901	0.029	0.169	0	0	0	1
Aspect [315 – 360]	59,901	0.021	0.142	0	0	0	1

Notes: Topographic data are computed by Geographical Informatin System from a Digital Elevation Model of 5 m resolution. Longitude and Latitude variables correspond to the centroid of each vineyard plot. Current GI are dummy variables that count for the vertical dimension in 2018 and Past GI comes from the map of 1860 mentioned in the main text. Aspect is discretized according to radians range reported between brakets.

Figure 3: **Nonlinear effects of tangible variables on GI designations**

Notes: Dotted lines represent the quadratic effects from model (0) of Table 5, centered at zero with all other explanotory variables at their sample means. Continuous lines represent the centered effects from 10 OGAMs with increasing darkened for increasing effective degrees of freedom of spatial smoothing terms. Model (I) to (V) of Table 5 are a subset of these OGAMs with maximum effective degrees of freedom uniformly distributed between 100 and 1000. The histograms at the bottom of each plots represent the marginal distributions of each explanatory variable in the region.

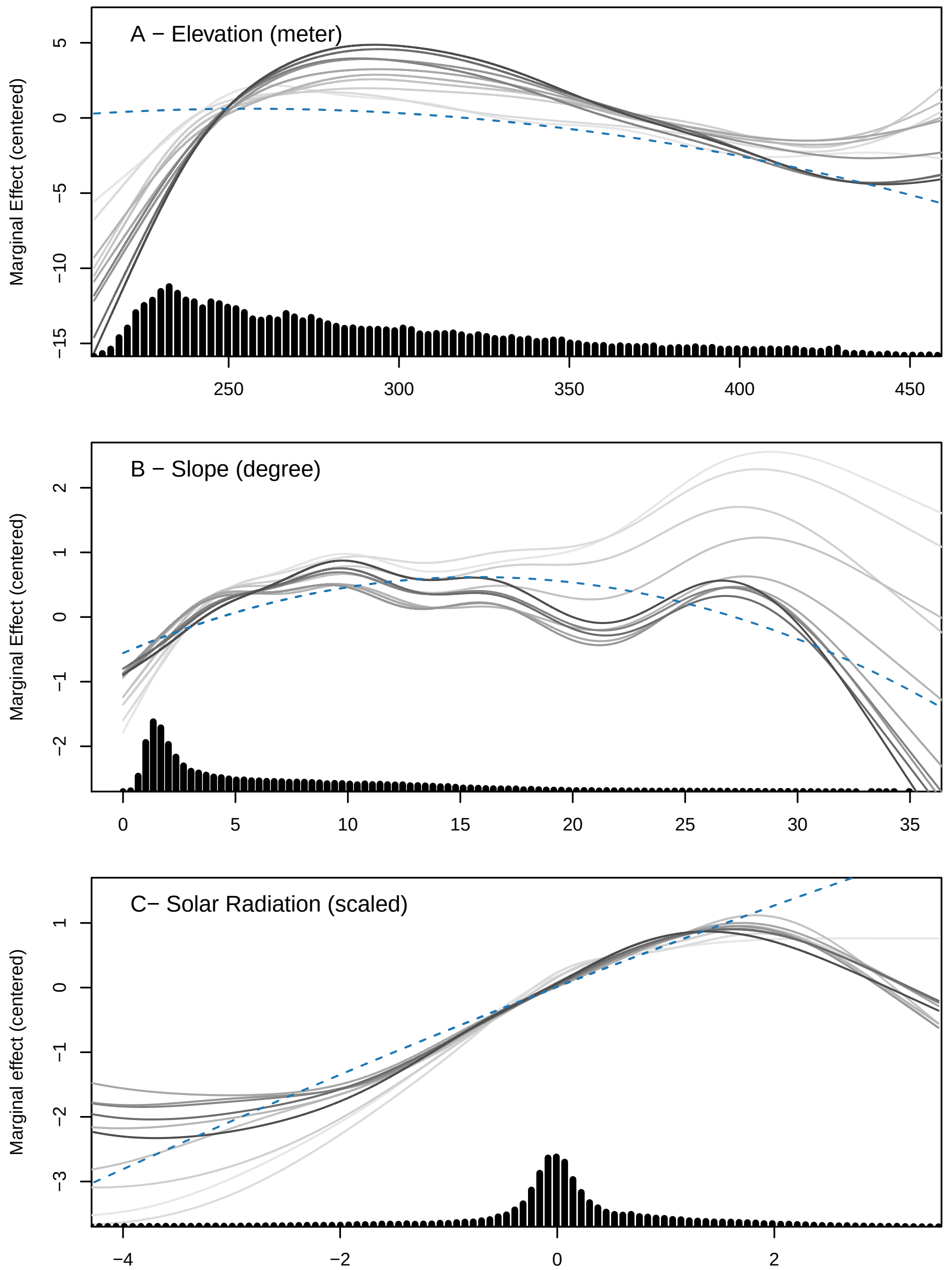

Figure 4: **Spatial smoothed effects from ordered GI designation models**

Notes: The smooth surfaces are predicted from spatial coordinates with others explanatory variables at their sample means, with a uniform normalization to be inside the unit interval. Panel A displays the smooth prediction from parametric ordered logistic model (0) of Table 5. Panels B to F display the prediction from the OGAMs (I) to (V) with increasing effective degrees of freedom as reported at the top of each plot.

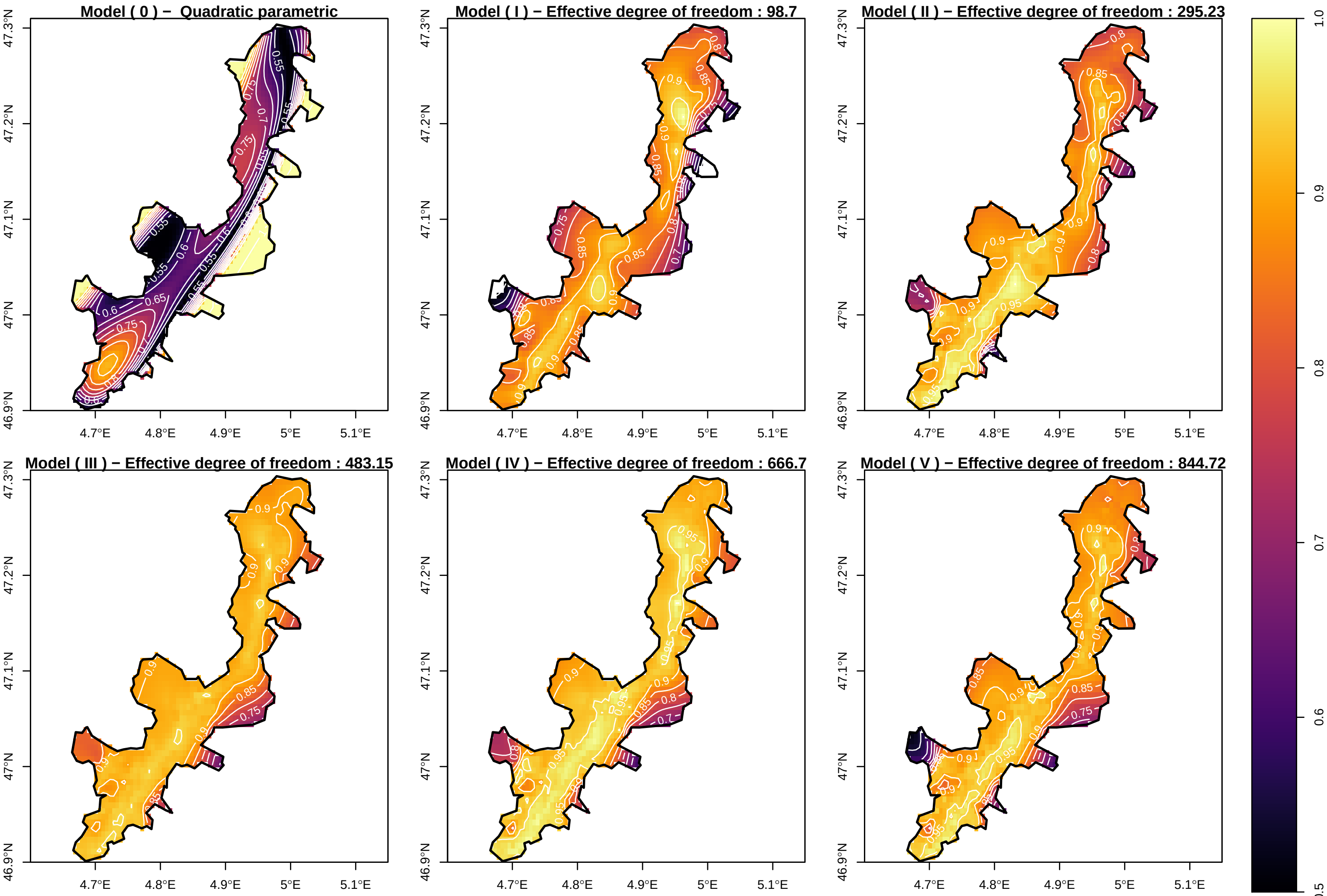

Figure 5: **F-statistics for the diagnostic of correlated residual effects**

Notes: log scale.

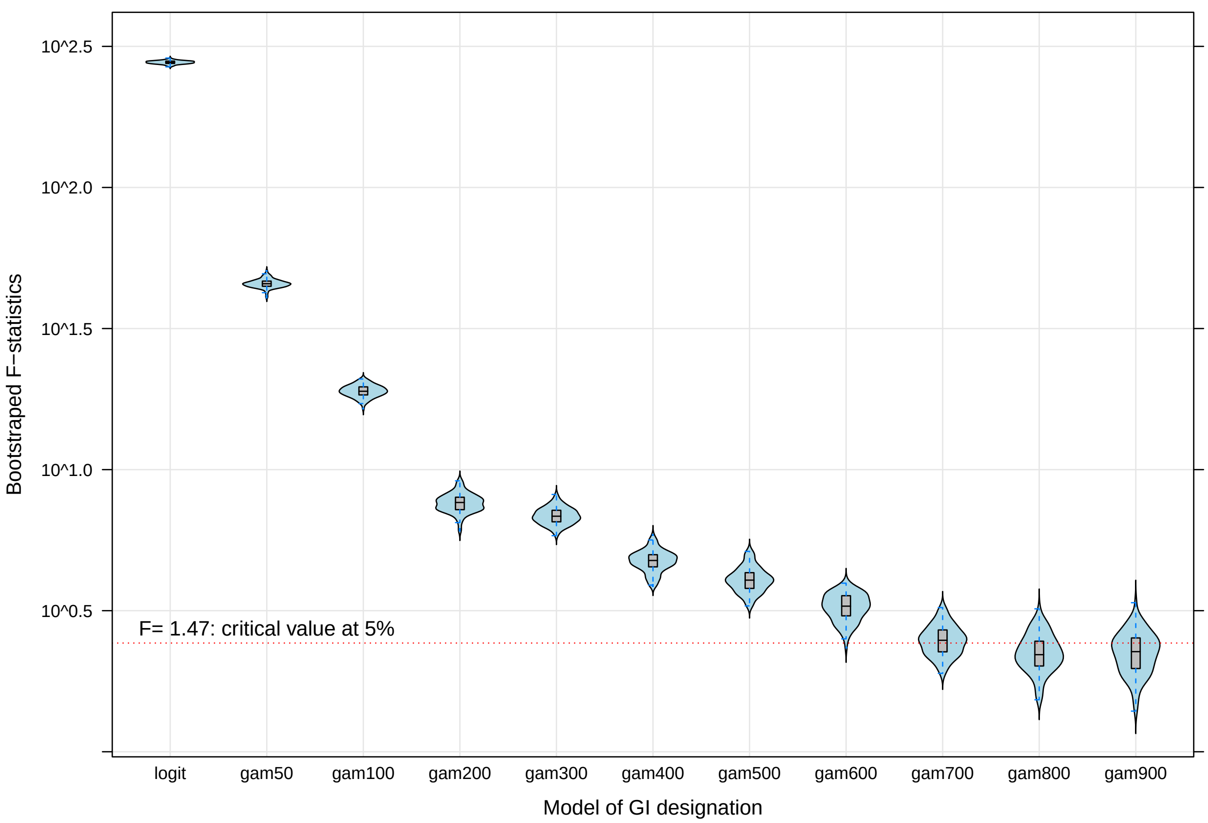

Figure 6: **Correlation between ranking and ordinal superiority**

Notes: more then average better GI and more than average privilegied.

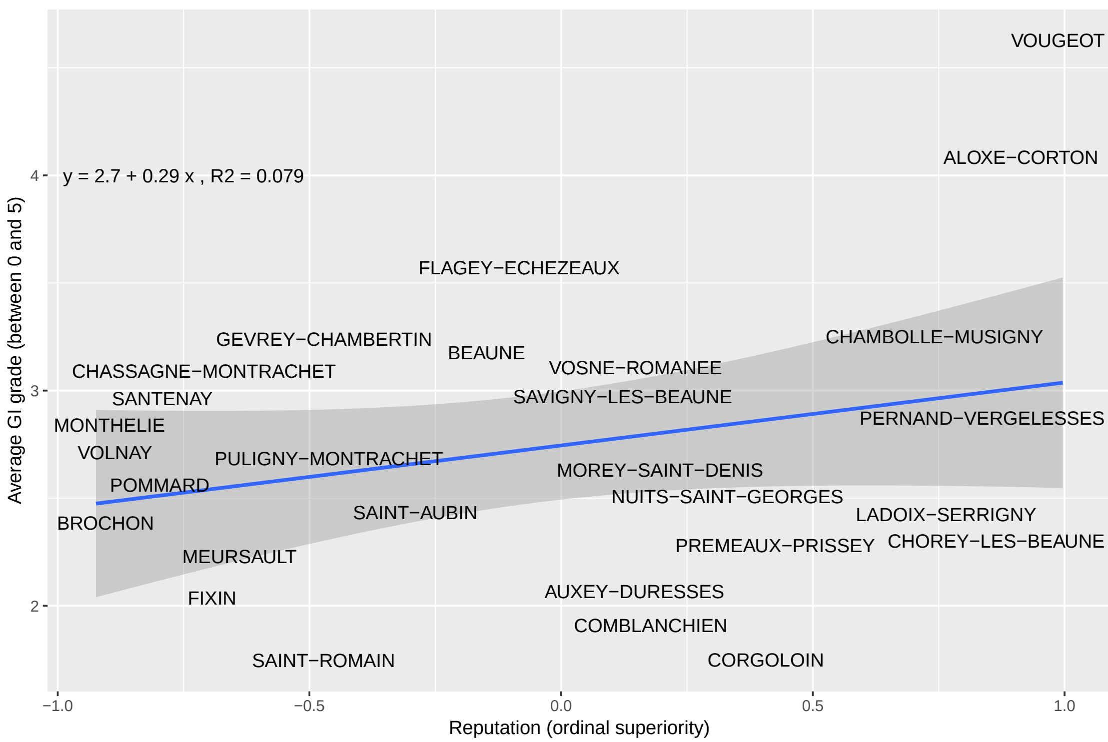

Table 5: **Joint variable significance for ordered models of 1936 GI designations**

Variable	(0)	(I)	(II)	(III)	(IV)	(V)
Elevation	2 410.9**	499.82**	647.37**	702.32**	541.9**	344.48**
	[2]	[8.461]	[8.231]	[8.81]	[8.379]	[7.653]
Slope	328.26**	387.33**	314.01**	254.41**	244.26**	153.01**
	[2]	[8.748]	[8.745]	[8.605]	[8.553]	[8.276]
Solar Radiation	668.18**	242.04**	160.07**	127.12**	122.95**	105.16**
	[2]	[8.543]	[8.326]	[8.115]	[5.031]	[5.876]
Spatial Coords	10 236**	17 521**	20 194**	22 302**	23 507**	23 801**
	[15]	[98.25]	[146.3]	[194.4]	[239.8]	[286.6]
Exposition	456.77**	119.85**	91.752**	91.921**	96.106**	90.193**
	[7]	[7]	[7]	[7]	[7]	[7]
Commune	10 625**	2 782.5**	1 843**	1 642.4**	1 283**	1 049.4**
	[25]	[25]	[25]	[25]	[25]	[25]
Nb Observ.	50 464	50 464	50 464	50 464	50 464	50 464
McFadden R^2	37.59	59.18	63.61	67.02	70.84	73.45
Pc good pred.	79.34	87.08	89.26	90.28	91.4	92.55
Akaike IC	51	33.81	30.27	27.57	24.53	22.48
Surrogate F	122.46	5.71	4.24	2.83	1.88	1.61

Notes: ** accounts for joint significance at 1% from the reported Chi-square statistics, effective number of freedom are in brackets. Column (0) corresponds to an ordered logit model with quadratic effects for elevation, slope and solar radiation (edf= 2) with a full interaction between 3-orders polynomials for longitude and latitude (edf= $3 + 3 + 3 \times 3 = 15$) and with respectively 7 and 25 dummy variables for exposition and *communes*. 5 *communes* have been dropped because they contained only one GIs in 1860. Models (I) to (V) are OGAMs with elevation, slope and solar radiation additively specified with a maximum of 9 edf, shrinked endogenously by a quadratic penalization. Spatial coordinates are specified in an increasing order of complexity with the maximum edf of 100, 150, 200, 250 and 300. The last row reports the average of bootstraped Fisher statistics for the joint nullity of *communes* dummies on surrogate residuals in the auxiliary regressions presented in the main text.

Figure 7: **Nonlinear effects of tangible variables on 1936 GI designations**

Notes: Dotted lines represent the quadratic centered effects of model (0) presented in the main text. Continuous lines represent the centered effects from OGAM models (I) to (V) with increasing darkened with increasing effective degrees of freedom. The histograms at the bottom of the plots represent the marginal distributions of each explanatory variable.

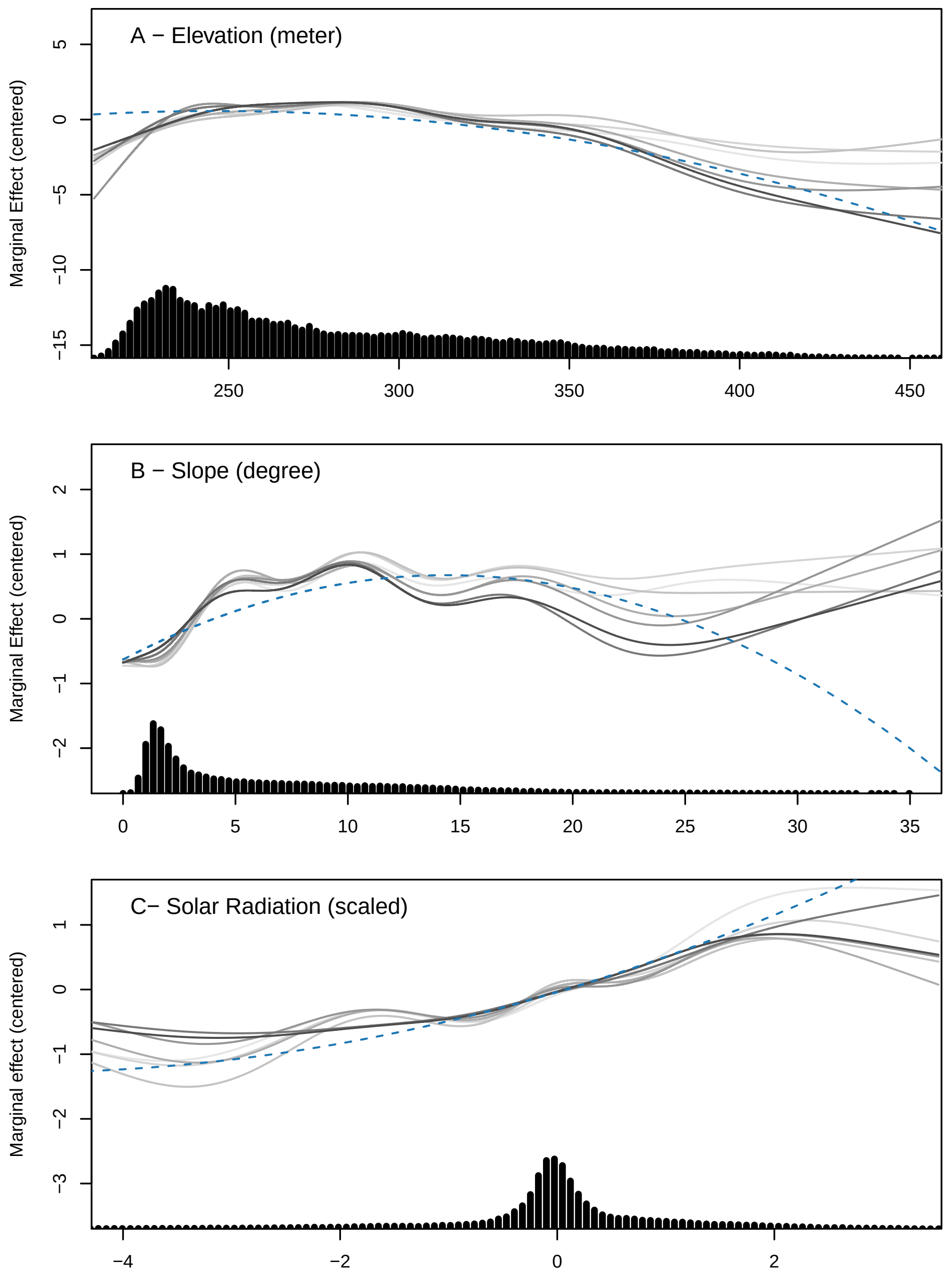

Figure 8: **Spatial smoothed effects from 1936 GI designation models**

Notes: Smooth surfaces are normalized predictions of the latent variables from models (0) to (V) with all other covariates at their sample means.

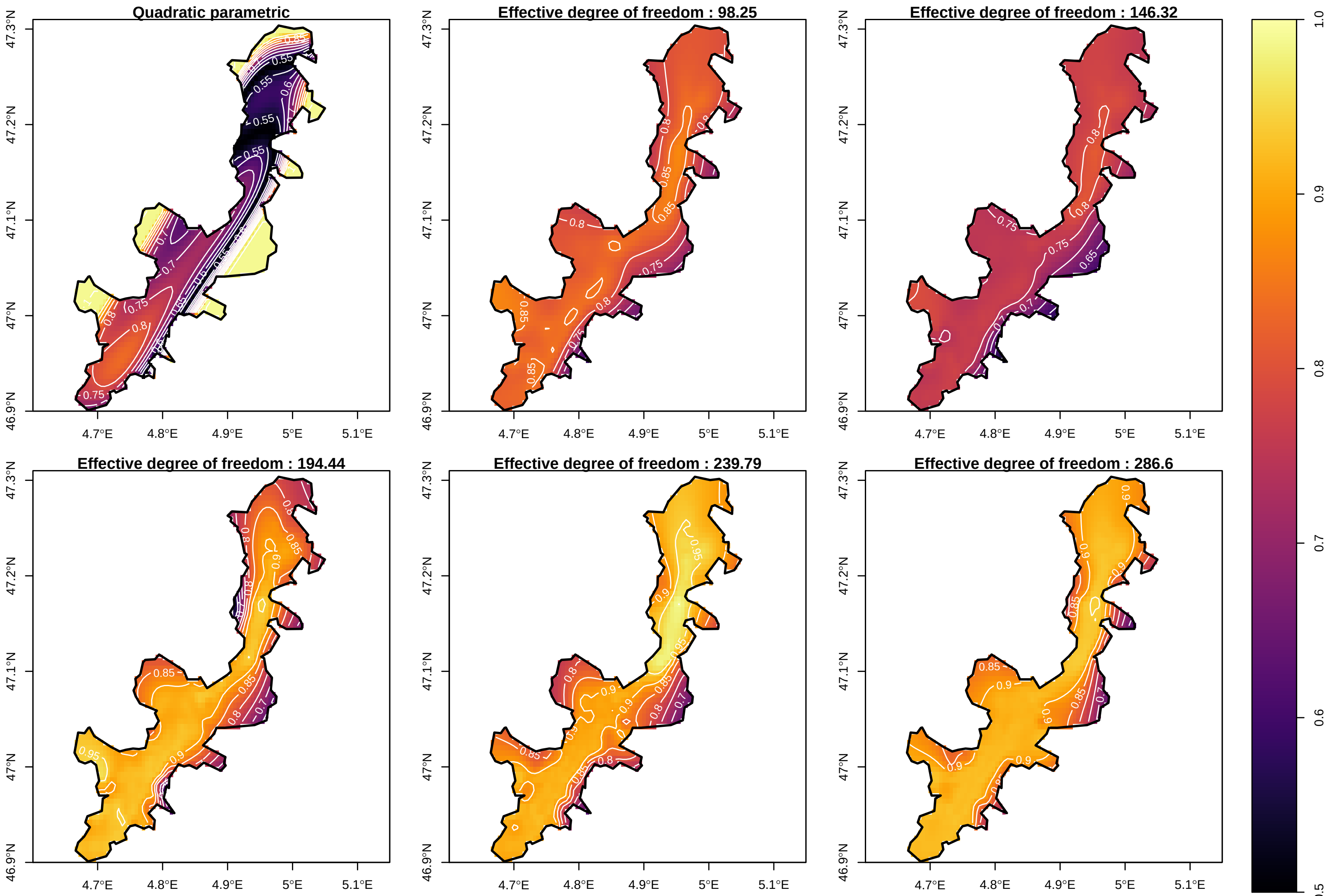

Figure 9: **Ordinal superiorty measures for the *communes* in 1936 GI designation scheme**

Notes: For a given *commune* c, ordinal superiority measures are computed from the difference between the own estimated fixed effect μ_c and the average fixed effect $\overline{\mu}$ according to: $\Delta_c = 2 \times \Lambda[(\mu_c - \overline{\mu})/\sqrt{2}] - 1$ as in the main text. The horizontal bars represent the range of measures according to different OGAMs with varying complexity for the effects of spatial coordinates, black dots represent the average of these measures. Relatively privilegied *communes* appear at the top of the Figure, whereas relatively disadvantged *communes* appear at the bottom.