The informational content of geographical indications

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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 ability to follow the tangible characteristics of production site instead of intangible factors such as the influence of producers on the designation process. We disentangle the informational content of wine-related GIs for the *Côte d'Or* region of Burgundy, France. Thanks to their hierarchical and nested structure, GIs have a high informational content in terms of tangible characteristics with a signal to noise ratio of about 4. We also apply the decomposition to alternative wine classifications from history and from counterfactual simulations to show significant improvements of GIs in the last century and potential guidelines for better designated GIs in the future.

Keywords: Food certification, wine economics, strategic quality disclosure, variance decomposition, ordered semi-parametric model.

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 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 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).

The main objective of this work is to estimate the informational content of actual, past and simulated GI designation schemes for about 60 000 vineyard plots. The informational content is defined as its ability to follow tangible 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 disentangle tangible from intangible information about production sites by decomposing the conditional variance of a latent quality index estimated from actual 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 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 of GIs from tangible characteristics. Knowing the geographical co-variations between tangible and intangible characteristics 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 difference between the spatial continuity of *terroir* and the discontinuity of administrative borders according to the axiom that nature does not make jumps.

This article is an empirical contribution to the literature about quality disclosure and strategic certification (see Bagwell, 2001; Dranove and Jin, 2010 for reviews). The vineyard quality index that we study is exclusively based on vineyard characteristics given by the nature, that contrasts to typical frameworks 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 makes the identification of the informational content of the quality signal easier and allows to analyze more transparently the role of history in the information conveyed by actual GIs put on the label of wine bottles. We argue that the long history of GIs designations allows to neglect the role of actual wine producers and their undoubtedly tangible 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 predetermined collective reputation (Tirole, 1996) reasonably independent from actual individual practices or skills of producers. In addition, the long run vineyard quality index 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). Because a GI name can not be sold without its associated vineyard quality from tangible characteristics, the GI information puts on the label by producers is not related to their own characteristics, which is another source of tangible information not studied here.

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 their aggregation (Ashenfelter and Quandt, 1999) and their consistence (Cao and Stokes, 2010; Bodington, 2017) 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, not directly comparable with more stable public GIs voluntarily put on wine labels by producers. This observation introduces the tedious question of the endogenous adoption of quality disclosure for GIs that is not a concern for expert review (Hollander et al., 1999). This could produce unintended economic consequences such as counter-signaling, in situations where the certification is not adopted to signal the high quality of products (Bederson et al., 2018). This is *a priori* not the case for wine-related GIs in Burgundy, because 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 wine labels.

The analysis shows a high informational content of actual GIs in terms of the underlying tangible vineyard characteristics, 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 intangible *commune* effects. This small administrative unit in France corresponds to the scale at which collective actions and lobbying have been operated historically, in particular the scale at which the *syndicats* (groups of wine producers) get structured (Jacquet, 2009). Nevertheless, this bias has decreased since the creation of GIs in 1936 trough continuous evolution of GIs designation schemes that happened. This decreasing bias from history is an illustration of the theory developed by Benabou and Laroque (1992) about strategic information transmission. We find that some producers or landowners could have profited from their private information about vineyard quality to manipulate the GI signal and extract rents through undeserved high rated vineyards in their administrative units. 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.

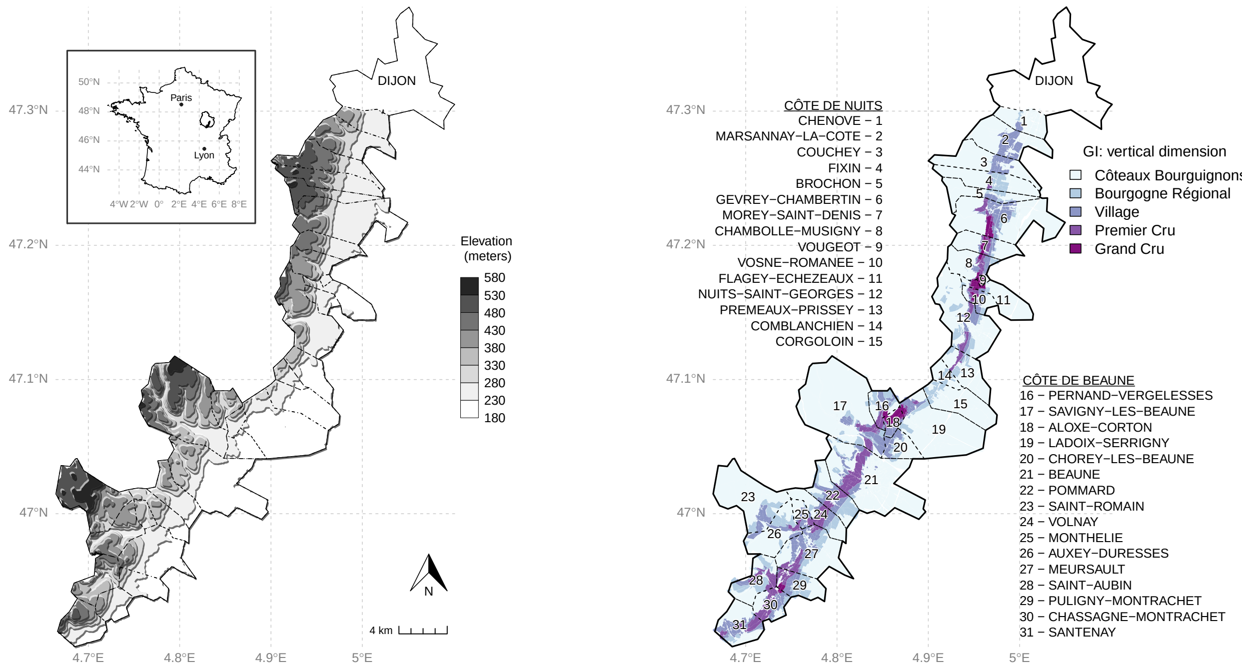
The following Section 2 presents in greater details the historical and regional contexts of the work, jointly with the data used. Section 3 presents the data generating process under consideration (also called the population structural model), the signal decomposition framework and the econometric strategy.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

2 Context and 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 from the north to the south 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 tangible 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 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 major determinant for the grape maturity cycle, its sugar content and structure of aromas. The latitude position of vineyards is also indirectly correlated with temperature 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 older and thinner). The longitude position of vineyards is indirectly correlated with precipitations on the area, 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. Recognizing the indirect effects of these observed topographical and position variables is important as fine climate data does not exist to be consistently used at the vineyard plot scale.

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, considered as the horinzontal dimension of GIs.



2.2 Historical context

Some archaeological evidences locate the first vineyards in the 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* or *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, according to Lavalle, 1855). However, the first exhaustive spatial delineation of the region is an administrative separation of *communes* following the decree of 1789 after the french revolution. What we consider as the horizontal dimension happened before the vertical dimension of actual GIs (Garcia, 2011, p.40). The delineation of *communes* was based on the spatial distribution of churches (usually built between the 9th and the

12th centuries) without the goal of signaling wine quality. The first exhaustive vertical 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) in particular. 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 1860 map by the *Comité d'Agriculture et de Viticulture de l'Arrondissement de Beaune*, the local organization of wine producers. 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. 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 reputation of the *commune* to which they belong. 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 ("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 common legal basis. In Burgundy, the first official GIs come from the map of 1860, jointly with the jurisprudence which has taken place since then. Some modifications are then 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 1936 and corresponds to Protected Designation of Origin for the European Union (https://ec.europa.eu/agriculture/quality/schemes_en).

2.3 Actual GI designations

Actual GIs are a nest between a vertical quality ranking in 5 items and a horizontal differentiation scheme through 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, 8 in the *Côte de Beaune* (southern part) and 24 in the *Côte de Nuits* (northern part) for a total area of 472.6 ha (4.2 % of acreages with GIs). It follows in the hierarchy 404 *Premiers Crus* on the area which have to be associated with their *commune* names on wine labels (ex: "*Les Chaumes*" from *Vosne-Romanée* or "*La Chapelle*" from *Auxey-Duresse*). There are 1 619 ha of *Premiers Crus* in the *Côte de Beaune* that count for 20.5 % of the sub-region and 433 ha in the *Côte de Nuits* (12.75 %). The third vertical level corresponds to *Bourgogne Village* with or without name (ex: *Pommard Village* with name and *Côte de Nuits Village* without). It counts for 2 500 ha (31.75 %) in the *Côte de Beaune* and 1 563 ha (46 %) in the *Côte de Nuits*. The vertical differentiation of GIs ends with *Bourgogne Régional* (2 788 ha, 24.73 % of the GI area) and *Coteaux Bourguignons* (1 899 ha, 16.85%) that are sometimes grouped in a same *régional* level. 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* and *Chardonnay* becomes the main varieties.

The picture of actual GIs on the area is not complete without the mention of the complexities that exists between the vertical and the horizontal dimensions, which could lead to difficulties for consumers to distinguish their respective informational content. First note that the terms *commune* and *village* are often used as synonymous for the administrative delineations in rural areas of France, whereas the first is related to the horizontal dimension and the second for the vertical dimension. Secondly, a same name for a vertical item from *Grand Cru*, *Premier Cru* or even *Villages* can be located on two different *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*, and the *Vosnes-Romanée Village* is shared between the *communes* of *Vosnes-Romanée* and *Flagey-Echézeaux*. Thirdly, at the beginning of the 20th century, 10 *communes* have added the name of their most famous *Grand Cru* to their administrative name, such as *Aloxe-Corton* or *Gevrey-Chambertin*. Consequently, the name of a *Grand Cru* is labeled in the horizontal information for wines that are not *Grand Cru*. This complexity reaches its maximum in the two *communes* of *Chassagne-Montrachet* and *Puligny-Montrachet* that share the same *Grand Cru Montrachet* and have chosen to add it to their administrative names. However, the legal obligation or prohibition to mention the vertical item *Grand Cru*, *Premier Cru*, *Village*, *Régional* or *Coteaux Bourguignons* as the main information on wine bottle labels suggests that this information is clearly identifiable to informed consumers.

2.4 Summary Statistics

The precision of the econometric estimation for disentangling the sources of variations of the GIs depends on a balanced distribution of tangible variables and vertical items between and within the horizontal *commune* items. The left panel of Figure 1 shows that each *commune* approximately contains the whole range of elevation, slope and exposition of the area. The right panel shows that administrative delineations of *communes* articulate with each other on the north-south gradient, which ensures sharp climatic differences between them. Figure 3 in the Appendix displays the acreages and shares of each vertical items for each horizontal *commune* items. Every *commune* has at least 2 vertical items among the 5 possible. The majority of *communes* counts 3 different veritcal items with an average number of 3.87 items by *commune*. Vineyards ranked as *Village*, *Premier Cru* and *Grand Cru* are present in respectively 28, 24 and 11 *communes* that count respectively for 90 %, 77.4 % and 35.5 % of all of them.

Table 4 in Appendix A presents some summary statistics about the exhaustive plot-level data that we use on the 31 *communes* of the region. For about 60 000 vineyard plots of a tiny average size of 0.2 ha (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 (the coefficient of variation is about 100 %). The solar radiation is distributed from 0.58 to 1.23 millions of Joules with an average of about 1.05 millions J. To add flexibility in the econometric estimations, the aspect variable is discretized in 8 dummy variables for different semi-quadrants, which shows that more than 50 % of vineyard plots have a south-eastern exposition, between 90 and 180 degrees. The Table also reports the current distribution of the vertical dimensions of GIs and the distribution in 1936 when the national INAO was created. We also use additional geological and pedological as fixed effects to control for sub-soil and soil characteristics of vineyards. Because such variables are not determinant in the empirical strategy that we propose, we do not report them here. Interested reader can have access to these variables through the Reproducibility Material, RM, from the link at the title page of this document.

3 Model of GI designation

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 intangible influences and the specification procedure that we propose.

3.1 Structure of GIs

The fine-scale variation of natural characteristics (i.e., *terroir*) between vineyard sites is the basis of the GI classification scheme. Vineyard quality index 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 plot. From this scalar quality, GIs are designated through a continuous latent variable y^* defined as the difference between the long run quality signal and idiosyncratic random term ξ called designation noise:

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

The mapping between tangible *terroir* characteristics X^* and the objective quality index 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 more generally 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 consumers' surveys that we do not use here. Instead, we 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 objective quality.

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:

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

with $\alpha^c_0 = -\infty < \alpha^c_1 < \cdots < \alpha^c_5 = +\infty$ for all *commune* $c \in \{1, \dots, 31\}$ by construction. The exponent c on the thresholds marks the *commune* in which the vineyard is located among the 31 *communes* of the area under consideration, it represents the horizontal dimension of GIs. The variation in the thresholds between *communes* corresponds to the differential treatments 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: $\alpha_3^{c_1} < \alpha_3^{c_2}$ and $\alpha_4^{c_1} < \alpha_4^{c_2}$. This means that the quality requirements for *Premier Cru* of the *commune* c_1 are less stringent and, consequently, the average 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 tangible 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:

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

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 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 at least j_1 (the GI quality rank of vineyard 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 is equal to the ordinal superiority

[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: $\mathbb{E}(\xi \mid X^*) = \mathbb{E}[\mathbb{E}(\xi \mid X^*, c) \mid X^*] = 0$.

[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 compared to 1.

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). This measure of ordinal superiority computes the bias in GI designation independently of the conditioning tangible characteristics X_1^* of vineyard plots. This allows a direct comparison between the horizontal dimension c of GIs 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 the comparison, this means $\alpha_j^c = \alpha_j - \mu_c$. The ordinal superiority measure between 2 plots located in 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. The resulting 30 statistics provide objective measures of the differential treatments that have been applied between *communes* according to the GI vertical classification of their vineyards. The presence of significant ordinal superiority measures indicates some bias in the GIs signal and the ordinal superiority measure are used to estimate the size of the bias.

3.2 Informational content

The 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). Following the former authors, we consider GIs as an information structure, i.e., a joint distribution between the states of the world (long run vineyard qualities index) 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 wine labels allows the consumers to recover wine quality, according to 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 presents the variance of the latent 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 any GI signal can reach for the data generating process under consideration. This corresponds to the case where the continuous quality grade are conveyed to consumers as a continous score put on the wine label.

The *joint decomposition* of Equation 6 comes from the law of total variance applied to the continuous quality grade (Bowsher and Swain, 2012). It disentangles 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 the discretization 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 the *total signal* 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 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 complexities 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 be zero. In such a case, the vertical dimension is unbiased and provide all the relevant information about 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:

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

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 any preferential treatment of certain *communes*, this signal is still 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. Finally, 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 estimation of the unknown function $q(\cdot)$ that relates tangible attributes of vineyards to the long run quality index is subject to 2 empirical challenges that we consider jointly: the specification of the functional form for the effect of a given tangible variable x_k and the presence of unobserved *terroir* variables that impact vineyard quality. For example, the data set that we use here does not contain fine-scale climate variables (such as temperature, precipitation) but one can also think to other unobserved *terroir* variables such as local variations in soil quality. These unobserved effects from the econometrician point of view are taken into account in GI designations by observations on the field because they are known by people involved in GI designations. This is a serious econometric concern due to the potential confounding effect 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 econometric 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 the 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 scheme for a given vineyard plot $i = 1, \ldots, N$. These observed tangible variables are elevation, slope, exposition, solar radiation, geology, pedology 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 the typical element 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 parametric ordered logit model that can be estimated by maximum likelihood:

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

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 index 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 (AIC).

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) from auxiliary regressions that do 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 $S \mid X, y \sim \lambda\,[\,B(X)^{\top}\beta - \alpha_y \mid y\,]$ 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 with:

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

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 the 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. Once this is attained, we estimate jointly the effect of tangible and intangible GI determinants in a full OGAM with the obtained degree of spatial smoothing as in any parametric regression framework. In the absence of residual spatial effects correlated with *communes* dummies, the estimated ordinal superiority measures are unbiased. Note that the F-statistics 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 first column (0) of Table 1 reports the joint significance statistics from a standard ordered logit model with additive quadratic effects for the three topographic variables, third-order polynomials with full interactions for spatial coordinates, and pedology, geology, exposition and *commune* fixed effects. The reported χ^2 statistics are equivalent to F-statistics for models with discrete outcomes. The tests indicate that all variables are significant at the 1% level, for an overall pseudo-R^2 of 36.7%. The most significant series of variables (i.e., with the highest significance statistic) is the set of 31 *commune* dummies that represent the intangible determinants from human influences on GI designations. This set is closely followed by the pedology fixed effects and the polynomials transformations of spatial coordinates that controls for the effects of longitude and latitude positions of vineyards. Elevation, solar radiation, geology, exposition and slope variables follow in decreasing order of joint significance, for an overall significance of tangible variables slightly higher than intangible variables (results not reported). The nonlinear effects of the 3 topographical variables on the latent quality index are reported in Figure 4 of Appendix. Elevation and slope variables have inverted-U effects with the highest vineyard quality at about 290 meters and 10 degrees. The effect of solar radiation is linearly increasing and the southern expositions provide the highest marginal probability of a high GI classification (see the Reproducibility Material, RM, from the link at the title page of this article). The top-left panel of Figure 5 in Appendix shows the marginal effects of spatial coordinates on the latent index. The third-order parametric specification with full interactions produces some ellipsoidal smooth patterns with two central kernels that describe a core-periphery structure. The coefficients estimated from *communes* fixed effects are interpreted in the next subsection in terms of ordinal superiority.

Columns (I) to (V) in Table 1 reports the same significance statistics from ordered generalized additive models (OGAMs) with increasing complexity in the spatial smoothing terms from the left to the right, as it appears from the effective degrees of freedom for spatial coordinates. The semiparametric structure of these models keeps the same degrees of freedom for pedology, geology, exposition and *commune* fixed effects with respectively 13, 14, 7 and 31 degrees. Increasing the complexity of the spline series of spatial coordinates increases sensibly the pseudo-R^2 to 75 % and the percent of good predictions to 90 % in the most complex OGAM reported in the last column (V). Simultaneously, the joint significance of spatial coordinates increases and the significance of all other explanatory variables decreases (except slope and exposition variables for which the decrease of significance is not monotone). As expected, the spatial pattern of GIs designations are increasingly grasped by spatial coordinates at the expense of other explanatory variables. Figure 4 in Appendix shows the comparative advantage of OGAMs over the parametric model (0) in

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

Variable	(0)	(I)	(II)	(III)	(IV)	(V)
Elevation	4 029.6**	4 123.2**	1 793.1**	1 189.9**	1 014.1**	867.04**
	[2]	[8.913]	[8.882]	[8.85]	[8.79]	[8.81]
Slope	531.9**	922.46**	343.61**	168.47**	155.46**	190.06**
	[2]	[8.3]	[8.241]	[8.331]	[8.173]	[7.722]
Solar Radiation	1 885.2**	2 091.3**	981.64**	797.71**	646.51**	530.96**
	[2]	[8.1]	[8.052]	[8.283]	[7.977]	[7.331]
Spatial Coords	7 602.7**	32 524**	59 294**	74 154**	78 445**	86 597**
	[15]	[98.59]	[295]	[483.2]	[666.6]	[841.4]
Pedology	8 810.7**	2 447.2**	713.07**	450.42**	408.64**	387.9**
	[13]	[13]	[13]	[13]	[13]	[13]
Geology	1 715.6**	977.42**	557.45**	500.46**	406.43**	440.86**
	[14]	[14]	[14]	[14]	[14]	[14]
Exposition	743.48**	61.043**	81.266**	171.5**	158.98**	130.52**
	[7]	[7]	[7]	[7]	[7]	[7]
Commune	9 767.6**	3 007.9**	2 295.2**	2 353.7**	1 721.6**	1 363.5**
	[31]	[31]	[31]	[31]	[31]	[31]
Nb Observ.	59 113	59 113	59 113	59 113	59 113	59 113
McFadden R^2	36.7	53.23	63.1	68.4	72.48	75.65
Pc good pred.	63.69	74.85	80.38	84.35	87.25	89.47
Akaike IC	104	77.22	61.4	53.09	46.76	41.93
Surrogate F	156.35	17.7	5.64	3.94	1.98	1.82

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 (df= 2) with a full interaction between 3-orders polynomials for longitude and latitude (df= $3 + 3 + 3 \times 3 = 15$) and with respectively 13, 14, 7 and 31 dummy variables for pedology, geology, 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 increasing order of complexity with the maximum edf of 100, 300, 500, 700 and 900. The last row reports the bootstraped F-statistics for the joint nullity of *communes* effects on surrogate residuals from auxiliary regressions without *commune* dummies.

estimating the marginal effects of each explanatory variable. Panel A shows that the strong effect of elevation on the 0-300 meters range is not found in the parametric model, as for the strong effect of slope on the 0-5 degrees range. These results are particularly stringent as these ranges concentrate the majority of vineyard plots. In terms of spatial smooth effects reported in Figure 5 of Appendix, OGAMs produce more detailed spatial variations that the broad ellipsoid pattern from the parametric model (0). This suggests some fine-scale spatial variations of the latent quality index according to GI designation scheme. The significance of *commune* fixed effect is impacted by increasing the complexity of spatial smoothing, while it stays the second most important set of variable in model (V).

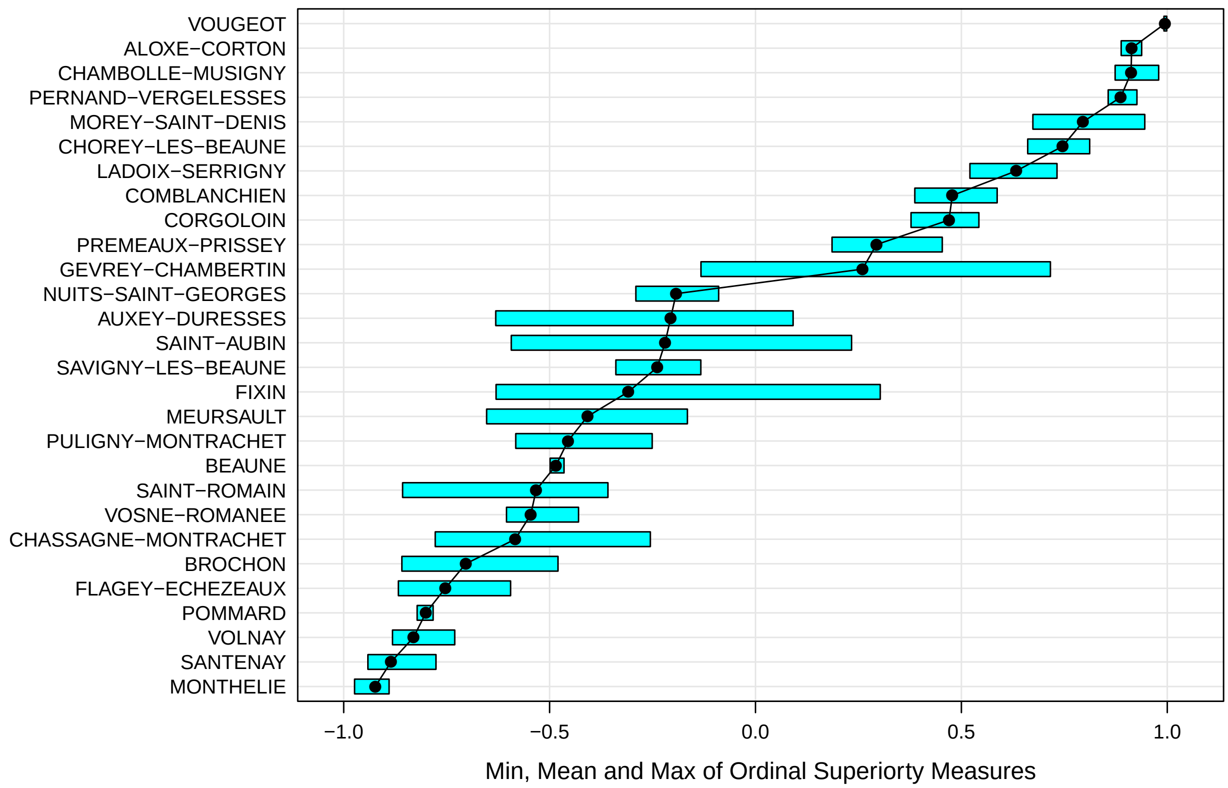
4.2 Ordinal superiority of *communes*

The last row of Table 1 reports the bootstrapped F-statistics about the joint significance of *communes* dummies on surrogate residuals from auxiliary models that do not account for such fixed effects. Figure 6 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 ordered logistic model (0) from which surrogate residuals are highly correlated between *communes*. Secondly, a maximum effective degrees of freedom of about 700 – that corresponds to model (IV) in Table 1 – is a sufficient complexity level to rule out potentially correlated omitted *terroir* effects, as the insignificance of *commune* dummies on the surrogate residuals from the auxiliary regressions can not be rejected according to the median of the bootstrapped statistics. This indicates persistent effects of intangible human-related characteristics on the GI designation scheme, even for precisely controlled *terroir* effects. Similar vineyard plots from one side or another from administrative borders are shown to have significantly different probabilities of being in different vertical levels of GIs.

Ordinal superiority measures from models with respectively 700, 800 and 900 maximum edf are distributed inside the -1 and 1 interval in a way that a positive value indicates an advantage relatively to the average and a negative value indicates a disadvantage (Agresti and Kateri, 2017). From Figure 2, only vineyard plots from 4 *communes* are not different from the average *commune* in terms of the designation of their vineyards along the vertical dimension of GIs. *Communes* from the *Côte de Nuits* at the North of the region are more advantaged on average the those of the *Côte de Beaune* at the South, as 8 *communes* from this part of the region are among the 11 most advantaged. The proximity to Dijon where trials about the use of vineyard names take place between 1860 and 1936 is one potential explanation for this result, jointly with the fact that it was usual that rich and

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 as 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 the OGAMs with 700, 800 and 900 maximum edf 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.



influencing people living in Dijon owns some vineyards at the *Côte de Nuits*, closer to Dijon than *Côte de Beaune* (Wolikow and Jacquet, 2018). The *communes* that have a *syndicat* (a group of wine producers) engaged in collective action appear to be privileged while the separation is not clear-cut.[3] This hierarchy of advantaged and disadvantaged *communes* does not follow strictly their past or actual reputations, as some advantaged *communes* are not reputed (*Ladoix-Serrigny* and *Chorey-les-Beaune*) and some reputed *communes* are disadvantaged (*Flagey-Echezeaux* and *Pommard*). We find the ordinal superiority measures are only weakly positively correlated with average levels of actual GIs (R^2= 0.06, see Figure 7 in the Appendix).

[3] Jacquet (2009) (p.189, 211) reports the *communes* of *Vougeot*, *Aloxe-Corton*, *Ladoix-Serrigny*, *Gevrey-Chambertin*, *Vosne-Romanée* and *Santenay* as having experienced the first *syndicats*, with some internal conflicts for *Santenay*.

4.3 Informational content of GIs

Table 2 below reports the decomposition computed from equations (5) to (8) with $q(X_i^*)$ predicted from the five OGAMs reported in Table 1 with increasing complexity order of spatial coordinates (the empirical formulas used are reported in RM Appendix A.4, jointly with the R code to compute them). As expected, the total signal reported in the first row of Table 2 is increasing from the left to the right and the total noise is decreasing.[4] In contrast to this monotonic relationship between the total signal and the complexity of the spatial smoothing terms, the results from joint, vertical and horizontal decomposition are more stationary between specifications. For all models, the vertical and horizontal dimensions of GIs have a high information content. From the last column of Table 2, the joint signal of about 78% is 4 times higher than the average joint noise of about 19%. The vertical dimension has a higher informational content than the horizontal dimension, with a signal to noise ratio of 2 (= 65/32) compared to 0.33 (= 24/73). The horizontal residual terms, which represents the marginal informational content of the vertical dimension once the horizontal dimension is taken into account, is higher than the horizontal signal from only using the horizontal dimension. This result reinforces the superiority of the vertical dimension to convey quality information, while it content a smaller number of items (5 instead of 31). From the vertical residual terms (i.e., 6th row), we see that the vertical dimension of GIs has about 20% (= 13/65) of bias in conveying information about vineyard quality, while this bias due to the preferential treatments between *communes* can be assessed by consumers through the horizontal dimension.

4.4 Alternative GI designation schemes

We estimate the same ordered models with the GIs of 1936 as outcomes. This year corresponds to the creation the French national institute for GI management (INAO). At this period, the vertical dimension of GIs counts only 3 levels as reported in the summary statistics of Table 4 in Appendix:

[4] As the variance of errors is normalized to identify ordered models and the variance of y^* from the data generating process is constant between models, the increase in the total signal and the decrease in total noise are two sides of the same coin, they come from the increase in the variance of the latent quality index predicted from tangible variables.

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

		Effective degrees of freedom for spatial smoothing				
Decomp.	Term	(99)	(295)	(483)	(667)	(841)
Total	Signal	85.30	94.47	96.03	97.31	97.49
	Noise	14.70	5.53	3.97	2.69	2.51
Joint	Signal	69.73	70.15	76.71	75.19	78.62
	Noise	15.60	24.35	19.35	22.15	18.90
Vertical	Signal	54.05	48.77	51.68	56.25	65.18
	Residual	15.68	21.38	25.03	18.94	13.44
	Noise	31.25	45.70	44.36	41.07	32.31
Horizontal	Signal	18.34	16.61	25.60	22.62	23.82
	Residual	51.41	53.56	51.14	52.59	54.83
	Noise	66.99	77.88	70.46	74.72	73.70

Notes: The effective degrees of freedom for spatial smoothing terms in parenthesis show that the columns correspond to model (I) to (V) from Table 1. 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 horizontal residual. The vertical noise equals the sum of the vertical residual and the joint noise and the horizontal noise equals the sum of horizontal residual and joint noise.

Régional < *Village* < *Grand Cru* with respectively 57%, 41% and 3% of actual vineyard plots.[5] The Table of joint significance, the plots of the marginal effects and the spatial smooth effects are reported in Table 5, Figure 8 and Figure 10 in the Appendix. For these older GIs, the control for omitted *terroir* variables is reached for smaller maximum edf of spatial coordinates (bootstrapped F-statistics are reported in the bottom of Table 5 in Appendix, the violin plot is only reported in the RM, p.XX). The hierarchy of the joint significance of explanatory variables is surprisingly comparable with what is obtained for actual GIs. The *commune* and pedology fixed effects, jointly with spatial coordinates have the highest significance, followed by elevation, geology, solar radiation, slope and exposition. The marginal effects of elevation and slope have also an inverted-U pattern with close maximum values and the spatial smoothed patterns are also very close to what is found on actual GIs. Contrariwise, the ordinal superiority measures are more contrasted between *communes* (see Figure 9 in Appendix and Figure XX in RM, p.XX). For given *terroir* characteristics, the

[5] We drop the *communes* of *Chenôve*, *Marsannay-la-Côte*, *Couchey*, *Comblanchien*, *Corgoloin* and *Saint-Romain* as they contains only one vertical level in 1936, so their fixed effects are not identified (see RM, p.XX).

commune where a vineyard is located was a more important determinant of GIs designations in the middle of the 20th century than actually. This is equivalent to claim that the GI designation scheme is increasingly 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.

The first column of Table 3 reports the decomposition of the latent quality index according to the 1936 GIs. The GIs of 1936 have a lower joint informational content than actual GIs with a joint signal to noise ratio close to 1 (= 48/49.5). Simultaneously, the informational content of the vertical and the horizontal dimensions are more balanced, while the vertical dimension stays more informative. The vertical dimension of old GIs has a signal to noise ratio of 0.54 (= 34.4/63.1) compared to 0.32 (= 23.8/73.7) for the horizontal dimension. Because the *commune* delineations have not changed since 1936, the informational content of the horizontal dimension does not change. Note that the lower informational level of the vertical dimension of the GIs of 1936 is not exclusively due to the higher importance of *communes* in GI delineation (i.e., intangible determinants), an immeasurable part of the loss could be attributable to the lower number of vertical items (3 instead of 5 in current GIs). These results indicates significant improvements of the informational content of GIs in the last century, jointly with the decrease of bias from intangible determinants.

We perform different simulations of counter-factual GI designations schemes as reported in columns S.0 to S.VI in Table 3. The six vertical designation schemes are simulated by changing the underlying latent predictions of the quality index (in S.I, S.II and S.III) and by changing the number of vertical items in the GI schemes (in S.IV, S.V and S.VI). The detailed formula and the R codes used to simulate alternative GI designation schemes are reported in RM (p.XX). We do not consider changing the horizontal dimension of GIs as changing the administrative boundaries of *communes* is not policy-relevant. The scheme S.0 is a benchmark scheme that tries to reproduce actual GI designations, by adding simulated designation noises from surrogate residuals to the predictions of the latent quality index. This noised index is mapped to the vertical dimension of the simulated GIs with estimated thresholds and *commune* fixed effects. The second column S.0 in

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	97.49	97.49	97.49	97.49	97.49	97.49	97.49	97.49
	Noise	2.51	2.51	2.51	2.51	2.51	2.51	2.51	2.51
Joint	Signal	48.00	78.21	80.96	79.47	81.52	79.02	79.48	78.87
	Noise	49.52	19.31	16.55	18.05	15.99	18.50	18.03	18.64
Vertical	Signal	34.41	64.60	68.16	69.74	72.59	65.62	66.12	65.48
	Residual	13.59	13.61	12.80	9.73	8.94	13.40	13.36	13.40
	Noise	63.08	32.89	29.33	27.75	24.90	31.87	31.37	32.01
Horizontal	Signal	23.82	23.82	23.82	23.82	23.82	23.82	23.82	23.82
	Residual	24.19	54.42	57.17	55.67	57.73	55.22	55.69	55.08
	Noise	73.70	73.70	73.70	73.70	73.70	73.70	73.70	73.70

Notes: Latent quality index used to simulate GI designation schemes is predicted from model (V) of Table 1, which provides the best fit of actual GIs. The first column reports the informational content of the GIs of 1936. The scheme S.0 is a benchmark simulation which adds surrogate residuals to the latent quality index to mimic actual GIs. S.I drops the random idosynchratic terms, S.II drops the intangible determinants through averaging *commune* effects and S.III drops both random terms and intangible determinants of GIs. Schemes S.IV, S.V and S.VI add a vertical level on actual GIs, respectively for *Bourgogne*, *Village* and *Premier Cru*, by an additional threshold fixed at the mean.

Table 3 shows that the decomposition terms are very close to those obtained in the last column of Table 2. Then, we drop the designation errors from surrogate residuals in S.I, we drop the intangible *commune* effects in S.II and we drop both designation errors and *commune* effects in S.III. The 3 last designation schemes S.IV, S.V and S.VI represent an increase in the number of vertical items of GIs from the actual 5 to 6 items. The *Bourgogne*, *Village* and *Premier Cru* levels are respectively divided in 2 different levels by adding a threshold fixed at the mean of the estimated thresholds used for S.0. Each of these schemes corresponds to the creation of an additional item (like, for example, *Bourgogne supérieur*, *Village supérieur* ou *Premier Cru supérieur*) that allows consumer to distinguish them from the wine labels.

The numbers reported in Table 3 show that dropping the intangible effects associated to *commune* effects is the most important policy to do to increase the informational content of the vertical dimension of GIs. Conversely, reducing the designation noise is more important to increase the joint signal, which corresponds to the assumption that consumers use the information of both dimensions of GIs. These two policy changes of GIs seem to be additively cumulative for increasing the informational content of both vertical and joint signals. In particular, the marginal gain of dropping the *commune* effects is about the same with and without designations noise. Table 3 also shows that dropping the *commune* effect in designation scheme increase more the joint signal than adding a 6th vertical level as in S.III ,S.IV or S.V. Among these latter alternative schemes, we find that splitting the intermediate level *Village* is more efficient, while the differences are small. Note that the measure of the informational content that we propose is not directly related to the value of the GI information, as it treats symmetrically high and low levels of GIs. More research is needed to convert these results in terms of the efficient amount of information to give to consumers, as the information about high levels of GIs would be more valuable as the wine is more expensive. In all cases, these potential improvements from the vertical dimension of GIs have no impact on the informational content of the horizontal dimension that keeps the same order of magnitude among simulations.

5 Conclusion

We present a framework to model the geographical indications (GIs) and disentangle their informational content, i.e., their ability to describe the tangible characteristics of production sites. Applied to the wine-producing region of *Côte d'Or* (Burgundy, France), we find significant effects of both tangible and intangible characteristics of vineyard plots, described respectively as streaming from natural and human outcomes. In particular, the presence of intangible effects is robust to the precise control of the omitted *terroir* variables under the assumption that, as a natural pattern, they vary smoothly in space. This implies that historical elements such as the reputation of landowners or producers, their influence with the decision makers or their collective actions have some persistent effects on GI designation scheme. Nevertheless, this differential treatment between administrative units decreases on the long run of history with the continuous changes in the scheme that have taken place under the control of the French national institute in charge of GIs (INAO).

We interpret this result in regard to the dynamic analysis of strategic transmission information developed by Benabou and Laroque (1992). The authors show that when an information is not fully reliable (because of the human influence on the GI designation process here), the possibility of honest mistakes (because of designation noise here) produces some confusions for consumers. Consequently, market incentives keep the learning process of consumers incomplete and leave a constant scope for market manipulation. According to the authors, this negative economic outcome "is limited only in the long run by the public's constant reassessment of their credibility" (p.947). This analysis is particularly relevant for the signaling of wine quality as we study it here, knowing the difficulties to define and observe the notion of *terroir* and to make agreement about the quality of wines that get the problem of verifying the relevance of the informational content of GIs by consumers worse.

These benefits of the long run history on the informational content of GIs put some doubt on the idea that the flexibility is required in regards to changing preferences of consumers and changing determinants of wine quality (in face to climate change in particular, as argued by White et al., 2009). As a human institution, which requires the involvement of producers with a private information about vineyard and wine quality, the unbiasedness of the GIs signal would probably not be reached spontaneously following changes. Moreover, the regular modifications that would be required to follow the changing preferences or changing environment would increase the correlation between tangible and intangible characteristics and, consequently, decrease the informational content of GIs for consumers. The stability of GIs and their third-party management count probably for a big part of their value that is actually observed on the wine markets.

Our empirical strategy is based on the difference between the assumed spatial continuity of *terroir* and the discontinuity of administrative borders from which we disentangle the tangible and intangible determinants of GIs. Thanks to the small size of vineyard plots on the region, smooth functions of centroids' geographical coordinates (longitude and latitude) allow to control for the fine-scale variations of unobserved heterogeneity from the *terroir*. The estimated spatial patterns of the latent quality index grasped by these functions are not *a priori* exclusively related to tangible characteristics that matter for wine quality. In particular, spatial interactions about reputation or influence between vineyard plots in close proximity on both sides of a *commune* border. We nevertheless find that the main decomposition results about the informational content of GIs and the general results of a signal-to-noise ration equals to 4 are robust to the degree of spatial smoothing used in regressions. Taking into account fine-scale variations of *terroir* is important to estimate the ordinal superiority measures but not determinant of the informational content of GIs.

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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]	59113	0.002	0.003	0.000	0.001	0.002	0.177
Elevation [1000 m]	59113	0.286	0.056	0.210	0.241	0.319	0.505
Slope [degree]	59113	5.772	5.478	0.000	1.556	8.747	36.970
Solar radiation [millions J]	59113	1.060	0.049	0.581	1.048	1.076	1.230
Longitude [degree]	59113	4.837	0.104	4.665	4.740	4.955	5.003
Latitude [degree]	59113	47.060	0.110	46.900	46.980	47.170	47.300
Actual GI [*Coteaux*]	59113	0.164	0.370	0	0	0	1
Actual GI [*Régional*]	59113	0.229	0.420	0	0	0	1
Actual GI [*Village*]	59113	0.428	0.495	0	0	1	1
Actual GI [*Premier Cru*]	59113	0.147	0.354	0	0	0	1
Actual GI [*Grand Cru*]	59113	0.032	0.177	0	0	0	1
1936 GI [*Régional*]	59113	0.565	0.496	0	0	1	1
1936 GI [*Village*]	59113	0.407	0.491	0	0	1	1
1936 GI [*Grand Cru*]	59113	0.027	0.163	0	0	0	1
Aspect [0 – 45]	59113	0.046	0.210	0	0	0	1
Aspect [45 – 90]	59113	0.186	0.389	0	0	0	1
Aspect [90 – 135]	59113	0.362	0.481	0	0	1	1
Aspect [135 – 180]	59113	0.212	0.409	0	0	0	1
Aspect [180 – 225]	59113	0.100	0.300	0	0	0	1
Aspect [225 – 270]	59113	0.044	0.206	0	0	0	1
Aspect [270 – 315]	59113	0.030	0.170	0	0	0	1
Aspect [315 – 360]	59113	0.021	0.142	0	0	0	1

Notes: Topographic variables are computed with a Geographical Information 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 1936 mentioned in the main text. Aspect is discretized according to radians range reported between brakets.

Figure 3: **Distribution of the vertical dimension within and between the horizontal dimension**

Notes: For each *commune* on the y axis (the horizontal dimension of GIs), the bars represent the cumulative vineyard area designated in each item of the vertical dimension represented with different colors. The number reported are the percentage for each *commune* that each vertical item represents.

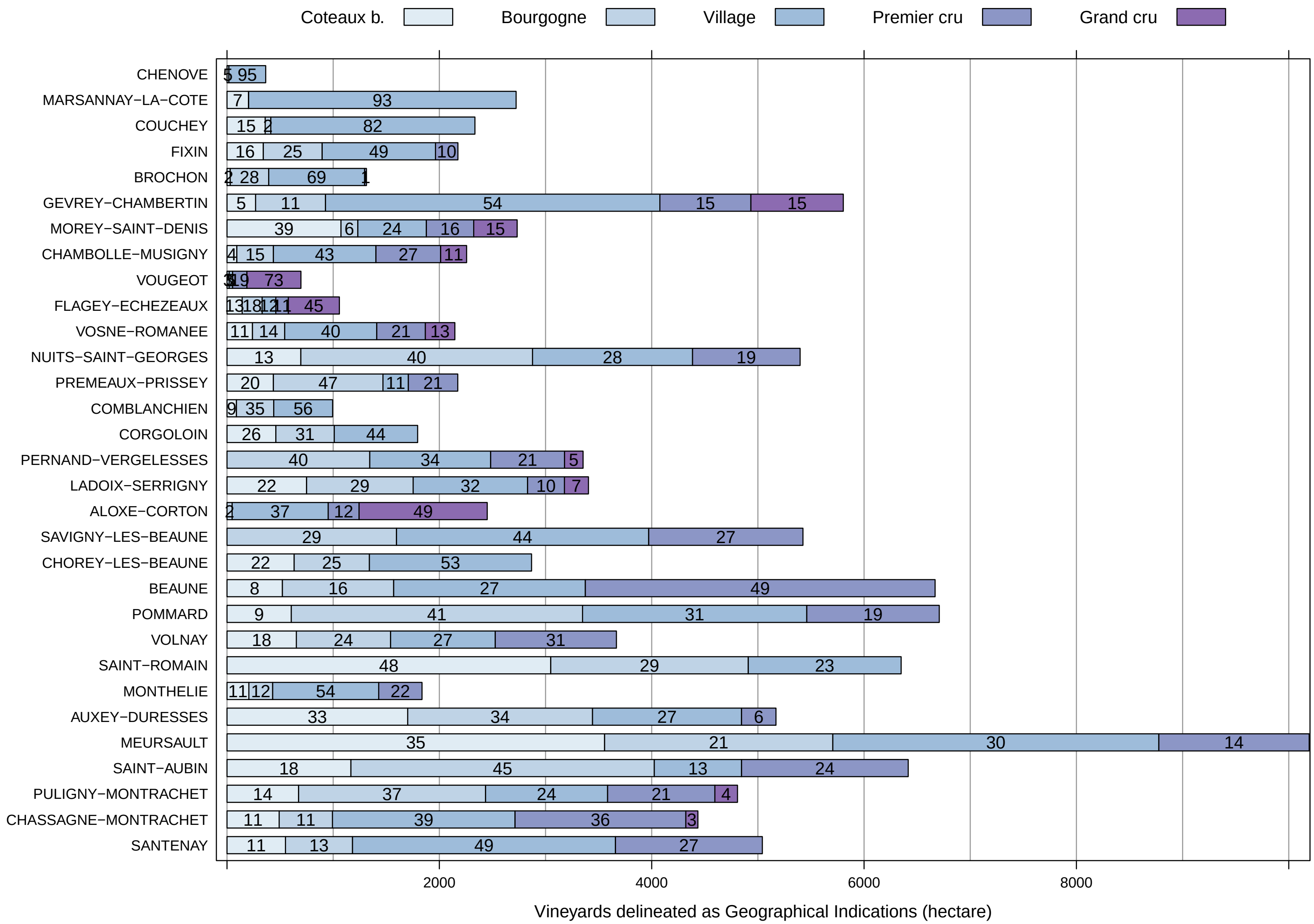

Figure 4: **Nonlinear effects of topographic variables on GI designations**

Notes: Dotted lines represent the quadratic effects from model (0) of Table 1, 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 for spatial smoothing terms. Model (I) to (V) of Table 1 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.

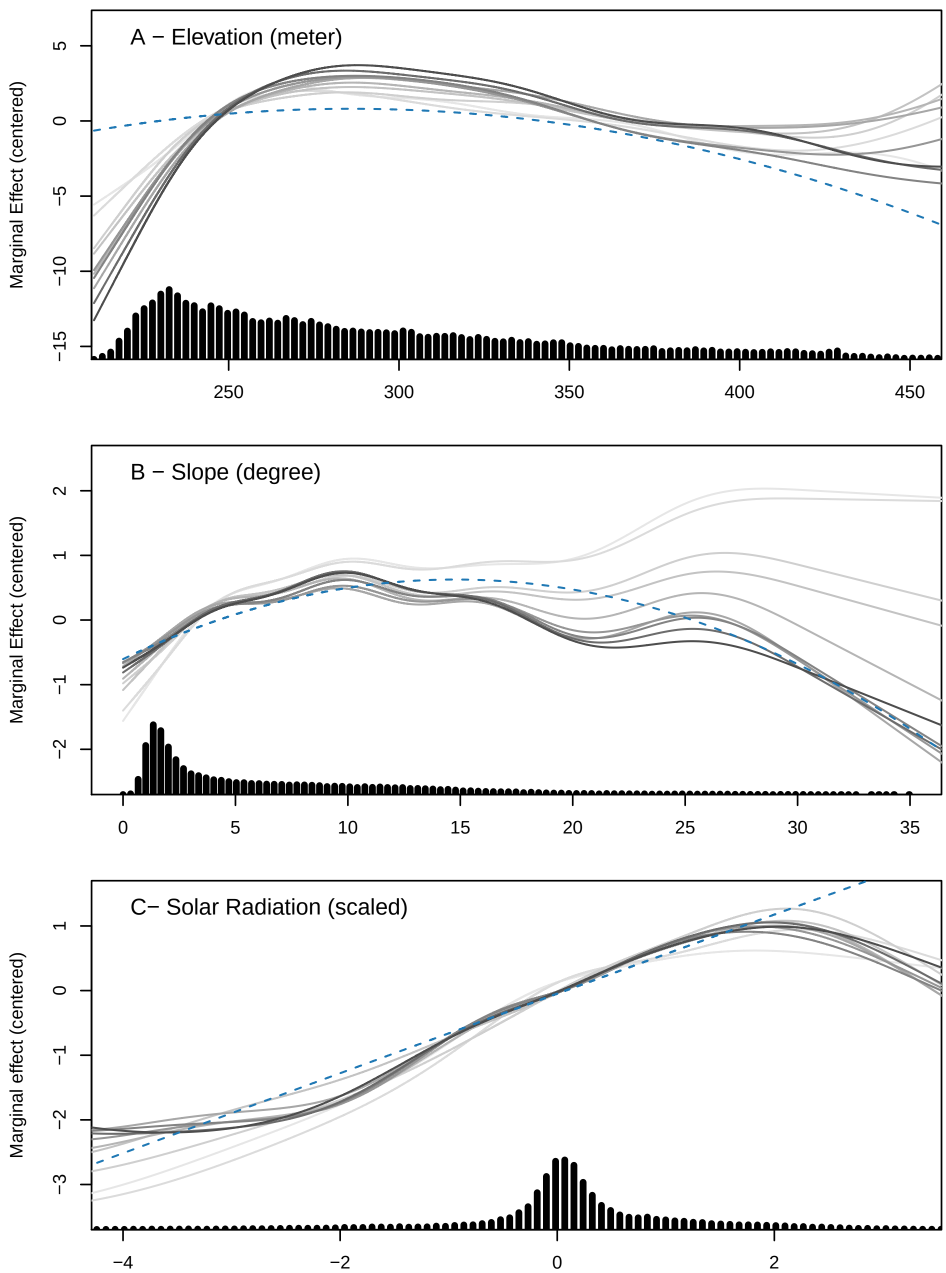

Figure 5: **Spatial smoothed effects from ordered GI designation models**

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 1. 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.

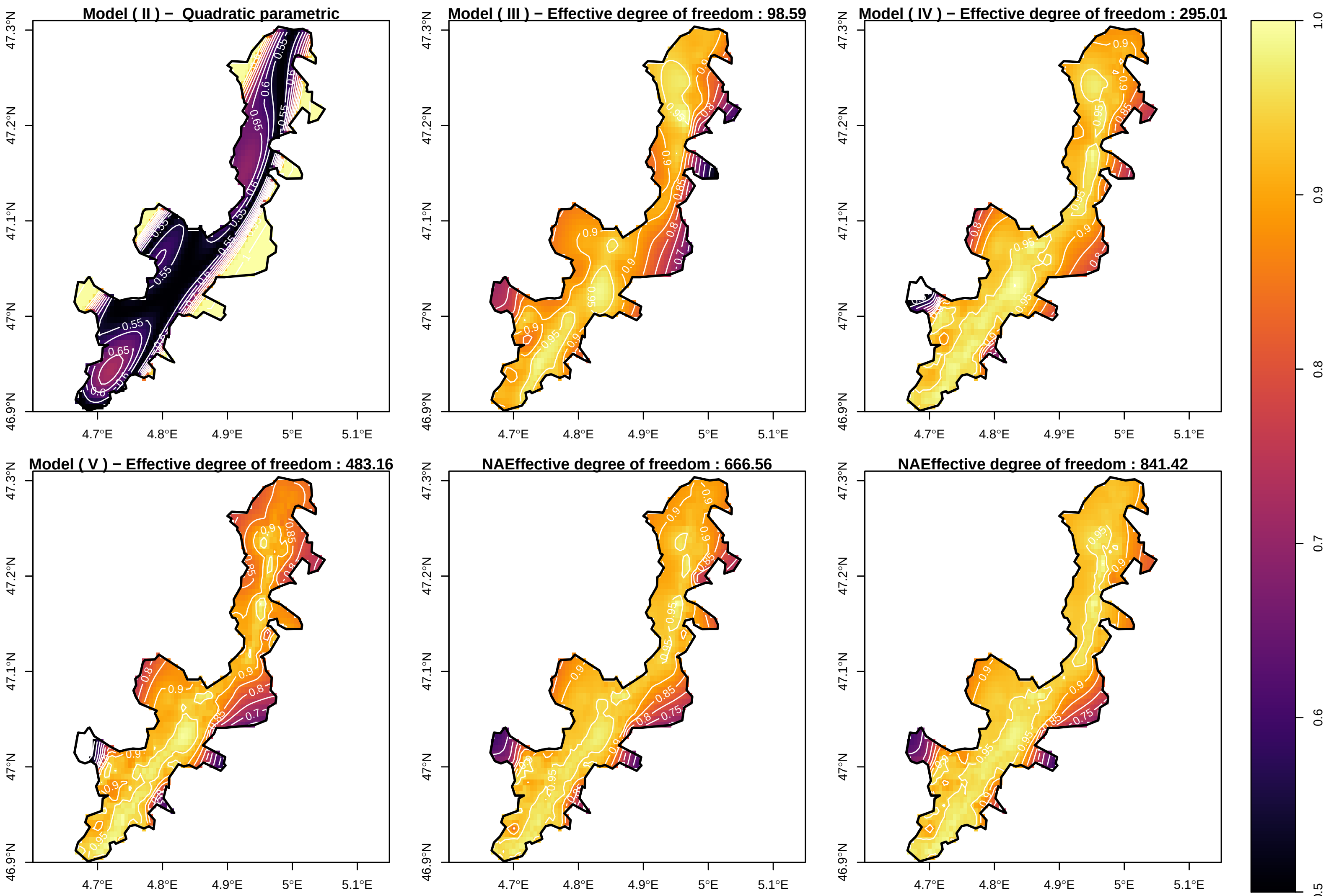

Figure 6: **F-statistics for the diagnostic of correlated residual effects**

Notes: log scale.

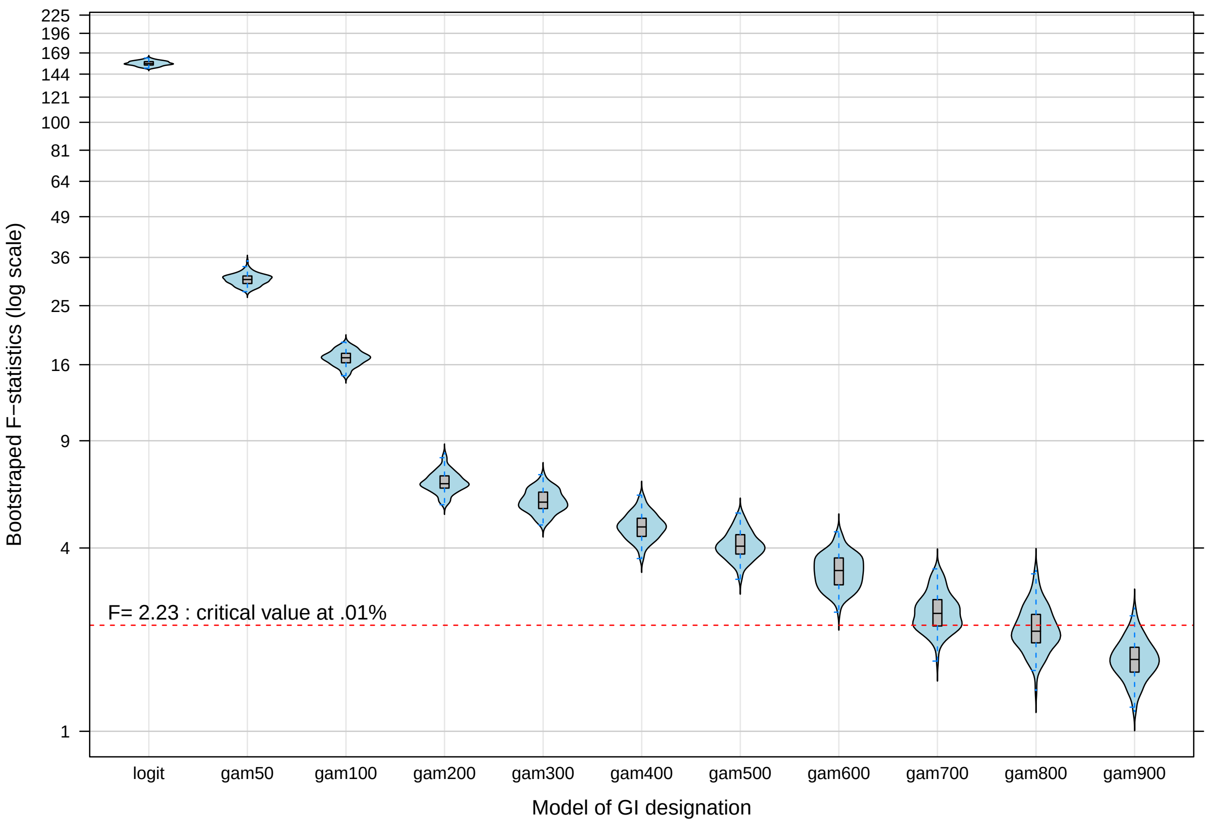

Figure 7: **Correlation between ranking and ordinal superiority measures**

Notes: The ordinal superiority measures come from the mean of Figure 2 in the main text. The average GI grade for each *commune* is the area-weighted mean of GIs coded from 1 to 5. Privilegied *communes* (according to ordinal superiority measures) does not appear to have systematically more than average high GIs.

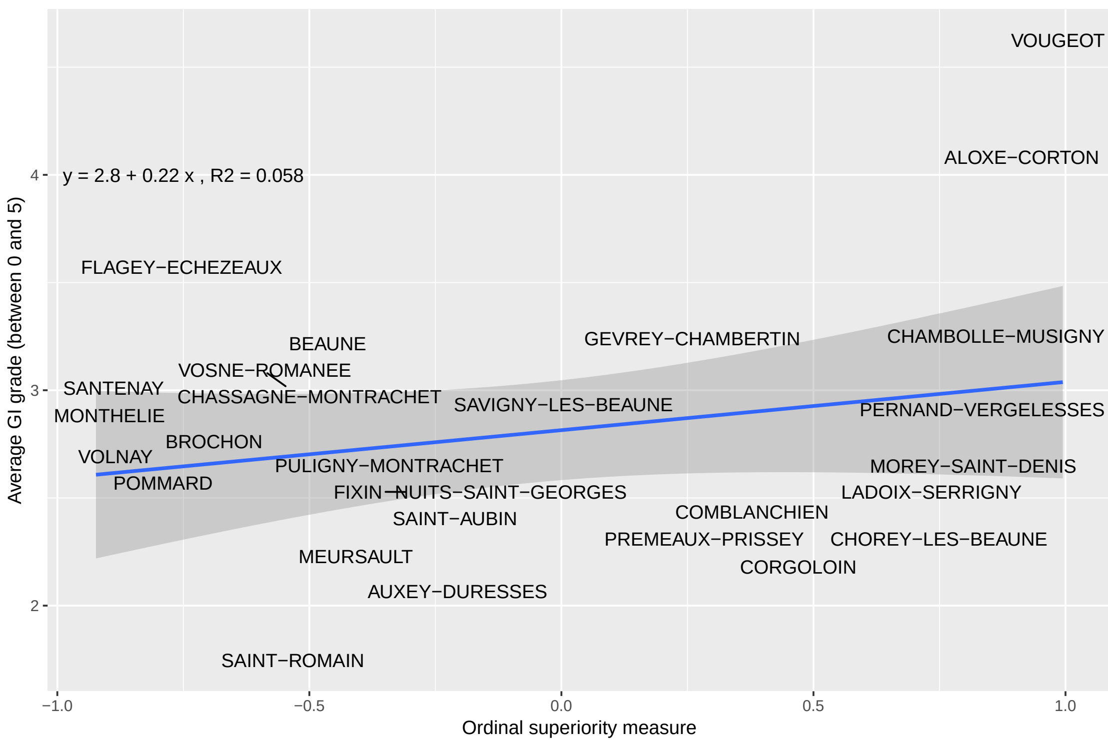

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Table 5: **Joint variable significance for ordered models of 1936 GI designations**

Variable	(0)	(I)	(II)	(III)	(IV)	(V)
Elevation	982.42**	1 196.2**	197.72**	144.79**	265.02**	253.01**
	[2]	[8.826]	[7.628]	[8.232]	[8.659]	[7.42]
Slope	409.2**	478.13**	466.46**	297.06**	190.45**	169.07**
	[2]	[8.754]	[8.729]	[8.743]	[8.774]	[7.493]
Solar Radiation	859.1**	208.81**	139.42**	99.245**	87.676**	142.83**
	[2]	[8.04]	[1.082]	[8.114]	[7.419]	[7.425]
Spatial Coords	5 814.5**	6 760**	14 559**	17 285**	18 979**	20 906**
	[15]	[48.73]	[97.95]	[147.1]	[194.3]	[235.3]
Pedology	4 099.2**	2 820.6**	898.79**	599.37**	537.03**	539.28**
	[13]	[12]	[12]	[12]	[12]	[12]
Geology	982.42**	1 047**	692.13**	710.2**	585.81**	509.32**
	[14]	[14]	[14]	[14]	[14]	[14]
Exposition	287.18**	177.45**	131.87**	58.532**	43.002**	64.03**
	[7]	[7]	[7]	[7]	[7]	[7]
Commune	8 600.1**	3 720.9**	2 639.2**	2 177.2**	1 831.7**	1 264.7**
	[25]	[25]	[25]	[25]	[25]	[25]
Nb Observ.	50 000	50 000	50 000	50 000	50 000	50 000
McFadden R^2	44.63	49.68	61.32	66.06	69.82	72.36
Pc good pred.	81.86	83.74	87.88	89.84	91.35	92.21
Akaike IC	45	41.21	31.82	28.09	25.12	23.12
Surrogate F	92.72	8.45	5.4	3.43	2.75	2.03

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 (df= 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 1935. 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.

Figure 8: **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.

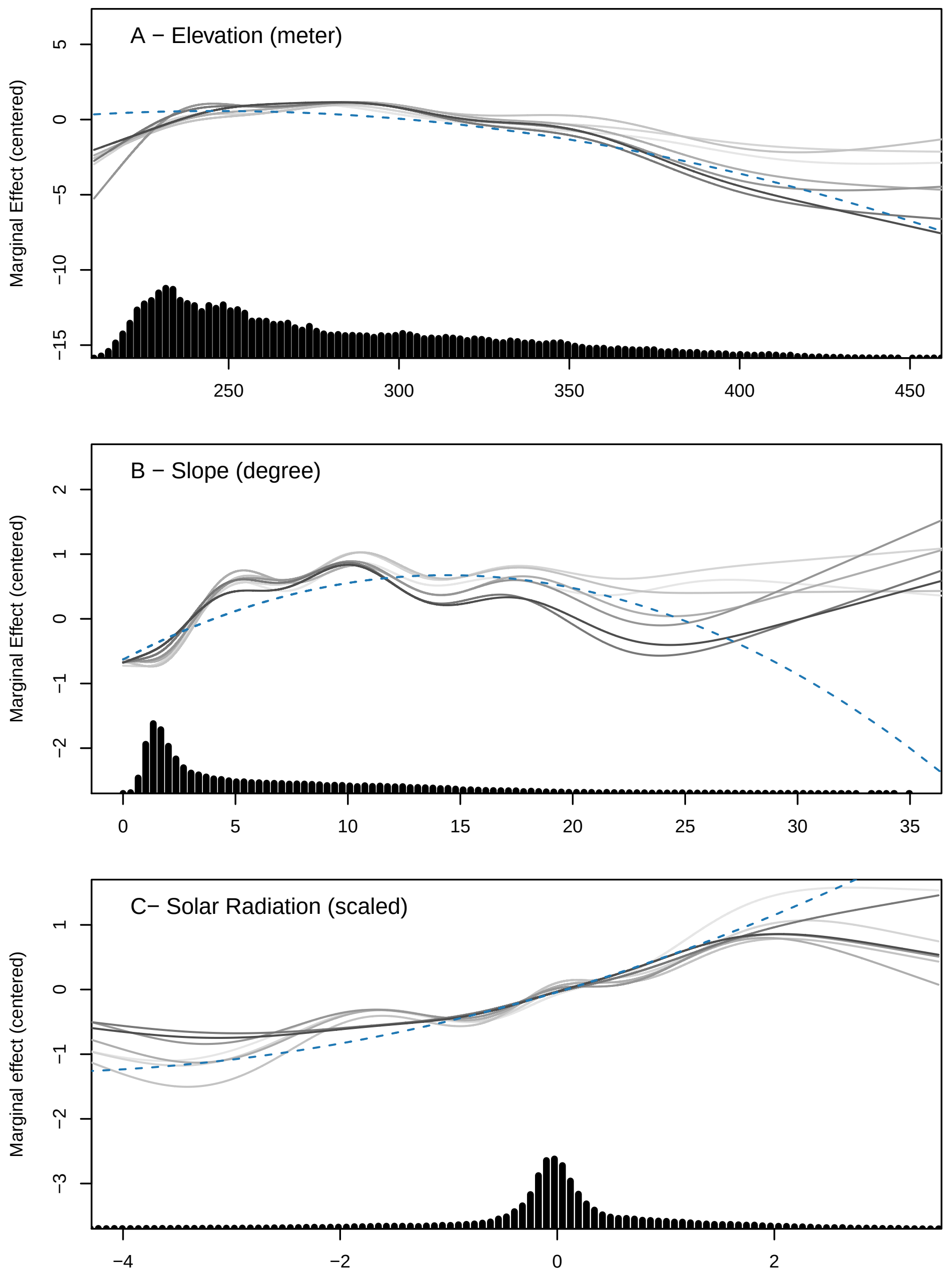

Figure 9: **Spatial smoothed effects from 1936 GI designation models**

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

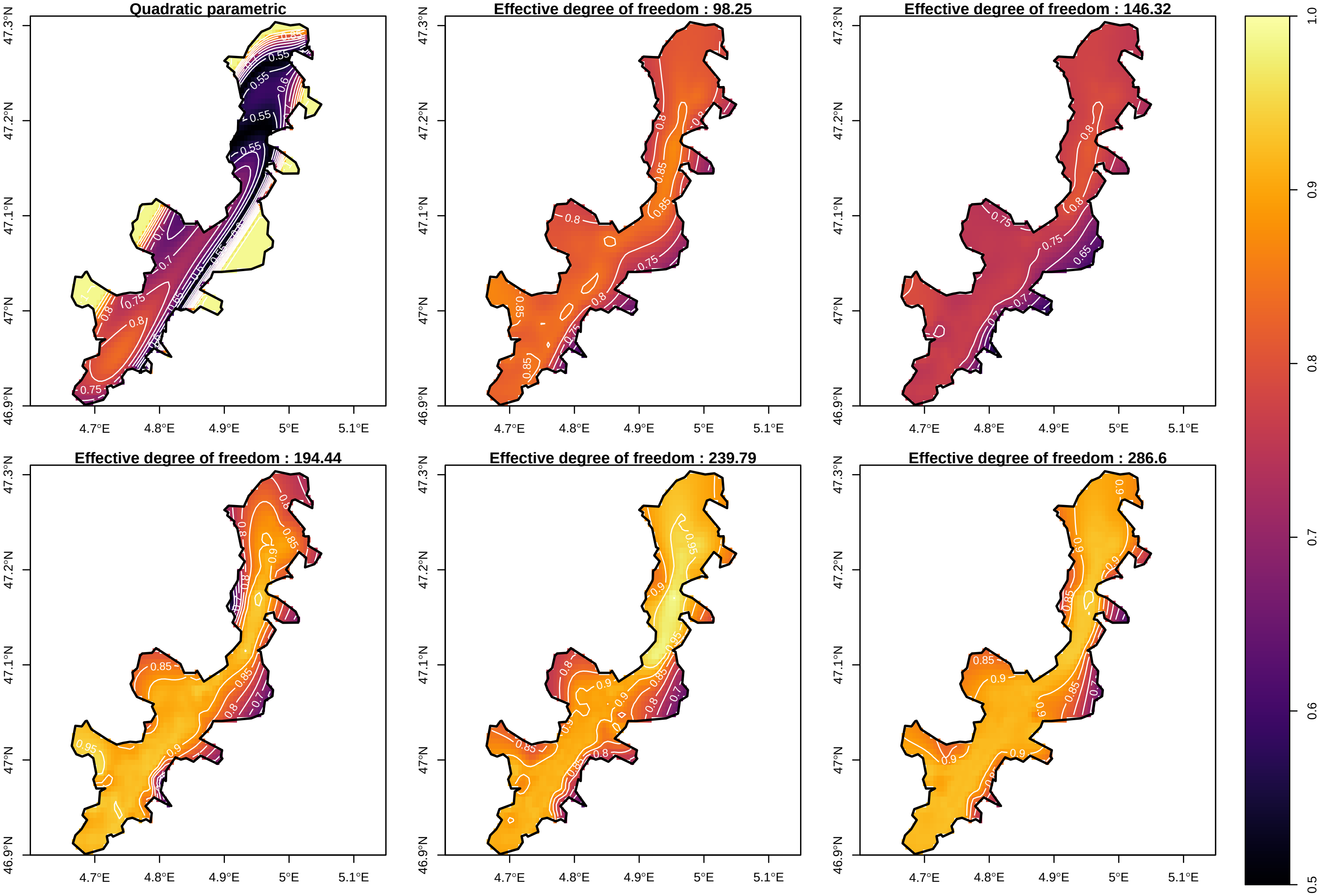

Figure 10: **Ordinal superiorty measures for the *communes* in 1936 GI designation scheme**

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.