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. We define the informational content of the GI proxy as its ability to describe the tangible characteristics of a production site, instead of intangible factors from the political bargaining on the designation process. Empirically, we disentangle this informational content of wine-related GIs for the *Côte d'Or* region of Burgundy, France. Due to their hierarchical and nested structure, GIs have high informational content while we found some persistent lobbying effects. We apply the signal decomposition to alternative wine classifications from history and counterfactual simulations to show significant gains of efficiency in the last century and provide 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 market relations (Josling, 2006; USTR, 2017), but distinguishing good quality products from those of bad quality is recognized as being fundamental for consumers and producers when the quality cannot be assessed before deciding to buy or sell (Akerlof, 1970; Nelson, 1970). Thus, one major point in the debate is the extent to which geographical indications (GIs) provide information about product quality (Winfree and McCluskey, 2005; Yu et al., 2017). We studied this informational content of GIs through the econometric relationship between the natural and human characteristics of the vineyards and wine-related GIs of the *Côte d'Or* region (Burgundy, France).

The main objective of this article was to identify the informational content of current, past, and simulated GI designation schemes for an exhaustive data set of 60 000 vineyard plots. We defined the informational content as the ability to describe the tangible characteristics of production sites, and measured it by the variance of a latent quality index according to the principle that more informative signals lead to greater variability (Ganuza and Penalva, 2010). We propose disentangling tangible information from intangible information with ordered logit models explaining the GI hierarchy by the natural and administrative attributes of vineyard plots. The first set of variables relates to the tangible 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 variables relates to the political bargaining that have historically impacted the GI designation process, modeled with municipality-specific thresholds. Through the reputation of landowners, their influence with decision-makers or their collective actions, some administrative units have had privileged treatment that made their vineyard plots higher in the GI hierarchy than similar plots from another administrative units. We formally show that significant threshold variations bias the signal, and decrease the efficiency of GI designation schemes. Moreover, using historical data, we found this bias was decreasing on the last century, and we drawn GI simulations to show how to improve the informational content of GIs in the future.

Knowing the geographic co-variations between tangible and intangible characteristics, and the difficulty controlling for all tangible variables that impact vineyard quality (i.e., *terroir* variables), the major empirical challenge at hand is to disentangle these two sources of variations in the GI signal. In effect, wine quality strongly depends on the natural conditions prevailing at production sites (Jackson and Lombard, 1993; Bokulich et al., 2014; Knight et al., 2015; van Leeuwen et al., 2018). Even with fine-scale data as we used here, all the *terroir* variables are not (and probably never will be) actually observable for econometric or statistical analysis. One can think of the need to control for local climate patterns (Labbé et al., 2019), soil microbes (Bokulich et al., 2014; Gilbert et al., 2014), or any other form of spatial heterogeneity (Pickett and Cadenasso, 1995) that could confound the lobbying effect associated to the administrative location of a given vineyard plot. We estimate semiparametric ordered generalized additive models (OGAMs) that exploits the precise location of vineyard plots to control for the unobserved spatial heterogeneity through fine-scale smooth functions of geographic coordinates (Wood et al., 2016). This identification strategy is based on the structural difference between the assumed spatial continuity of *terroir* and the discontinuity of administrative borders according to the axiom that nature does not make jumps (as in any regression discontinuity design). This original estimation method is shown to significantly outperform more classical approaches that use polynomial functions of geographic coordinates both in terms of goodness-of-fit and of causal inference validity.

Wine is an experience good well-suited to studying 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 for wine production has a long history dating back to the Middle Ages, with numerous modifications to the actual scheme (Jullien, 1816; Morelot, 1831; Lavalle, 1855; Danguy and Aubertin, 1892; Garcia, 2011; Wolikow and Jacquet, 2018). Thus, the GIs that we study are based on the fine-scale location of the vineyard plots, with both a vertical and horizontal dimension of differentiation. The vertical dimension is a quality ranking with five levels: *Côteaux Bourguignons* < *Bourgogne Régional* < *Bourgogne Village* < *Premier Cru* < *Grand Cru*. The horizontal dimension is 1 of the 31 *communes* (i.e., administrative municipalities) without an explicit hierarchy between them, such as *Beaune*, *Gevrey-Chambertin*, *Pommard*, or *Fixin*. Such a hierarchical and nested structure is common 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 horizontal dimension also corresponds to the spatial scale at which the lobbying was made for GI designations (Jacquet, 2009). This conjunction between GI and administrative scales is not particular to Burgundy, as similar patterns are found for Bordeaux (Fourcade, 2012). Moreover, GIs could be presented as cartels with embedded quality signaling and quantity control, both determined at the same scale (Marette et al., 1999; Marette and Crespi, 2003).

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[1] that we study is based exclusively on natural vineyard characteristics, in contrast to typical frameworks in which quality is strategically determined 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 identification of the informational content of the quality signal easier and allows more transparent analysis of the role of lobbying in the information conveyed by actual GIs put on the labels of wine bottles. We argue that the long history of GI designations allows us 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) that is reasonably independent from the actual individual practices or skills of producers. In addition, the vineyard quality index relies exclusively on the unchangeable location of production sites, which precludes spurious correlations from the assortative matching between quality and name as in Tadelis (1999). Because a GI name cannot be separated from its associated vineyard quality based on tangible characteristics, the GI information put on the label by producers is not related to their own characteristics, which is another source of tangible information not studied here.

[1]We use the concept of vineyard quality index in reference to the hierarchical structure of GIs that is modeled from a continuous latent variable crossing ordered thresholds. This quality is revealed from the GI designation scheme.

A large body of literature about wine quality disclosure is concerned with expert reviews and the use of this information by consumers. Such ratings have been shown to have mainly short-term effects, both on the demand for (Friberg and Grönqvist, 2012) and the price of wines (Ali et al., 2008; Dubois and Nauges, 2010). The major problems with their aggregation (Ashenfelter and Quandt, 1999; Cardebat and Paroissien, 2015) and consistency (Cao and Stokes, 2010; Bodington, 2017) create some doubts about their own interest to consumers (Ashenfelter and Jones, 2013). Ratings by experts, judges, or websites have also been shown to be significantly divergent from historical GIs for Bordeaux wines (Thompson and Mutkoski, 2011), probably because of their fundamental differences. Ratings are exogenous year-to-year sources of information and not directly comparable to 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, which is not a concern for expert review (Hollander et al., 1999). This could have unintended economic consequences, such as counter-signaling, in situations in which the certification is not adopted to signal the high quality of products (Bederson et al., 2018). This is probably not the case for 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, wine producers and sellers in the region comply with the GI requirements such as the compulsory indication of GIs as the main informational message on wine labels.

We finally propose to evaluate the informational content of GI designation in terms of tangible attributes from an original framework based on variance decomposition (Bowsher and Swain, 2012). This allows to decompose the vineyard quality index into a part that is described by the vertical dimension of GIs, the part that is described by the horizontal part of GIs, and a noised part that is not described by GIs. The application of this framework to our empirical results shows high informational content of both dimensions of actual GIs, with 4-times higher signal variance than noise variance (corresponding to an R^2 of ~ 80%). The vertical part of the GIs is found to be more informative than the horizontal part, even if we control for lobby effects. In addition, applying the same signal decomposition on historical GIs from 1936 shows that the informational content of the vertical dimension has slightly increased in the last century, through continuous evolution of GI designation schemes by the national institute in charge of geographical indications (INAO). This historical increase of the informational content of GIs illustrates the theory developed by Benabou and Laroque (1992) regarding strategic information transmission. We found that some producers or landowners could have profited from private information on vineyard quality manipulating the GI signal and extracted rents through undeserved high rating for vineyards in their administrative units. However, the hierarchical GI certification appears increasingly less biased on the long run, or more efficient in the sense of De and Nabar (1991); the probability that two identical vineyard plots in different *communes* have the same classification is increasing. We also found that a monopolistic certifying party discloses useful information in the form of rank orderings, as predicted by Guerra (2001). This contrasts with models in the literature that found weak, if any, welfare gains associated with 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 current economic importance in Burgundy come from their long history and independent management by INAO.

2 Context and data

2.1 The *Côte d'Or* region

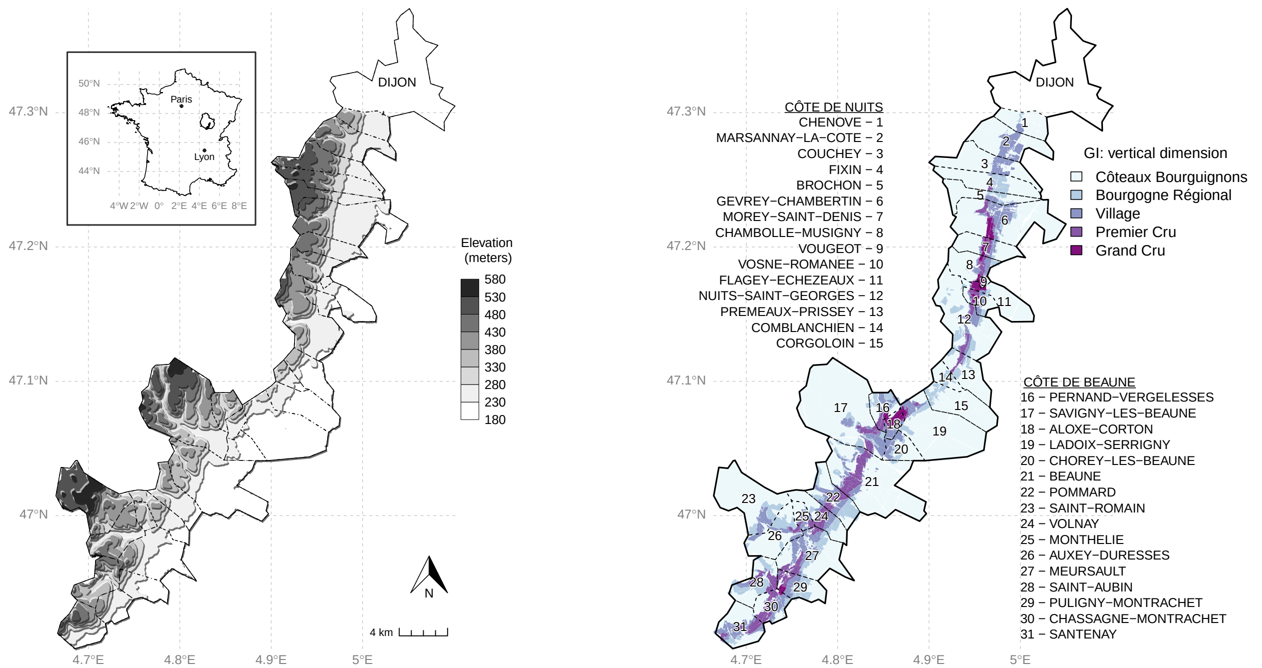
The *Côte d'Or* (literally, slope of gold) is a northeastern French administrative unit (*département*) included in the larger wine-producing region of Burgundy (Figure 1). We studied a subset of the most famous vineyards in this region (named *Climats* locally), which was granted World Heritage Status by UNESCO in 2015 (https://whc.unesco.org/fr/list/1425). The area under consideration is a strip of approximately 65 km from the north to south and 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) results in some rounded patterns with fine-scale variations in 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 harvest are major determinants of the grape maturity cycle, sugar content, and the 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 generally older and thinner). The longitude position of vineyards indirectly correlates with precipitation on the area, as a 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 an indirect effect through its correlation with the wind, which is known to have strong importance for dry grapes and to concentrate aromas. Note that we do not use climate data due to their typical coarse scale, which makes them unsuitable to the narrowness of our study area and the tiny size of vineyard plots. For example, historical climate data from *Météo-France* are usually available at the 8 km resolution where the vineyard strip depicted in Figure 1 is at most 5 km large. Moreover, topography (available at a 5 m resolution in our data) is regularly used to downscale climate observations to artificially increase the resolution of climate variables. Using such interpolations to measure climate variables are unappropriated to our econometric analysis as they produce a strong redundancy with raw topographic variables.

2.2 Historical context

Some archaeological evidence located the first vineyards in the region in antiquity (Garcia, 2014). The first written evidence dated from the 7th century, with abbey archives describing the donation of vineyards between groups of Benedictine monks whose names are still used in actual GI classifications (e.g., *Abbayes de Bèze* or *de Saint-Vivant*). The origin of Burgundy's vineyard

Figure 1: **Topography and geographical indications (GIs) of the vineyards of the *Côte d'Or***

Notes: The 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 the 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 horizontal dimension of GIs.



classification can be found in the work of the Cistercian monks who delineated plots of land that produced wine of distinct character (12th century according to Lavalle, 1855). However, the first exhaustive spatial delineation of the region was an administrative separation of *communes* following the decree of 1789 after the French revolution. What we consider the horizontal dimension developed 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 of vineyard quality was created by Lavalle (1855), a Professor of Natural and Medical History at Dijon University, inspired by the writings of other scientists, particularly Jullien (1816) and Morelot (1831). He providesd a ranking of vineyards on four levels, from the best *Tête de Cuvée* to *Première*, *Deuxième* and *Troisième Cuvées*. The interaction between the horizontal and vertical dimensions is of particular importance in his work: "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" (p.162, translation from the author).

These two spatial delineations were merged in an 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 used extensively as a legal basis to regulate wine trade in the region. It paved the way for court trials, collective actions, and lobbying for the right to use the names of both dimensions that are not yet called GIs. The capacity of producers and owners to negotiate or influence judgments and delineations is determined by the reputation of the *commune* to which they belong (Jacquet, 2009). The author showed that there was unequal treatment between *communes* in terms of the vertical differentiation of vineyards, whereas the separation between advantaged and disadvantaged *communes* was not well established: "the reputation of the wine-growing *communes* of Burgundy is not an objectively measurable phenomenon" (Jacquet, 2009, p.189; translation by the author). In 1936, a French national institute, INAO, was created to legally manage what became the GIs of all wine regions of the country on a common legal basis. In Burgundy, the first official GIs came from the map of 1860 and the jurisprudence occurring thereafter. Some modifications were then implemented during the 20th century with the creation of *Premiers Crus* in 1943 and the fine-scale digitization of plot-level delineation in a Geographical Information System after 2000. The GIs have been called *Appellation d'Origine Contrôlée* in France since 1936, corresponding to Protected Designation of Origin for the European Union (`https://ec.europa.eu/agriculture/quality/schemes_en`).

2.3 Current GI designations

Current GIs are a nest between a vertical quality ranking of five levels and a horizontal differentiation scheme through 31 administrative municipalities (*communes*, Figure 1, right panel). The highest quality vineyards are labeled *Grands Crus*, each of which has its own independent appellation name (e.g., "*Clos de la Roche*" or "*Chevalier-Montrachet*"). There are 32 *Grands Crus* in the area, 8 in the *Côte de Beaune* (southern part) and 24 in the *Côte de Nuits* (northern part), with a total area of 472.6 ha (4.2% of acreage with GIs). In the hierarchy, it follows 404 *Premiers Crus* in the area that have to be associated with their *commune* names on wine labels (e.g., "*Les Chaumes*" from *Vosne-Romanée* or "*La Chapelle*" from *Auxey-Duresse*). There are 1619 ha of *Premiers Crus* in the *Côte de Beaune*, accounting 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 a name (e.g., *Pommard Village* with name and *Côte de Nuits Village* without), accounting for 2500 ha (31.75%) in the *Côte de Beaune* and 1563 ha (46%) in the *Côte de Nuits*. The vertical differentiation of GIs ends with *Bourgogne Régional* (2788 ha, 24.73% of the GI area) and *Coteaux Bourguignons* (1899 ha, 16.85%), which are sometimes grouped in the same *Régional* level.

The picture of current GIs in the area is not complete without mentioning of the complexities that exist between the vertical and horizontal dimensions, which could lead to difficulties for consumers distinguishing their respective informational content. Note that the terms *commune* and *village* are often used synonymously for the administrative delineations in rural areas of France, whereas the first is related to the horizontal dimension and the second to the vertical dimension. In addition, the same name as a vertical levels from *Grand Cru*, *Premier Cru* or even *Villages* can be found in 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*. Furthermore, at the beginning of the 20th century, 10 *communes* 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*, which share *Grand Cru Montrachet* and have chosen to add it to their administrative names. However, the legal obligation to mention the vertical level *Grand Cru*, *Premier Cru*, *Village*, *Régional* or *Coteaux*

Bourguignons as the main information on wine bottle labels suggests that this information is clearly identifiable by consumers.

2.4 Summary Statistics

The precision of econometric estimations for disentangling the sources of variation in GIs depends on a balanced distribution of tangible variables and vertical levels 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, whereas 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 4 in the Appendix presents the acreages and shares of each vertical level for each horizontal *commune*. Every *commune* has at least two of the five possible vertical levels. The majority of *communes* count three different vertical levels, with an average number of 3.87 levels per *commune*. Vineyards ranked as *Village*, *Premier Cru* and *Grand Cru* are present in 28, 24, and 11 *communes* accounting for 90%, 77.4%, and 35.5% of all of them, respectively.

Table 4 in the Appendix presents the summary statistics about the exhaustive plot-level data that we use on the 31 *communes* of the region. For approximately 60 000 vineyard plots of a tiny average size of 0.2 ha (∼ 0.5 acres), the elevation is distributed between 200 and 500 m, with an average of 286 m. Slopes are an average 5.73 degrees wit high standard deviation (the coefficient of variation is ∼ 100%). The solar radiation is distributed from 0.58 to 1.23 million Joules, with an average of 1.05 million J. To add flexibility to the econometric estimations, the exposition variable is discretized in eight 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. Table 4 also shows the current distribution of the vertical dimensions of GIs and the distribution in 1936 when the INAO was created. We also use additional geological and pedological variables as fixed effects to control for sub-soil and soil characteristics. Because such variables are not central in the empirical strategy that we propose, we do not report them here. Interested readers can access these variables through the Replication Material (RM) from the link on the title page of this article.

3 Model of GI designation

First, we present the structural model of GI designation that is assumed to be the data-generating process. Next, we discuss the empirical challenge of separating the *terroir* effects from the intangible influences and the specification procedure that we propose. Finally, we describe the decomposition of the vineyard quality signal from the GI information available to consumers.

3.1 Structure of GIs

The fine-scale variation of natural characteristics (i.e., *terroir*) between vineyard plots is the basis of the GI classification scheme. The vineyard quality index is assumed 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 sum between the quality index and idiosyncratic random designation noise ξ:

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

The mapping between tangible *terroir* characteristics X^* and the objective quality index represents the cumulative knowledge from informed people that have contributed to the vineyard classification throughout history. At this stage, we consider the latent variable as an unbiased, though imperfect because of designation noise, 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 quality signal. The presence of designation noise is more generally due to the absence of a deterministic rule between vineyard characteristics and GIs; thus, the orthogonality between the designation noise and X^* is more a definition than an assumption. Determining the correlation between this quality signal and consumer preferences about wines and the related question of the value of GI information would require economic data about wine prices or consumer' surveys that we did not have here. Instead, we evaluated the relevance of the GI information according to this long-term 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 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:

$$y = j \quad \Leftrightarrow \quad \alpha_{j-1}^c < y^* < \alpha_j^c, \quad \text{for} \quad j = 1, \dots, 5, \tag{2}$$

where $\alpha_0^c = -\infty < \alpha_1^c < \cdots < \alpha_5^c = +\infty$ 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, and represents the horizontal dimension of GIs by municipality-specific thresholds. The variation in the thresholds between *communes* corresponds to the differential treatments that have been documented by historians and presented above. For example, a *commune* c_1 receives 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: $\mathbb{E}(y^* \mid y = 4, c = c_1) < \mathbb{E}(y^* \mid y = 4, c = c_2)$.[2]

Within a given *commune*, the ordered structure of GIs provides an efficient certification process as defined by De and Nabar (1991); the probability that a vineyard is classified into at least its own quality category is higher than the probability that another vineyard with lower quality will be classified into at least that category. For two vineyard plots, 1 and 2, with differentiated tangible

[2]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 article, which has the same rationale as the orthogonality of designation noise in regard to *terroir* variables presented above and even implies it by the law of iterated expectations: $\mathbb{E}(\xi \mid X^*) = \mathbb{E}[\mathbb{E}(\xi \mid X^*, C) \mid X^*] = 0$.

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 $-\xi$. The efficiency of the GI designation scheme is also verified in the absence of threshold variations between *communes* (i.e., if α_j^c is constant among c for each j), which is equivalent to lack of bias in the GI signal.

The efficiency property and 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 lesser quality vineyard plot 2 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 given to *commune* c_2 is a source of bias in the GI classification that contradicts the efficiency of the vertical GI differentiation ($\alpha_{j_1}^{c_2} > \alpha_{j_1}^{c_1}$ is a necessary condition to have a higher probability for the vineyard plot 2 compared to 1). In particular, the probability that another given plot from another *commune* (e.g., plot 3 from *commune* c_3) of the same quality as plot 1 but higher in the GI classification scheme is equal 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. This measure of ordinal superiority determines the bias in the 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 (e.g., c_1 in Equation 4), this implies $30 \times 5 = 150$ measures of ordinal superiority. Therefore, we assume an additive separability between the horizontal and vertical intercepts to simplify the comparison, $\alpha_j^c = \alpha_j - \mu_c$. The ordinal superiority measure between two identical 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 the number of ordinal superiority measures to be divided by 5. 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 GI signal, and the ordinal superiority measures provide estimate the size.

3.2 Ordered Generalized Additive Model

The estimation of the unknown function $q(\cdot)$ that relates tangible attributes of vineyards to the vineyard quality index is subject to two 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. These unobserved effects for the econometrician are taken into account in GI designations by observations in 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 of these *terroir* variables be observable, which is unfortunately not the case and probably never will be. Instead, we propose estimating an Ordered Generalized Additive Model (OGAM, Wood et al., 2016; Wood, 2017; Kammann and Wand, 2003; Lausted Veie and Panduro, 2015 for econometric applications) that allows a semiparametric specification of the effect of each observed tangible variable and to control for omitted *terroir* variables through bivariate smoothing of geographic coordinates. This identification strategy is based on the definition of *terroir* as the full set of natural variables that impact vineyard quality index. As they originate 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 administrative delineations of *communes* related to intangible human determinants of GIs.

Consider that we only observe the realizations of a subset $X_i \subset X_i^*$ of all *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 geographic coordinates. By noting C_i the row vector of dimension 31, with the typical element c_{ih} equal to 1 if vineyard i is located in *commune* h and zero otherwise, the specification of a logistic distribution for the reduced-form errors leads to a classical parametric ordered logit model that can be estimated by maximum likelihood:

$$\text{Prob}(y_i > j \mid X_i, C_i) = \Lambda[B(X_i)^\top \beta + C_i^\top \mu - \alpha_j], \tag{5}$$

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 for the effects of all observed tangible variables X_i, we specify them through a series of functional transformations noted as $B(\cdot)$ with an associated vector of coefficients β. From an initial set of K observed tangible variables (with $K < K^*$), the series and 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 example, 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.

The results presented below will show that polynomial specifications have limited performance in accounting for the complex interactions between natural characteristics of vineyards and the continuous quality index used in GI designations. Thus, we turned to semiparametric thin plate regression splines that have optimal smooth approximation properties (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 overfit. Accordingly, the complexity of the spline transformations is determined endogenously for a given maximum basis reduction for each variable through a quadratic penalty. The penalized deviance is minimized by penalized iterated weighted least squares and the smoothing parameter is estimated using a separate criterion from the 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 by the effective degrees of freedom that account 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 a source of additional uncertainty, whereas Wood et al. (2016) provide some corrections for inference and traditional goodness of fit measures, such as Akaike Information Criteria (AIC). Unfortunately, goodness of fit measures give little guidance about the causal inference of *communes* effects that measure the intangible effects that bias the GI signal. We propose to determine the sufficient level of spatial smoothing with an heuristic procedure based on auxiliary regressions and surrogate residuals recently defined by Liu and Zhang (2018) (see Appendix A.1 for details).

3.3 Informational content

The formal analysis that we develop about the informational content of GIs is based on the framework of Ganuza and Penalva (2010) for information signal ordering, in addition to the variance decomposition formulas provided by Bowsher and Swain (2012). We consider GIs as an information structure, i.e., a joint distribution between the states of the world (vineyard quality index) and the GIs. We propose evaluating the extend to which the observation of y and c allows consumers to recover vineyard quality, assuming that a more informative signal leads to a more dispersed distribution of conditional expectations. Contrary to Ganuza and Penalva (2010), we measure the dispersion through conditional variance of the signals, this leads to four nested variance decomposition:

$$\textit{Total decomposition :}\ \mathbb{V}(y^*) = \mathbb{V}[q(X^*)] + \mathbb{V}[\xi] \tag{6}$$

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

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

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

The *total decomposition* in Equation 6 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 noise ξ. This decomposition represents the maximum informational content that any GI signal can achieve for the data-generating process under consideration. This corresponds to the case in which the continuous quality grade is conveyed to consumers as a continuous score on wine labels.

The *joint decomposition* in Equation 7 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 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 $q(X^*)$ was 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.

The *vertical decomposition* in Equation 8 separates the *joint signal* into 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 for 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 limited cognitive ability in understanding 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 would be zero. In such a case, the vertical dimension would be unbiased and provide all of the relevant information about quality available to consumers. The only loss in information would be due to the discretization of the continuous quality index and the *joint signal* would be equal to the *vertical signal*.

The *horizontal decomposition* in Equation 9 is symmetric to vertical decomposition, as it defines a *horizontal signal* and a *horizontal residual*. This means that decomposition of the *joint signal* between a *vertical* and *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 dependent on the *communes*. In the absence of any 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. Thus, 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.

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 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 is the set of 31 *commune* dummies that represent the intangible determinants of lobbying effects on GI designations. This set is closely followed by the pedology fixed effects and the polynomial transformation of spatial coordinates that controls for the effects of the 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 that is slightly higher for tangible variables than intangible variables. The non-linear effects of the three topographical variables on the latent quality index are reported in Figure 5 of the 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 linearly increases and southern exposition provides the highest marginal probability of a high GI classification (see the Replication Material, RM p.XX, from the link on the title page of this article). The top-left panel of Figure 6 in the Appendix shows the marginal effects of spatial coordinates on the latent index. The third-order parametric specification with full interactions produces some smooth ellipsoidal 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 report the same significance statistics from OGAMs with increasing complexity in the spatial smoothing terms from left to 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 13, 14, 7 and 31 degrees, respectively. Increasing the complexity of the spline series of spatial coordinates increases 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 patterns of GI designations are increasingly grasped by spatial coordinates at the expense of other explanatory variables. Figure 5 in the Appendix shows the comparative advantage of OGAMs over parametric model (0) in estimating the marginal effects of each explanatory variable. Panel A of Figure 5 shows that the strong effect of elevation in the 0-300 m range is not found in the parametric model, Panel B shows the same result for 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 6 of Appendix, OGAMs produce more detailed spatial variations than the broad ellipsoid pattern from the parametric model (0). This suggests some fine-scale spatial variations in the latent quality index according to GI designation scheme. The

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 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 third-orders polynomials for longitude and latitude (df= $3 + 3 + 3 \times 3 = 15$) and with 13, 14, 7 and 31 dummy variables for pedology, geology, exposition, and *communes* fixed effects, respectively. 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 *commune* effects on residuals from auxiliary regressions without *commune* dummies.

significance of *commune* fixed effects decreases sharply by increasing the complexity of spatial smoothing, whereas it remains the second most important set of variable in the model (V).

4.2 Ordinal superiority of *communes*

The last row of Table 1 reports the bootstrapped F-statistics for the joint significance of *commune* dummies on surrogate residuals from auxiliary models that do not account for such fixed effects.

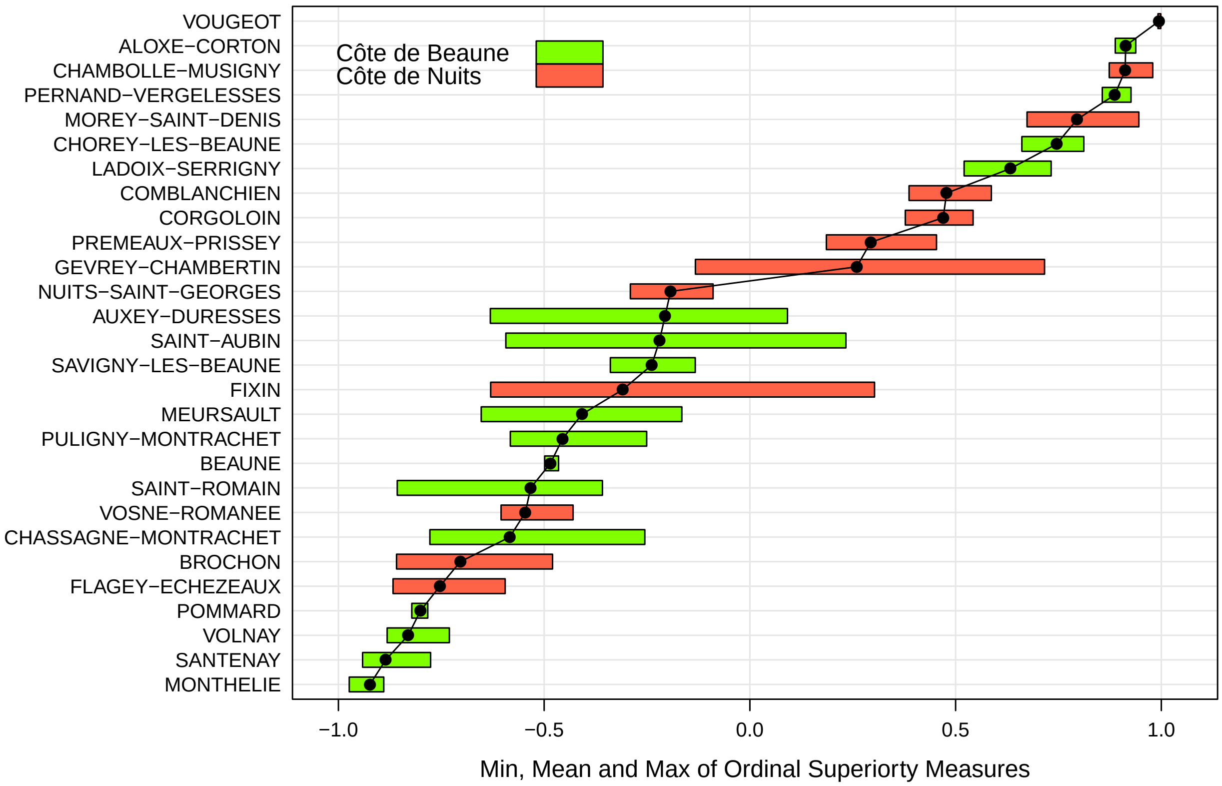
Figure 7 in the Appendix presents in more detail the relevance of smoothing spatial coordinates to control for unobserved *terroir* variables and improve the causal inference. Initially, it appears that OGAMs allow to decreasing significantly the correlation between auxiliary residuals and *commune* effects, compared to the parametric ordered logistic model (0). A maximum effective degrees of freedom of approximately 700, which 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 cannot be rejected according to the median of the bootstrapped F-statistics. This indicates persistent effects of intangible lobbying effects from political bargaining about the GI designation scheme, even for precisely controlled *terroir* effects. Similar vineyard plots from one side or another of administrative borders have significantly different probabilities of being in different vertical levels of GIs.

Ordinal superiority measures from models with 700, 800 and 900 maximum edf are reported in Figure 2. A positive measure indicates that the *commune* is advantaged relatively to the average *commune* (Agresti and Kateri, 2017). We see that only vineyard plots from four *communes* are not differently designated from the average *commune*. *Communes* from the *Côte de Nuits* in the north of the region are, on average, more advantaged than those of the *Côte de Beaune* in the south, as eight *communes* from this part of the region are among the 11 most advantaged. The proximity to Dijon, where trials of the use of vineyard names occurred between 1860 and 1936, is one potential explanation for this result, as well as the fact that it was usual that influential people living in Dijon own some vineyards in the *Côte de Nuits*, closer to Dijon than *Côte de Beaune* (Wolikow and Jacquet, 2018, see Figure 1). The *communes* that have a syndicate engaged in collective action appear to be privileged, but the separation is not clear-cut.[3] This hierarchy of advantaged and disadvantaged *communes* from GI designations is not significantly correlated with the average level of their vineyards, as some advantaged *communes* do not have vineyards of high level on average (*Ladoix-Serrigny* and *Chorey-les-Beaune*), and some *communes* with high level vineyards

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

Figure 2: **Ordinal superiorty measures in the current GI designation scheme**

Notes: For a given *commune* 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, whereas relatively disadvantged *communes* appear at the bottom.



are disadvantaged by the designation scheme (*Flagey-Echezeaux* and *Pommard*). We found that the ordinal superiority measures only weakly positively correlated with average levels of current GIs ($R^2 = 0.06$, $t = 1.27$, Figure 8 in the Appendix).

4.3 Informational content of current GIs

Table 2 reports the decomposition computed from equations (6) to (9) with $q(X_i^*)$ predicted from the five OGAMs reported in Table 1 with increasing complexity of spatial coordinates (the empirical formulas used are reported in RM p.XX, jointly with the R code to compute them). As expected, the total signal reported in the first row of Table 2 increases from left to right and the total noise decreases.[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 stable between specifications. For all models, the vertical and horizontal dimensions of GIs have high joint information content. From the last column of Table 2, the joint signal of approximately 78% is 4-times higher than the joint noise of 19%. The vertical dimension has 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, which represents the marginal informational content of the vertical dimension after the horizontal dimension is fully taken into account, is higher than the horizontal signal when only using the horizontal dimension. This result reinforces the superiority of the vertical dimension to convey quality information, though the dimension of the signal is lower (5 levels instead of 31 items). From the vertical residual terms (i.e., sixth row), we see that the vertical dimension of GIs has approximately 20% (13/65) bias in conveying information about vineyard quality, and this bias due to preferential treatment between *communes* can be assessed by consumers through the horizontal dimension.

4.4 Models of the 1936 GIs

We estimate the same set of ordered models with the GIs of 1936 as the outcome variable. At this point of history, the vertical dimension of GIs counted only three levels, as reported in the summary statistics in Table 4 in the Appendix: *Régional* < *Village* < *Grand Cru* with respectively 57%, 41%, and 3% of current vineyard plots.[5] The joint significance, the marginal effects of tangible variables, and the spatial smooth effects are reported in Table 5, Figure 9 and Figure 11, respectively, in the Appendix. For this older designation scheme, 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 reported in the RM, p.XX). Surprisingly, the hierarchy

[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, as they come from the increase in the variance of the latent quality index predicted by tangible variables.

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

Table 2: **Signal Decompositions from OGAMs with Spatial Coordinates**

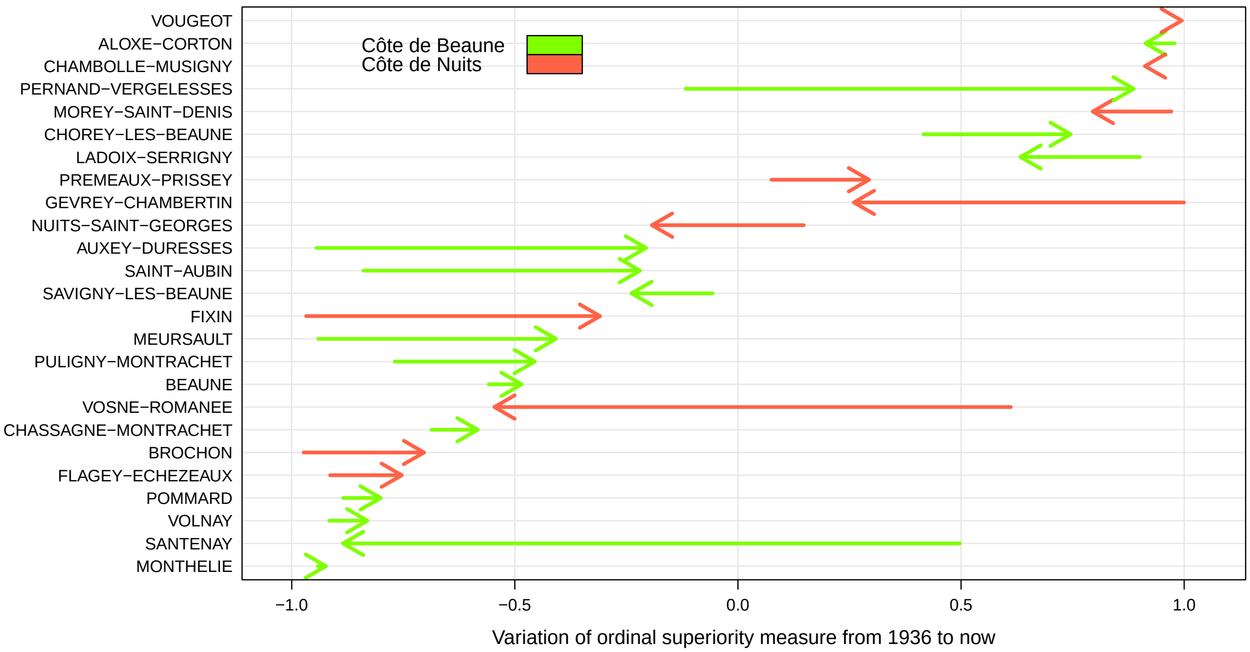
		Effective degrees of freedom for spatial smoothing				
Decomp.	Term	(99)	(295)	(483)	(667)	(841)
Total	Signal	85.30	94.47	96.03	97.31	97.49
	Noise	14.70	5.53	3.97	2.69	2.51
Joint	Signal	69.73	70.15	76.71	75.19	78.62
	Noise	15.60	24.35	19.35	22.15	18.90
Vertical	Signal	54.05	48.77	51.68	56.25	65.18
	Residual	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 parentheses 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 (6) to (9) in the text. For each column, the sum of *vertical signal* and *vertical residual* equals the *joint signal*, as does 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*.

of the joint significance of explanatory variables is very close to what is obtained for current GIs. The *commune* and pedology fixed effects, and geographic coordinates have the highest significance, followed by elevation, geology, solar radiation, slope, and exposition. The marginal effects of elevation and slope also have an inverted-U pattern with close maximum values, and the spatial smoothed patterns are also very close to what is found for current GIs. In contrast, the ordinal superiority measures are more varied between *communes* (see Figure 10 in the Appendix). The *communes* from the *Côte de Nuits* already appeared as relatively advantaged (seven *communes* among the 11 most advantaged) and the effect of the syndicates of producers appear more clearly than in current GIs (see footnote 3). Figure 3 shows that the *commune* where a vineyard is located was a more important determinant of GIs designations in the middle of the 20th century than it is currently. For 18 *communes* among 25 (72%) the ordinal superiority measure decreases in absolute values. This indicates that the GI designation scheme is increasingly efficient. Some *communes* such as *Santenay* and *Vosnes-Romanée* go from advantaged to disadvantaged since the creation of INAO, while the majority of *communes* stays in the same category.

Figure 3: **Variations of ordinal superiorty measures between 1936 and now**

Notes: For a given *commune* 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 arrows represent the change in the measures between the creation of INAO in 1936 and current GIs.



The first column of Table 3 reports the decomposition of the latent quality index according to the 1936 GIs. The GIs of 1936 have lower joint informational content than actual GIs with a joint signal to noise ratio close to 1 (48/49.5), which confirms the result of increasing efficiency of GIs on the last century. The bias from the vertical dimension double to become equals to 40% (14/35). The informational content of the vertical and horizontal dimensions are more balanced, whereas the vertical dimension stays more informative. The vertical dimension of 1936 GIs has a signal to noise ratio of 0.54 (34.4/63.1) compared to 0.32 (23.8/73.7) for the other 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 1936 GIs is not due exclusively to the higher bias in GI delineation from intangible determinants. A part of the loss could be attributable to the lower number of vertical items (3 instead of 5 in current GIs). These results indicate significant improvements in the informational content of GIs in the last century in combination with the decreased bias from intangible determinants.

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 current GIs. The first column reports the informational content of the GIs of 1936. Scheme S.0 is a benchmark simulation that adds surrogate residuals to the latent quality index in order to mimic current GIs. S.I drops the random idiosynchratic 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 for *Bourgogne*, *Village*, and *Premier Cru*, respectively, by an additional threshold fixed at the mean.

4.5 Informational content of simulated GIs

In order to provide guidelines for better designated GIs in the future, we performed different simulations of counter-factual GI designation schemes as reported in columns S.I to S.VI in Table 3. This consists in changing the GI designation schemes and evaluates the consequences on their informational content. The six vertical designation schemes under consideration were simulated by changing the predictions of the latent quality index (in columns S.I, S.II, and S.III), and by changing the number of vertical levels from five to six (in S.IV, S.V and S.VI). The detailed formula and R codes used to simulate alternative GI designation schemes are reported in RM (p.XX). We did not consider changing the horizontal dimension of GIs, because changing the administrative boundaries of *communes* in order to improve wine quality signaling is not policy-relevant. 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 shows that the decomposition terms are very close to those obtained in the last column of Table 2 from actual GIs. Next, 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. In the last simulated designation schemes S.IV, S.V and S.VI, *Bourgogne*, *Village* and *Premier Cru* levels are respectively divided into two 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, e.g., *Bourgogne supérieur*, *Village supérieur* ou *Premier Cru supérieur*) that allows consumer to distinguish them.

The decomposition reported in Table 3 show that dropping the intangible effects associated with *commune* effects is the most important policy to increase the informational content of the vertical dimension of GIs. Conversely, reducing the designation noise is more important for increasing the joint signal, which corresponds with the assumption that consumers use the information of both GI dimensions. These two policy changes for GIs seem to be additively cumulative for increasing the informational content of both the vertical and joint signals. In particular, the marginal gain of dropping the *commune* effects is about the same with and without designation noise. Table 3 also shows that dropping the *commune* effect in the designation scheme increases the joint signal more than adding a sixth vertical level as in S.III, S.IV or S.V. Among these latter alternative schemes, we found that splitting the intermediate level *Village* is more efficient, but 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 consumers, as information about high levels of GIs would be more valuable. In all cases, these potential improvements from the vertical dimension of GIs have no impact on the informational content of the horizontal dimension, which maintains the same order of magnitude among simulations.

5 Conclusion

We present a framework for modeling 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 found simultaneously a high informational content of the vertical levels of GIs, and some persistent differential treatments between administrative boundaries that bias the GI signal. This two-dimensional segmentation inspired many GIs among the wine-producing regions of the "old world", in France, Germany, and Italy for example. Similar empirical analysis have to be conducted to evaluate the external validity of our results, and identify the various determinants of the informational content of GIs between these regions. We also showed that the long history of GIs in Burgundy and their independent management by INAO has decreased the bias of the GI signal. This results is of particular importance to explain the differential performance on wine markets between the "old world" and the "new world".

The economic success of wines from this part of burgundy is not only attributable to the informational content of their GIs. Our results are nevertheless related to the general dynamic theory of strategic transmission information developed by Benabou and Laroque (1992). The authors show that, when information is not fully reliable (here, because of the lobbying effects on the GI designation process), the possibility of honest mistakes (here, because of designation noise) produces some confusion for consumers. Consequently, market incentives keep the consumers' learning process incomplete and allow market manipulation by producers. Accordingly, this negative economic outcome "is limited only in the long run by the public's constant reassessment of their credibility" (Benabou and Laroque, 1992, p.947). This analysis is particularly relevant for signaling wine quality, knowing the difficulties defining and observing the notion of *terroir* and agreeing about the quality of wines, which worsens the problem of consumer verification of the relevance of the informational content of GIs.

These benefits of the long-term history of the informational content of GIs would require some second thoughts about GI flexibility, which is sometimes wished to follow changing consumers' preferences, and changing determinants of wine quality (particularly in the face of climate change, White et al., 2009). As a human institution, which requires political bargaining and the involvement of producers with private information, the unbiased nature of the GI signal would probably not be reached spontaneously. Moreover, the regular modifications that would be required to follow the changing preferences or changing environment would increase the confusing 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 probably account for a great portion of their value that is currently observed in 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. Due to the small size of vineyard plots in the region, the smooth functions of geographic 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 exclusively related *a priori* to tangible characteristics that matter for wine quality. In particular, they can grasp some spatial interactions of reputation or influence between vineyard plots on both sides of a *commune* border. Nevertheless, we found that the main decomposition results for the informational content of GIs, and the general result of a signal-to-noise ratio of 4 are robust in regards to the degree of spatial smoothing used in regressions. Taking into account fine-scale variations in *terroir* is important to estimate the ordinal superiority measures, but not determinant of the informational content of GIs.

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A Appendix

A.1 About causal inference

We consider that the causal effects of *commune* dummies is identified once the smoothing functions of geographical coordinates control for all the spatial heterogeneity that is correlated with *commune* dummies. This sufficient level of spatial smoothing is expected to be reached once the residuals from auxiliary regressions that do not include *commune* fixed effects are not correlated with *communes* dummies. Using residuals for specification purposes 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). We use here the more accurate surrogate residuals defined by Liu and Zhang (2018).

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 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, as the originality of the surrogate approach is to randomly draw the realizations rather than compute them analytically. This allows an estimation of the full distribution of model errors instead of only their first moments and sensibly extends the potential applications in regression diagnostics (Liu and Zhang, 2018). We obtained the residuals from N random draws of the surrogate variable S_i with:

$$R_i = S_i - \mathbb{E}(S_i) = S_i + \alpha_{y_i} - B(X_i)^{\top}\beta \tag{10}$$

and regress them on the *commune* fixed effects. This allows us 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 base dimensions 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 jointly estimate 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 correlating with *commune* dummies, the estimated ordinal superiority measures are expected to be unbiased. Note that the F-statistics are bootstrapped to take into account the additional uncertainty attributable to the random draws used in the computation of surrogate residuals.

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 were computed by a Geographical Information System from a Digital Elevation Model with 5 m resolution. Longitude and latitude correspond to the center of each vineyard plot. Current GI are dummy variables that account for the vertical dimension in 2018, and Past GI comes from the 1936 map. Aspect is discretized according to radian range reported in brakets.

Figure 4: **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 is the percentage the each vertical item represent in each *commune*.

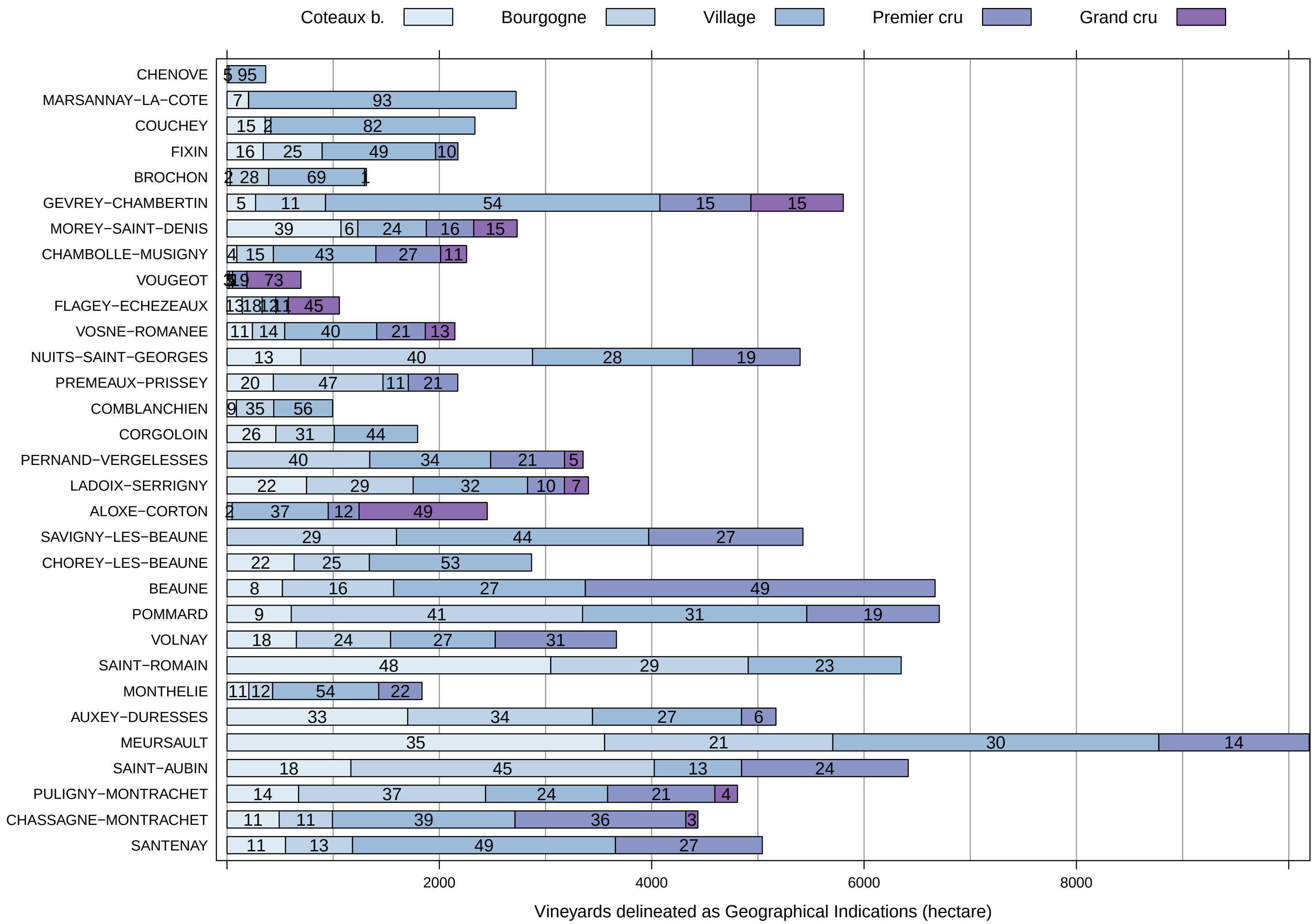

Figure 5: **Nonlinear Effects of Topographic Variables on GI Designations**

Notes: Dotted lines represent the quadratic effects from model (0) in Table 1, centered at zero with all other explanatory variables at their sample means. Continuous lines represent the centered effects from 10 OGAMs with increasing darkening for increasing effective degrees of freedom for spatial smoothing terms. Models (I) to (V) in 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 plot represent the marginal distributions of the explanatory variables.

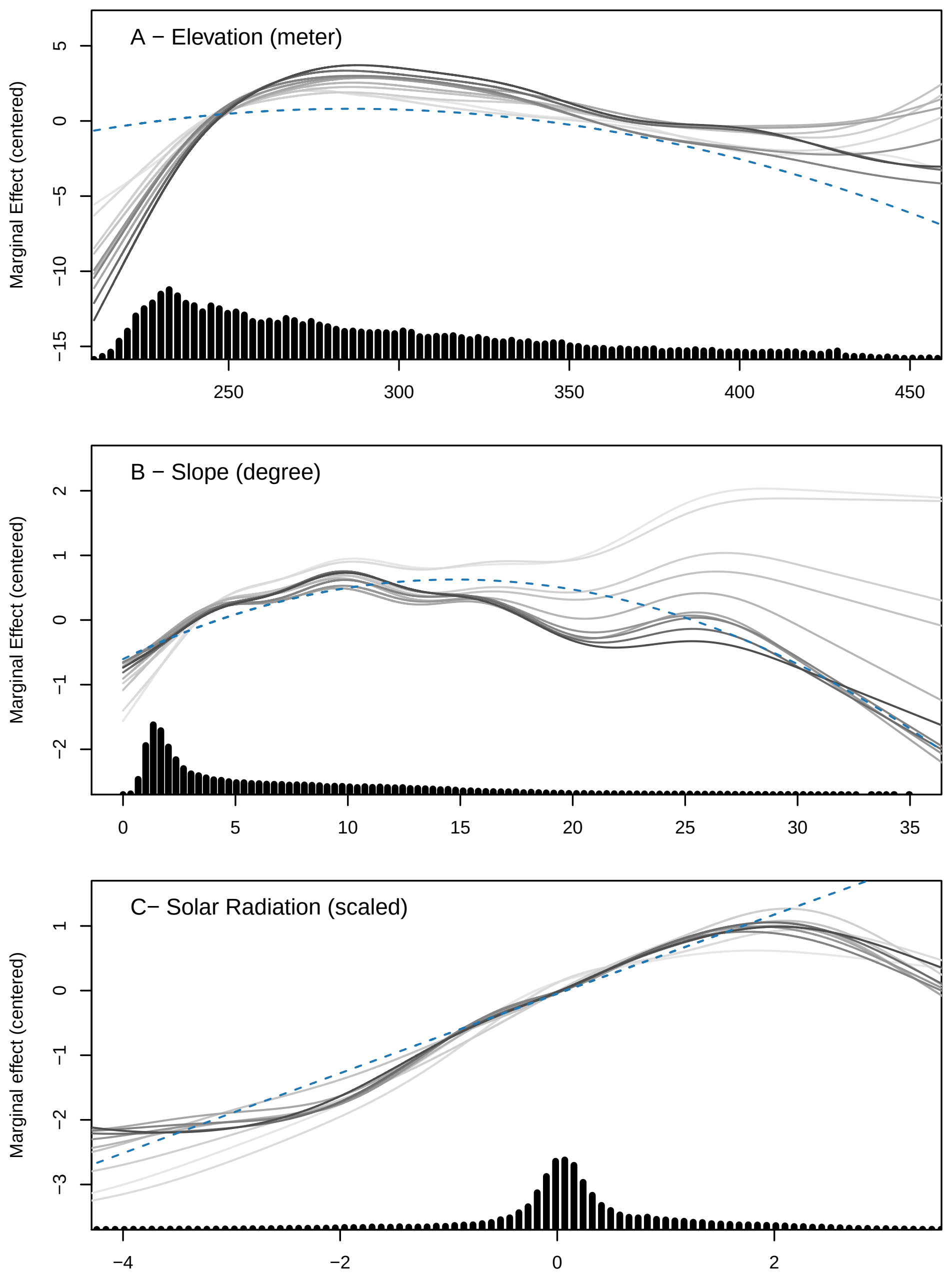

Figure 6: **Spatial Smoothed Effects from Ordered GI Designation Models**

Notes: The smooth surfaces are predicted from spatial coordinates with other explanatory variables at their sample means, with a uniform normalization to be inside the unit interval. A. The smooth prediction from parametric ordered logistic model (0) in Table 1. B to F. the prediction of OGAMs (I) to (V) with increasing effective degrees of freedom as reported at the top of each plot.

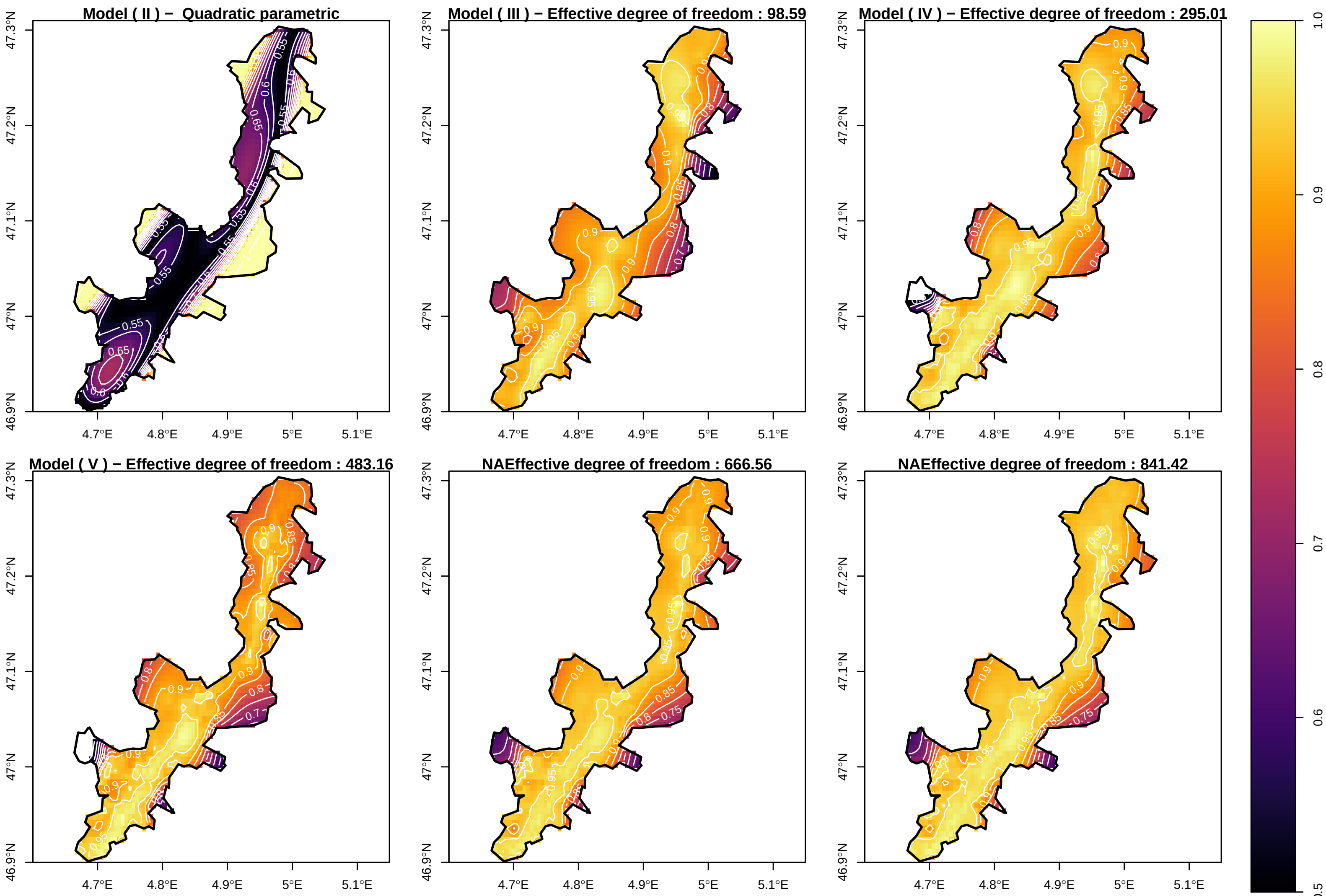

Figure 7: **F-statistics for Correlated Residual Effects**

Notes: For each model on the x-axis, the Figure reports the distribution of the bootstrapped F-statistics (log scale). Increasing the complexity of spatial effects from left to right decreases the significance of the *commune* effects on the surrogate residuals from auxiliary regressions.

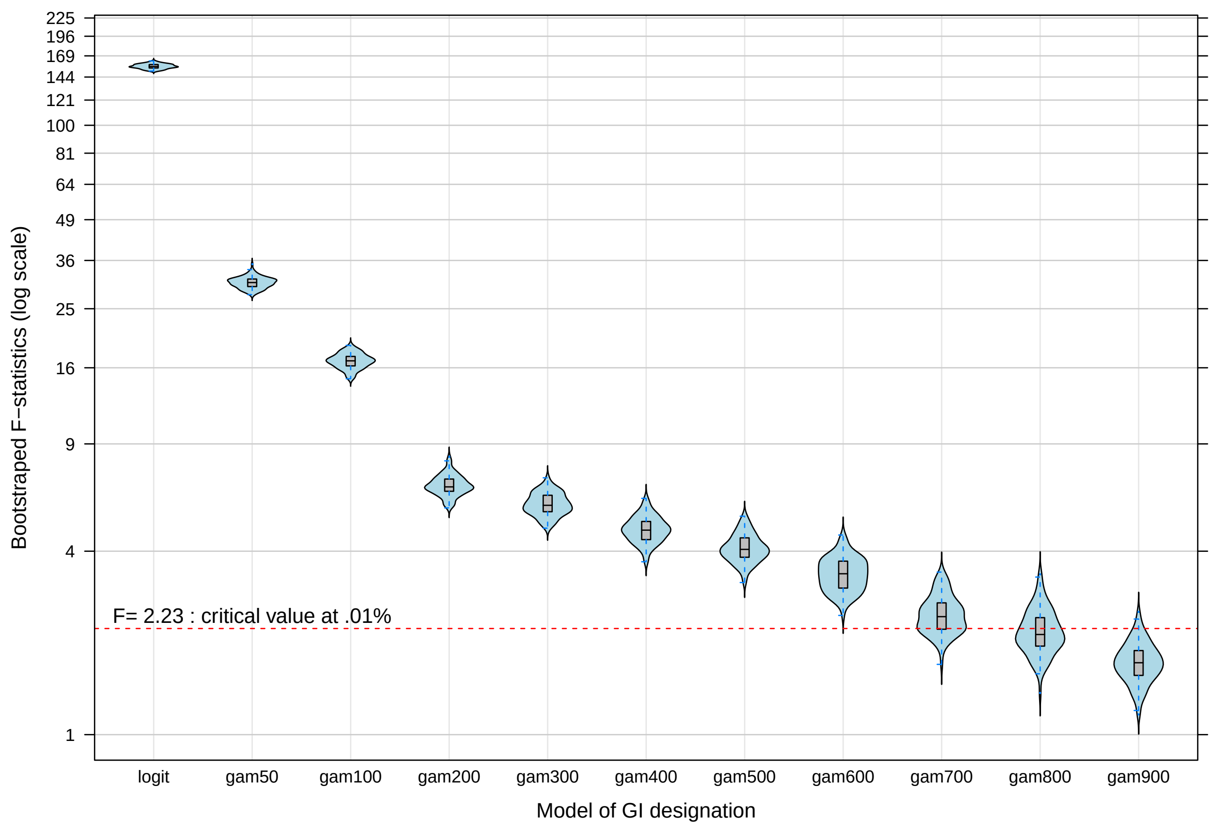

Figure 8: **Correlation between GI Grade and Ordinal Superiority Measures**

Notes: The ordinal superiority measures come from means in Figure 2. The average GI grade for each *commune* is the area-weighted mean of GIs coded from 1 to 5. Privileged *communes* (according to ordinal superiority measures) do not appear to have systematically more high GIs than average (t = 1.27).

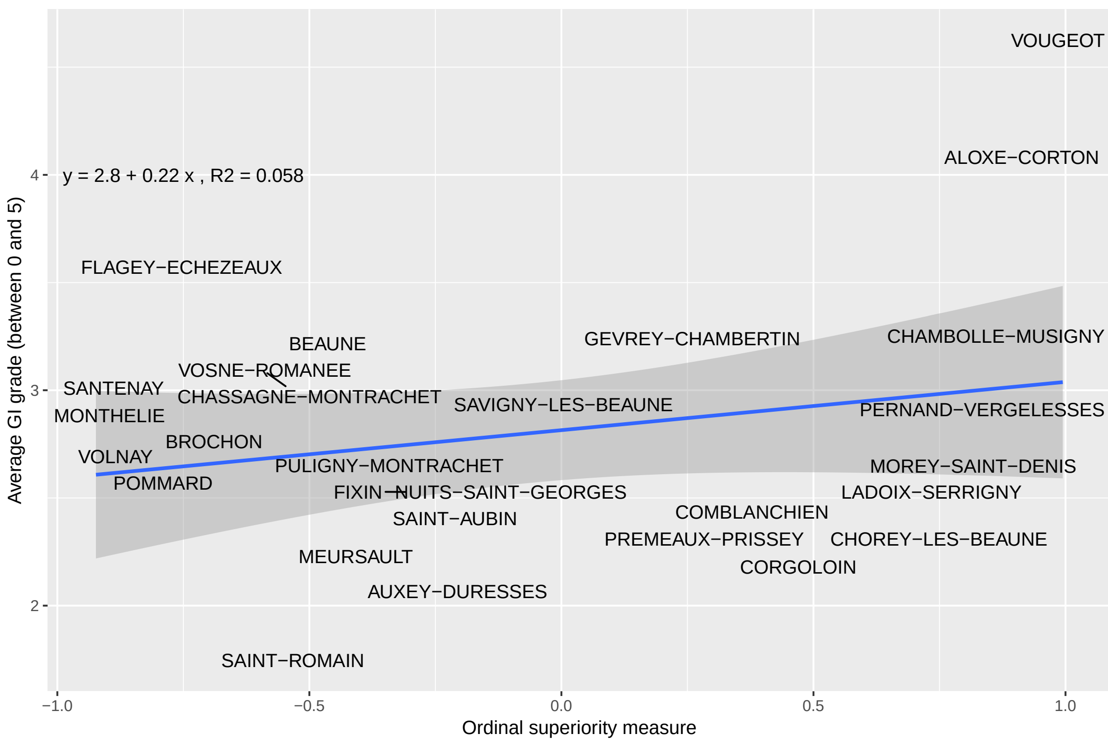

Table 5: **Joint Variable Significance for Ordered Models of the 1936 GI Designations**

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-squared statistics. The effective degrees 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= $3 + 3 + 3 \times 3 = 15$), with 7 and 25 dummy variables for exposition and *communes*, respectively. Five *communes* were dropped because they contained only one GI 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 increasing order of complexity with the maximum edf of 100, 150, 200, 250 and 300. The last row reports the average of bootstrapped Fisher statistics for the joint nullity of *commune* dummies on surrogate residuals.

Figure 9: **Non-linear effects of tangible variables in the 1936 GI designations**

Notes: Dotted lines represent the quadratic centered effects of model (0) presented in Table 5. Continuous lines represent the centered effects from OGAMs (I) to (V) with increasing darkening with increasing effective degrees of freedom. The histograms at the bottom of the plots represent the marginal distributions of each explanatory variable.

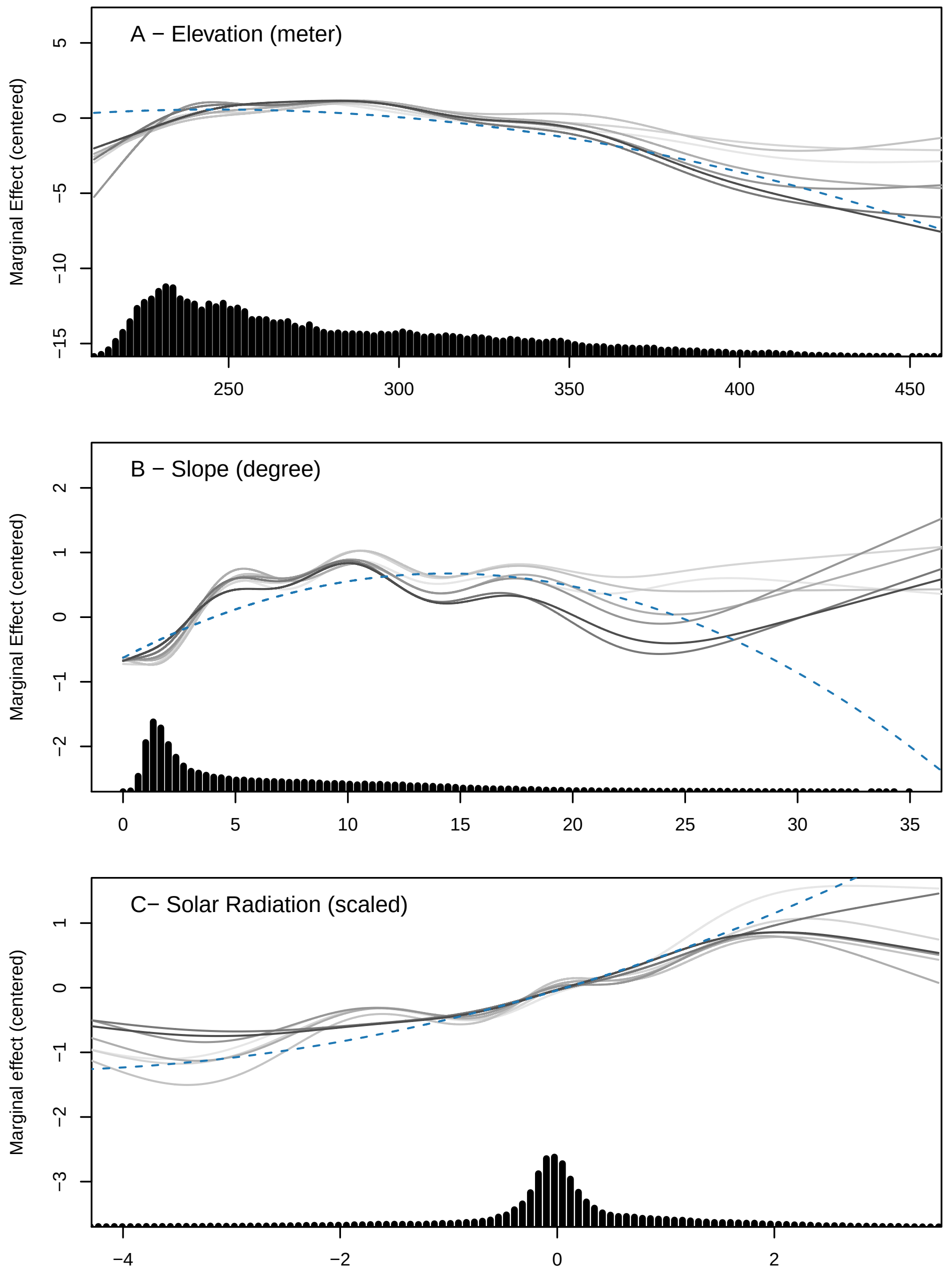

Figure 10: **Spatial Smoothed Effects from 1936 GI Designation Models**

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.

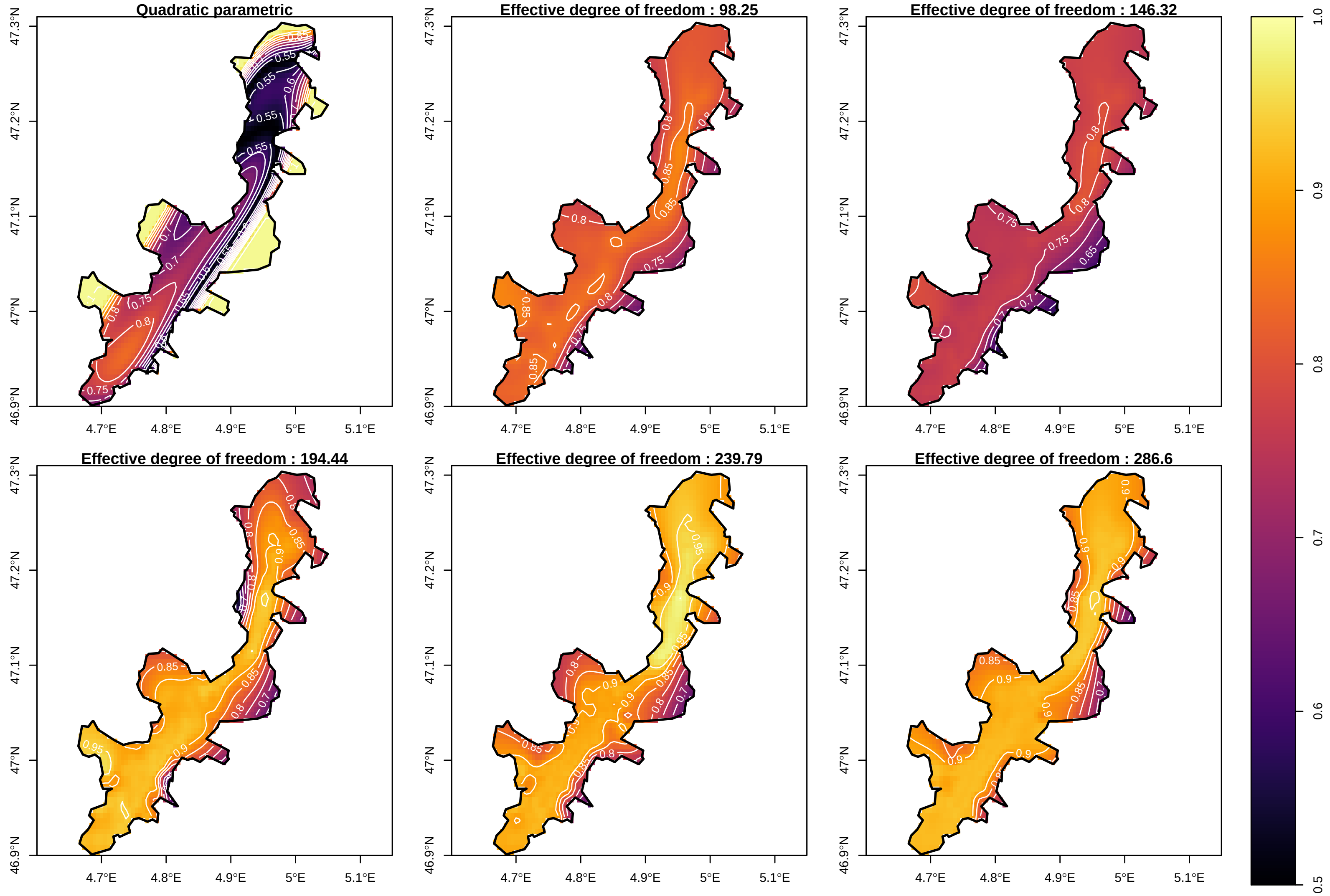

Figure 11: **Ordinal Superiority Measures for the *communes* in the 1936 GI designation scheme**

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.