**Do Geographic Indication Labels Pay off? Estimating GIs' Implicit Price Dispersion in the Italian EVOO Market.**

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## Abstract

We use a scanner database of Extra-Virgin Olive Oil sales in the Italian market and an Unconditional Quantile Regression estimator to assess the dispersion of GIs' implicit prices along two dimensions: for each GI across the price distribution; and at specific points of the price distribution across GIs. Our results show the existence of three different patterns of GIs' implicit prices across the price distribution, supporting the existence of different equilibria values of the same attribute, likely due to differential quality perception along the price spectrum. Also, we find that GIs' implicit prices are less dispersed at low points of the price distribution, however, the implicit price dispersion is large at higher price quantiles, suggesting the presence of asymmetries (i.e. information costliness, local competition) at higher price levels.



**JEL codes:** Q18; L66; D28

**Keywords:** Geographic Indication, Extra Virgin Olive Oil; Unconditional Quantile Regression; Implicit Price Dispersion

## Introduction

Geographical Indications (GIs) are quality labelling schemes used to promote and differentiate locally produced agricultural and foods products whose quality is intrinsically related to a limited geographic area or to a traditional production method (see Art 22.1 of WTO's TRIPS agreement for a formal definition). The European Union regulates GIs under Regulation (EU) No 1151/2012 using three labels: Protected Designations of Origin (PDO), Protected Geographical Indications (PGI) and Traditional Specialty Guaranteed (TSG). One of the main policy rationales for the creation of GIs is to provide farmers with a labeling tool for differentiating their products and escape from price competition (Regulation (EU) No 1151/2012).

The market for products with GIs has been subject of extensive analysis from agricultural economists over the last 20 years (Loureiro and McCluskey, 2000; Bonnet and Simioni, 2001; van Ittersum et al., 2007; Tsakiridou et al., 2009; Resano-Ezcaray et al., 2010; Vecchio and Annunziata, 2011). Studies consistently find that GI labels increase consumers' acceptance of food and agricultural products (Resano-Ezcaray et al., 2010) and that consumers are willing to pay a premium for products with GIs labels (*e.g.* Loureiro and McCluskey, 2000; Bonnet and Simioni, 2001; van Ittersum et al., 2007; Tsakiridou et al., 2009; Vecchio and Annunziata, 2011; Deselnicu et al., 2013).

As farmers bear the cost of compliance with GIs production protocols (European Commission, 2005; Regulation (EU) No 1151/2012), the existence of a positive WTP for GI labels is a necessary, but not sufficient condition in order to achieve the objective of supporting rural economies and improving the income of farmers (Regulation (EU) No 1151/2012). Most theoretical research on GI products finds them to have positive welfare effects, as they can increase the efficiency in quality provision (Menapace and Moschini, 2012). However, in a model where quality is endogenous and consumers value two quality dimensions – the GI and the sensorial quality of the GI products, Desquilbet and Monier-Dilhan (2015) show that if the GI regulation acts as a minimum quality standard instead of a denomination standard, GI firms profits decrease. In Yu, Bouamra-Mechemache, and Zago (2018) model firms can participate in a GI while also using their own brand (that is, the case of nested names), which is usually the case of many food products carrying GIs. They find that, if price discrimination is possible, the incentives to establish both collective and nested-names are welfare improving. Thus, the theoretical literature provides conflicting findings on the potential market outcomes of GIs.[1]

One of the common assumption of the literature mentioned above is that GI labels are "perfect" quality signal, where information is perceived equally be all consumers. However, Bonroy and Constantatos (2008) show that, if labels are "imperfect," that is where information from different types of labels is not internalized in the same way by all consumers, labels improving consumers' beliefs (not necessarily information); and welfare losses may occur. Firms, however may be able to charge higher prices, which will be a transfer from consumers to producers. Bonroy and Constantatos (2008) indicate three factors that make a label imperfect: the lack of 1) accuracy; 2) consumers' trust in the entity granting the label; and 3) consumers understanding for the label. Assuming that GI labels are accurate, the other two issues remain. With respect to the trust in the label granting agency, in the context of GIs it is possible that consumers are either unaware of the existence of a particular GI (unless they live in the area/region where the product is grown), or not familiar with products from specific region, thus a GI logo/label may not mean much for them. With respect to the lack of consumer understanding, the issue at hand is related to the costliness for consumers to acquire and internalize the information. As recent literature review reports EU consumers' awareness of GI labels at "low to medium" levels and that the role of these labels on affecting consumers decision making is probably low and that it depends on other quality cues (Grunert and Aachmann, 2016) it is likely

[1] Market power may be another issue. Yu and Bouamra-Mechemache (2016) show that, in presence of a quality standard set by upstream firms, a concentrated retail industry could exert a larger degree of market power than a scenario where no standard was in place. However, Saitone and Sexton (2017) argue that in food supply chains where credence attributes are created at the farm-level (like in the case of GIs), downstream buyers (i.e. retailers) prospecting to internalize consumer's WTP for such credence attributes may have no incentive to exercise buyer power. A limited number of empirical analyses have investigated whether GIs influence differentially the market power exercised by different actors along the supply chain, with mixed results depending upon the market analyzed. For example, Sckokai, Soregaroli & Moro (2013) find evidence of retailers' oligopsony and oligopoly power for Italian DOP cheeses (Grana Padano and Parmigiano Reggiano), but Mérel (2009) finds no evidence of market power for Comté cheese in France.

that at least some of the exiting GI labels are "imperfect" and that issues not fully explored by the existing theoretical literature may arise.

In differentiated product markets information costliness can lead to systematic differences in price charged to consumers, similar to the concept of price dispersion, which is proper of "homogenous product" markets.[2] In presence of high search costs, and "local" competition, different prices for differentiated products may coexists even after heterogeneity in consumers' willingness to pay (WTP) for specific products is taken into account (e.g. Barron, Taylor and Umbeck, 2004; Lewis, 2008). In the context of vertically differentiated products, if consumer search costs are high some firms have the ability to charge higher prices than their competitors (Wildenbeest 2011). Thus, in presence of imperfect GI labels, heterogeneous market valuation of the GI label, or the dispersion of its implicit price, may occur.

In this analysis we investigate whether the implicit price of different GIs can be heterogeneous along two dimensions, that is, for each of the GIs, and across the price distribution, and for a specific pricing point, across the different GIs. For our analysis we use a scanner database of sales of Extra-Virgin Olive Oil (EVOO) in the Italian market, and a modified hedonic price model estimated using an Unconditional Quantile Regression – UQR – (Firpo et al. 2009) estimator.[3] Once the implicit prices of several GIs in the market in analysis are estimated, their dispersion will be measured using the coefficients of variation (that is, their standard deviation divided by mean) along two different dimensions. By assessing their variation across the price distribution we can assess which GI label signals higher quality at the different levels of the price distribution, whereas, by measuring their dispersion at a specific pricing point, and across GIs, we can assess whether their dispersion grows with prices, which would indicate that the GIs feature to reach consumers with higher WTP may not

[2] Assessing dispersion of prices in a differentiated market context is not new. Wolff (2015) for example, assesses the trade-off between price dispersion and quality level in the online diamond market. He interprets his findings that price dispersion increases with diamond's quality as due to shoppers paying little attention to diamonds' prices as they perceive higher prices as a quality cue. Bonanno *et al* (forthcoming) show that in market with credence attributes, the larger the number (in both relative and absolute terms) of products carrying credence attributes (or the overall number of credence attributes in their portfolio) the higher they are able to price their products.

[3] Alternatively, one could use local polynomial regression as in Costanigro Mittelhammer and McCluskey (2009).

be uniform across the price distribution. As our data allows us to recover information for each GIs only for products sold by national brands, we perform our implicit price dispersion analysis only for nationally branded GIs, using PL GIs as a reference (similar to the cross-category hedonic price analysis by Hassan,and Monier-Dilhan, 2006).

The use of quantile regression methods is widespread in the hedonic price analysis literature focused on the housing market (*inter alia* Ziet, Ziet and Simans, 2008; Farmer and Lipscomb 2010; Zahirovic-Herbert and Chatterjee, 2012; Nicodemo and Raya 2012; Waltl 2018), although the use, specifically of UQR is still limited (e.g. Nicodemo and Raya 2012). The use of quantile regression to estimate heterogeneous implicit prices in agricultural economics is also limited to few examples (mainly Costanigro, McCluskey and Goemans, 2010; but also Caracciolo et al. 2016). Recently these methods have been used to study different determinants of farmland value / prices (as in Peeters, Schreurs, and Van Passel 2017; and Lehn and Bahrs 2018). We decided to use UQR instead of conditional quantile regression (CQR) (Koenker and Bassett, 1978) since it will allow us to measure the implicit price of GI labels (as well as other product attributes') across the price distribution. CQR instead would only allow us to estimate implicit prices at different levels of the conditional (on other attributes) price distribution.

As a case study, we choose the Italian Extra Virgin Olive Oil (EVOO) Market for different reasons. In the first place, Italy is the EU member state with the largest number of agro-food products carrying a GI label (either PDO or PGI) with 269 products, followed by France (219), Spain (180), Portugal (125), and Greece (101). Italy has also the largest number of GI EVOOs - 46 out of all 125 GI EVOOn the EU - 42 PDOs and 4 PGIs. Second, Italian consumers show a marked preference for Italian EVOOs with "credence" quality attributes such as origin (GI labels or "100% Italian), production methods (Organic) as well as safety and health attributes. Production of GI certified olives has been increasing, albeit slowly (2% circa), with sales of GI EVOOs in 2013 amounting to 2.9 million litres, for a value of € 31 million,, followed by Organic EVOOs - 2 million liters for a value of € 18 million (Unaprol, 2015; Ismea 2018). Third, while the Italian EVOO market is organized as an oligopoly, with the top eight leading brands (Monini, Bertolli, Olio Carli, Carapelli, Dante, De Cecco, Farchioni and Sasso) having jointly 50% of the market, PLs dominate the market with 20.8% share, and the overall value of EVOO GIs is about 6% (Confocooperative 2016). Fourth, the largest shares of EVOOs sales in Italy take places through the grocery retail channel (68%); direct sales take up about one quart of the market (26%) and remaining sale values are for non-domestic consumption (6%).

The paper proceeds as follows. First we illustrate how, in presence of multiple price equilibria, traditional hedonic price models do not represent a suitable framework of analysis. Then we present our empirical model, the data used in the analysis, and provide more details regarding the estimation methods used. A discussion of the results follows, and concluding remarks and limitations conclude.

## The model

In this analysis we employ a modified version of Rosen (1974) hedonic price model. The traditional hedonic price framework assumes consumers select a product embedding a bundle of attributes (that is the vector $\mathbf{z}=(z_1, z_2, \ldots, z_k)$) which maximizes their utility ($u$) subject to a budget constraint ($y$). Likewise, producers maximize profits ($\pi$) by setting a product's price given the attributes of the product ($\boldsymbol{z}$) and the technology ($t$) available. The first order conditions of consumer and producer maximization problems generate two group of curves: the consumer's bid function and the producer's offer function. The consumer's *bid function* $\varphi = \varphi(\mathbf{z}; u, y)$ captures the monetary amount a consumer is willing to pay (WTP) for different levels of product characteristics in the vector $\mathbf{z}$, holding utility and income constant. Instead, the producer's *offer function* $\psi = \psi(\mathbf{z}; \pi, t)$ measures the price that a producer is willing to accept (WTA) for selling a product having features $\mathbf{z}$ for a given profit and technology levels.

Under the standard hedonic models assumptions of full information and perfect competition, consumers' bid function match producers' offer function generating a unique market price equilibrium, which, for a product with a vector of attributes $\mathbf{z}$, is $p(\mathbf{z}) = p(z_1, z_2, z_3, \ldots, z_K)$. This is represented in the left-hand panel of Figure 1 which portrays the hedonic price function, $p^{o}(\mathbf{z})$, where bid/offer curves match and are labeled with the superscripts 1 and 2. Differentiating $p(\mathbf{z})$ with respect to each attribute in the vector **z**, will give the implicit price of that attribute.

The most suitable empirical approach to estimate hedonic price function involves the use of simple standard econometric tools such as Ordinary Least Squares, regressing data on products prices on the products' attributes. For product *j* in market *m* at time *t*, this takes the general form:

$$P_{jmt} = f\left(\mathbf{z}_{jmt}, \boldsymbol{\beta}\right) + \varepsilon_{jmt} \quad (1)$$

Where the error term $\varepsilon_{jmt}$ accounts for idiosyncratic random shocks and unexplained product heterogeneity, and the functional form *f*( . ) is not specified *a priori*.

Multiple market prices equilibria $p(\mathbf{z})$ may however exist because of unobserved consumer heterogeneity in WTP for the product (and its attribute) as well as asymmetric, or, costly information which may lead to bid (offer) functions for the same product to differ across buyers (sellers). These multiple prices equilibria $p(\mathbf{z})$ exist in the price space delimited by an upper bound, generated by the consumers with the highest WTP for a certain product $p^{HIGH}(\mathbf{z})$ , and a lower bound, $p^{LOW}(\mathbf{z})$ identified by producers with the lowest WTA for the same product (Figure 1, right panel). The multiple price equilibria due to unobserved consumer/producer heterogeneity or asymmetric / costly information, can be captured by estimating the equation (1) using a quantile regression estimator as illustrated by Costanigro, and McCluskey (2011) and applied by Costanigro, McCluskey, and Goemans (2010).

## Model Specification, Data and Estimation

### *Model Specification*

We propose two different empirical specification of equation (1); in the discussion that follows product, market and time subscripts are omitted for brevity. In the first specification, the covariate vector **z** contains a binary variable *GI*, which takes the value of one for products with a GI label, and 0 otherwise; *PL*, another binary variables, taking the value of 1 for products sold as store brands, and

0 otherwise; and four vectors, $\mathbf{z}^{CA}$, $\mathbf{z}^{OC}$, $\mathbf{z}^{PK}$, and $\mathbf{z}^{Br}$. $\mathbf{z}^{CA}$ is a vector of credence attributes (*CA*) other than GIs, that is, "organic" or "100% Italian", indexed by *c* (*c=1,…,C*). The $\mathbf{z}^{OC}$ and $\mathbf{z}^{PK}$ vectors include other product features related to taste and packaging characteristics (respectively), and are indexed by (*o=1,...,O*) and *(h=1,...,H)*, respectively. The vector $\mathbf{z}^{Br}$ captures brand-specific indicator variables indexed by *b* (*b=1,…,B*). In the second model specification the indicator variable *GI* is replaced by the vector ***GI*** whose elements are indexed by *(g=1,...,G*); each element $GI^g$ of this vector will take the value of one if a product has a specific GI label (*e.g.* PDO Valli Trapanesi, Terre di Bari, Chianti Classico, PGI Toscana etc.), 0 otherwise.

Following other analyses (e.g. Costanigro, McCluskey and Mittelhammer, 2007; Costanigro, McCluskey and Goemans, 2010; Bimbo, Bonanno and Viscecchia, 2016; Waldrop, McCluskey and Mittelhammer, 2017; Bonanno et al. *Forthcoming*), we only estimate the first stage of the hedonic model. For simplicity (and ease of interpretation) we adopted a linear functional form of the estimated hedonic model. The two model specifications estimated are illustrated are:

$$
\begin{aligned}
P_{jmt} &= \alpha + \beta^{GI} GI_{jmt} + \sum_{c=1}^{C} \beta_c^{CA} z_{jmt}^{CA,c} + \sum_{o=1}^{O} \beta_o^{OP} z_{jmt}^{OP,o} + \delta^0 PL_{jmt} \\
&+ PL_{jmt}\left( \delta^{GI} GI_{jmt} + \sum_{c=1}^{C} \delta_c^{CA} z_{jmt}^{CA,c} \right) + \sum_{h=1}^{H} \beta_h z_{jmt}^{PK,h} + \sum_{b=1}^{B} \beta_b z_{jmt}^{Br,b} + \sum_{m=1}^{M} \lambda_m R_m + \sum_{t=1}^{T} \theta_t M_t + \varepsilon_{jmt}
\end{aligned} \tag{2}
$$

and

$$
\begin{aligned}
P_{jmt} &= \alpha + \sum_{g=1}^{G} \beta_g^{GI} GI_{jmt}^{g} + \sum_{c=1}^{C} \beta_c^{CA} z_{jmt}^{CA,c} + \sum_{o=1}^{O} \beta_o^{OP} z_{jmt}^{OP,o} + \delta^0 PL_{jmt} \\
&+ PL_{jmt}\left( \delta^{GI} GI_{jmt} + \sum_{c=1}^{C} \delta_c^{CA} z_{jmt}^{CA,c} \right) + \sum_{h=1}^{H} \beta_h z_{jmt}^{PK,h} + \sum_{b=1}^{B} \beta_b z_{jmt}^{Br,b} + \sum_{m=1}^{M} \lambda_m R_m + \sum_{t=1}^{T} \theta_t M_t + \varepsilon_{jmt}
\end{aligned} \tag{3}
$$

Note that in equations (2) and (3) we also control for a vector of *M* market-level (region), and *T* time (month) indicators, *Rm* and *Mt*, respectively to capture regional and monthly variation in EVOO prices.

Note that in equation (2) (equation (3)) we interact PL with the *GI* indicator (or the elements of the vector ***GI*** ) in order to estimate the separate out the implicit prices of *branded* GIs from those of PL ones, whose price is determined by retailers, which are likely to price their products according to different strategies than other GIs (Hassan and Monier-Dilhan, 2006). In order to capture additional heterogeneity in the pricing strategies across retailers' PLs and national brands, PL is also interacted with the elements of the credence attribute vector $\mathbf{z}^{CA}$.

Once all the estimated implicit prices for the GIs in equation (3) – that is, all the $\beta_g^{GI}$ coefficients - have been recovered, their dispersion will be assessed calculating the coefficient of variation (standard deviation divided by the mean) for each GI and across quantiles, and for each quantile (and across GIs).

*Data and Variables*

We use two years of monthly (November 2012 to November 2014), scanner data of EVOO sales from Italian hypermarkets and supermarkets, for 17 regions (encompassing the entire Italian territory), supplied by Information Resources Inc. (IRI) and provided by the University of Foggia. The data include information on sales volume and values of EVOOs (which are used to determine their prices in €/L) as well as other information regarding product characteristics, including package size, whether the product was sold as a national brand, or a private label, as well as information on whether the EVOO was "fruity" flavored, and whether it add additional flavors added (e.g., with the addition of spices or other flavorings, i.e. limes etc.) and whether was sold with a "100% Italian" label, organic or if the product had a PDO/PGI label.

The information contained in the database on the types of PDO/PGI, was cross-validated using information retrieved from manufacturers' websites, the front-of-package. Thus, for each product with PDO/PGI logo was possible to recover the detailed PDO/PGI name, for example, whether the EVOO carried PDO "Terre di Bari", "Garda", "Cilento" etc. Of the 46 different types of EVOO PDO/PGI produced in the Italian territory, our data included brands selling 31 PDO/PGIs products, as well as brands carrying multiple PDO/PGIs from specific regions (that is, Lombardy, Sicily, Tuscany) as well as one brand carrying GIs from multiple regions.

After exclusion of outliers, or products that are sold in large packages (1.5 liters or above, which are usually sold in tins which target different consumers than those purchasing oil “bottles”), the final dataset used in the estimation includes 114,136 observations. Table 1 presents a series of summary statistics of the data used in the estimation. The average EVOO's price sold in the Italian market is 7.457 €/Litre and more than 1 out of 2 products are sold with a credence attribute (55.4%). 26% of the EVOOs in our sample are products sold with a “100% Italian” claim; 18.9% with a GI label, and the remaining part (10.5%) as Organic. 6.9% of GIs in our data are sold as PLs. Further, 7.6% and 0.2%, respectively, of our sample are EVOOs sold as fruity or with additional flavors. The majority of the products in the data market (44.2%) are sold in 1-liter packages, whereas 43.7% and 12.1% in package sizes of 750 ml and 500ml, respectively.

*Empirical approach and estimation*

In order to determine the existence of GIs implicit price dispersions, we need to measure the relationship of GI labels in general, and more specifically of GIs sold as national brands, at different levels of the price distribution. By allowing the estimated implicit prices to vary in function of the different types of GI and across different levels of the price distribution, we will be able to assess the overall dispersion across the entire price and GIs ranges.

We estimate the parameters of equations (2) and (3) using the Unconditional Quantile Regression (UQR) estimator originally proposed by Firpo et al. (2009). We use UQR in place of conditional quantile regression (CQR) (Koenker and Bassett, 1978) as several other hedonic price analyses do (e.g. Ziet and Simans, 2008; Costanigro, McCluskey and Goemans, 2010; Farmer and Lipscomb 2010; Zahirovic-Herbert and Chatterjee, 2012; Caracciolo et al. 2016; Waltl 2018) because of its empirical advantages. First, CQR’s coefficients measure, if the implicit price of a GI EVOOs in the Italian market, conditional on the product being sold, in a specific market and showing a very specific set of product characteristics as it appears in the data (e.g., the implicit price will be based on the price of a products that is sold in region *R*, in month *M*, produced by manufacturer *N*, and so forth). Instead, the coefficients obtained using UQR, are directly interpretable as the (*ceteris paribus*) implicit price of the specific product attribute at a given level of the price distribution, leading to a clearer interpretation (Borah and Basu, 2013). Second, Borah and Basu (2013), suggest that in models with multiple covariates, UQR may be a more suitable estimation approach then CQR, since the conditional and unconditional distribution of the dependent variable may differ considerably in models adopting multiple covariates. Third, the use of UQR in place of CQR is also preferable for policy-relevant empirical analyses, where the key question focuses on establishing the relationship between some policy-relevant variables and the outcome variable at different points of the latter's distribution (e.g. Borah and Basu, 2013; Park, 2015; Bonanno *et al* 2018).

To estimate the parameter of our models we employ the Recentered Influence Function (RIF) regression approach, as in Firpo et al. (2009). As the details of this estimation procedure are discussed elsewhere (e.g. Firpo et al. 2009; Borah and Basu 2013; Park, 2015) we omit them for brevity. In this analysis we use bootstrapped standard errors as suggested by Firpo et al. (2009) and a Gaussian kernel density function to estimate the empirical distribution of EVOO's price in our data. Data manipulation and estimation were performed using STATA V. 14.

**Results**

The estimated parameters of equation 2 are presented in Table 2. The results show, in the first place, that GIs add a price premium to EVOOs products across the entire price distribution, with the only exception of PL GIs and priced at 3.18 €/Liter ($5^{th}$ quantile), associated to a price discount of 0.07€/Liter.

The implicit prices of GI labels increase with the product's price, reaching a maximum at the $75^{th}$ quantile for GIs of PLs (12.12 €/Liter) and at the $90^{th}$ quantile for GIs offered by national brands (8.24 €/Liter). The price premium attached to PL GIs is higher, than that of national brands, from the $25^{th}$ price percentile onward. The positive implicit prices are in line with several other studies reporting a positive consumer WTP for GIs labels/logos (e.g., Loureiro and McCluskey, 2000; Bonnet and Simioni, 2001; van Ittersum et al., 2007; Tsakiridou et al., 2009; Vecchio and Annunziata, 2011; Deselnicu et al., 2013). The result of PLs commanding a higher premium for their GIs than the national brands is in line with the result by Hassan and Monier-Dilhan (2006). However, as we illustrate below in our analysis of implicit price dispersions of the different GIs across the price distribution, we find that this result may be due to the large heterogeneity of GIs implicit prices for the national brands, which span from large positive values to negative ones.

Continuing with the results illustrated in Table 2, other credence attributes such as “100% Italian” and “Organic” add a price premium to EVOOs at most of the price quantile analyzed. These results can be explained by existing literature which has found EVOO Italian consumers preferring domestic products over foreign, and organic products over conventional (Caporale et al., 2006; Menapace et. al., 2011). In detail, national brands selling “100% Italian” EVOO and pricing their products below the 10 €/Liter point (that is, the 75$^{th}$ quantile) benefit of price premia ranging from 0.213 €/Liter, to 1.74 €/Liter (25$^{th}$ quantile); however, they lead to a discount of, respectively 0.514 and 0.415 €/Liter for at the 90$^{th}$ and 95$^{th}$ price quantile, suggesting that the “100% Italian” label no longer acts as a quality cue for products sold at the highest price points. A similar pattern emerges for the “100 % Italian” claim attached to PLs, with implicit prices ranging from 0.084 to 2.03 €/Liter for products priced below 6.57 €/Liter (50$^{th}$ price quantile) and resulting in a much larger discount then national brands at higher price quantiles (discount as large as -2.038 €/Liter). Organic claims instead add a price premium regardless of whether the product is sold as PL or as a national brand. In the case of branded products, “Organic” claim show positive implicit prices across the entire price distribution, increasing from 0.231 €/Liter, at the 5th price quantile, to reach 2.338 €/Liter, for the 75th quantile, and then decreasing to 1.839 and 2.167€/Liter at the 90th and 95th price quantiles, respectively. Similarly, “Organic” claim associated to private label adds a price premium that increases from 0.074 €/Liter, at the 5$^{th}$ price quantile, to 3.449 €/Liter, at the 50$^{th}$ quantile. A positive and significant price premium is also found at higher price quantiles 0.147 €/Liter and 1.445 €/Liter at the 90th and 95th quantiles, respectively. “Organic” leads instead to a price discount of -2.057€/Liter for EVOO priced at the 75th quantile.

The fruity flavor results in positive implicit prices across the price distribution, with an inverse U shape. Implicit prices range from 0.190 €/Liter (5th quantile) to 0.247 €/Liter reaching maximum values of 0.629 and 0.661 €/Liter at the 50th and 75th quantile. Instead, fruity taste is associated with a price discount of -0.346 €/Liter for products priced at 95th quantile. Adding flavors adds value to EVOO products for 6 out of the 7 quantiles analyzed, for positive implicit prices varying from 0.526 €/Liter (5th quantile) to 2.472 €/Liter (95th quantile). Last, EVOOs sold in package sizes smaller than 1-liter benefit (at most price levels) of a price premium. Glass packages of 500ml generate price premium of 0.604 €/Liter, for the 5th quantile, which increases onward to 10.858 €/Liter, for the 95th quantile. Instead, EVOO sold in packages of 750 ml benefits of a lower price premium compared to the same product sold in packages of 500ml until the 90th quantile.

The estimated implicit prices at different levels of the price distribution for the different PDO/PGIs in our data, obtained using equation (3), are reported in table 3. In order to maintain the exposition tractable, only UQR estimates obtained at the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles are presented (first to seventh column of table 3). The last three columns of table 3 contain the average value of the GIs implicit prices (assessed across quantiles), their standard deviation, and their coefficients of variation (in absolute values, to accommodate for negative average implicit prices). Before proceeding with the illustration of the results of the GIs implicit price dispersion, it should be mentioned that the estimated GIs implicit prices for PL, as well as the average of the estimated non-PL GI implicit prices are quantitatively close to those obtained using equation 2, as it can be seen from the values reported in Figure 2.

The values in table 3 show that the coefficients of variation of the implicit prices show large ranges of values across PDO/PGIs. The coefficients of variations vary to reach values as high as approximately 50.98 (PDO Colline Salernitane) to values as low as 0.69, for the PDO Terre di Bari, which is also the GI with the largest share in our data and along with PLs, the EVOO with a GI label showing the lowest price. Overall, it should be mentioned that only 4 of the GIs considered show a range of implicit prices with lower coefficient of variation than PLs, suggesting the existence of implicit price dispersion for the majority of PDO/PGI EVOO branded products exceeding those of store brands.

We observe three overall patterns of the GIs implicit prices across quantiles, indicating the existence of (at least) three tiers of GI EVOOs in the Italian market. The first pattern, observed for the majority of the GIs is an inverted U shape (23 GIs); 12 GIs show the maximum implicit price at the 75$^{th}$ quantile of the price distribution; for 10 the maximum implicit price is reached at the 90$^{th}$ quantile, and for one at the 50$^{th}$ quantile. Five of the GIs implicit price showing an inverted U shape pattern, show negative values at the highest quantiles, indicating that at the highest portions of the price distributions, the presence of these GIs result in a discount, as they may fail to signal higher quality among “super-premium” GI EVOOs. The second pattern, observed for 6 GIs, is of increasing implicit prices along the price distribution; in all the cases, the implicit prices grow at a growing rate along the price distribution, to reach values as large as (approximately) €40/Liter (for Valpolicella and Brisighello). These six GIs may be suitable to be in a super-premium segment, as they have the highest estimated implicit prices for all GIs in our data at the 75$^{th}$, 90$^{th}$ and 95$^{th}$ price quantiles. The third pattern, also observed for six GIs, is that of implicit prices which are positive and increasing up to the 50$^{th}$ price quantile, and then from the 75$^{th}$ percentile onwards, show negative (or small positive) values, and an upward trend, mostly leading to a discount. This pattern may indicate that some GIs can only signal a relatively high quality level at low-median price point, and their ability of being seen as high quality level disappears sharply once higher price points are reached.

For the second assessment of the dispersion of GIs implicit prices, we analyze their coefficients of variations across GIs, at each quantile. The minimum and maximum estimated GI implicit prices at each quantile, as well as their coefficient of variation are depicted in Figure 3. The coefficient of variation shows small differences at the 5$^{th}$, 10$^{th}$ and 25$^{th}$ quantile (respectively, 0.381, 0.368 and 0.375), showing an even smaller magnitude at the 50$^{th}$ quantile (0.209). At higher quantiles, however, the dispersion of the different GIs implicit prices increases, to reach values as large as 1.5 at the 95$^{th}$ price quantile. If one considered implicit prices as providing a signal of the perceived value/quality of specific attributes in the market, this result would indicate that the quality signal given by GIs priced in the lower half of the price distribution may be similar across GIs, and that efforts of differentiating across GIs may not be as fruitful. Conversely, as one moves towards higher price levels, there will be a wider range of perceived quality across GIs, with some labels being able to obtain higher prices and being perceived as more “unique” than others.

## Conclusions

In this analysis we estimate the dispersion of implicit prices associated with different GIs in the Italian Extra-Virgin Olive Oil market. Our main three findings are that 1) GIs implicit prices dispersion varies across GI; 2) they are more dispersed at higher values of the price distribution and 3) the pattern taken by each GI label implicit price can differ quite markedly. A possible explanation of our results is that higher prices may not signal quality uniformly across the GIs in the Italian EVOO market as quality seeker consumers may not perceive the higher prices as a quality cue in about two thirds of the EVOO GIs in our data. However for about one sixth of the GIs in our data we do observe increasing implicit prices, consistent with the expectations of higher prices being quality cues.

This analysis has several limitations. In the first place, our dataset includes only two thirds of EVOO PDO/PGI sold in the Italian territories; even though the richness of the dataset allows us to detect a considerable amount of variation in GIs’ implicit prices, it is possible that the extent of dispersion could be even larger if one considered all the products in the market. Second, our dataset covers only sales of EVOOs in supermarkets and hypermarkets; even though about two thirds of EVOO sales in Italy occur through this channel, it is possible that, by not including specialty stores some specialty products may be excluded from our sample. Similar to the previous point, if any sample selection biased occurred, it would likely results in s downward biased price dispersion measures. Third, and last, for ease of interpretation, we only adopted a linear specification of the estimated hedonic price equation; additional model specification tests should be performed to assess whether the simple linear functional form is suitable for our model to appropriately fit our data.

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Figure 1 - Representation of equilibrium prices and hedonic price curves.

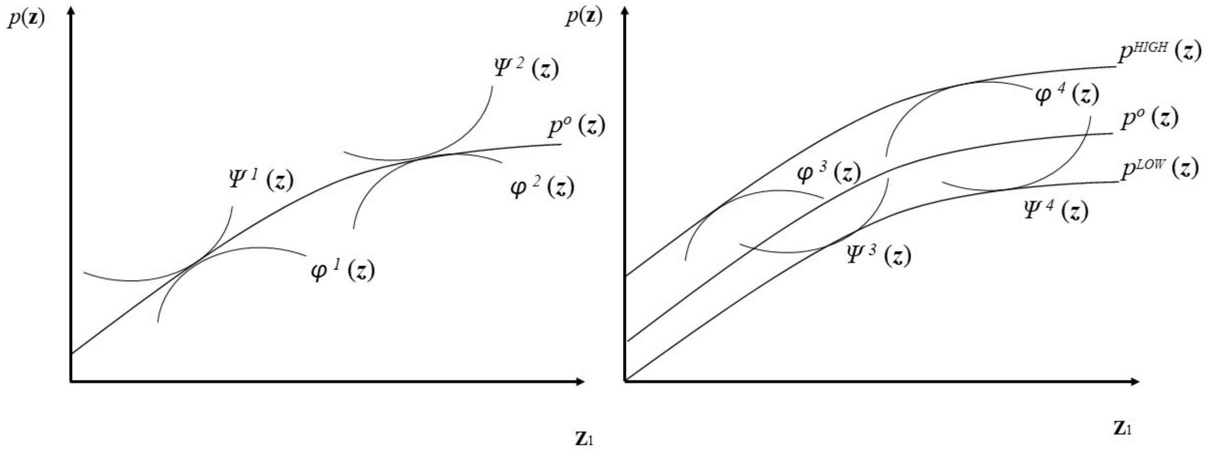

Figure 2 – Estimated implicit prices for PLs and Non-PLs GIs; equation (2): dotted Lines; equation (3) solid lines.

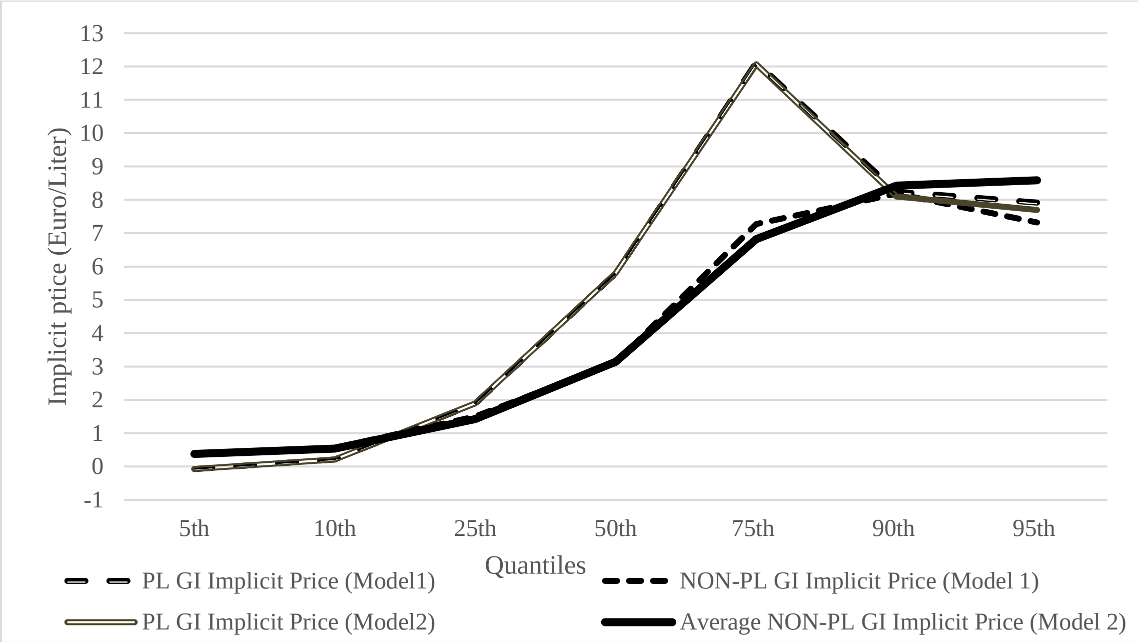

Figure 3 – Minimum and Maximum implicit prices for Non-PLs GIs and Coefficient of Variation

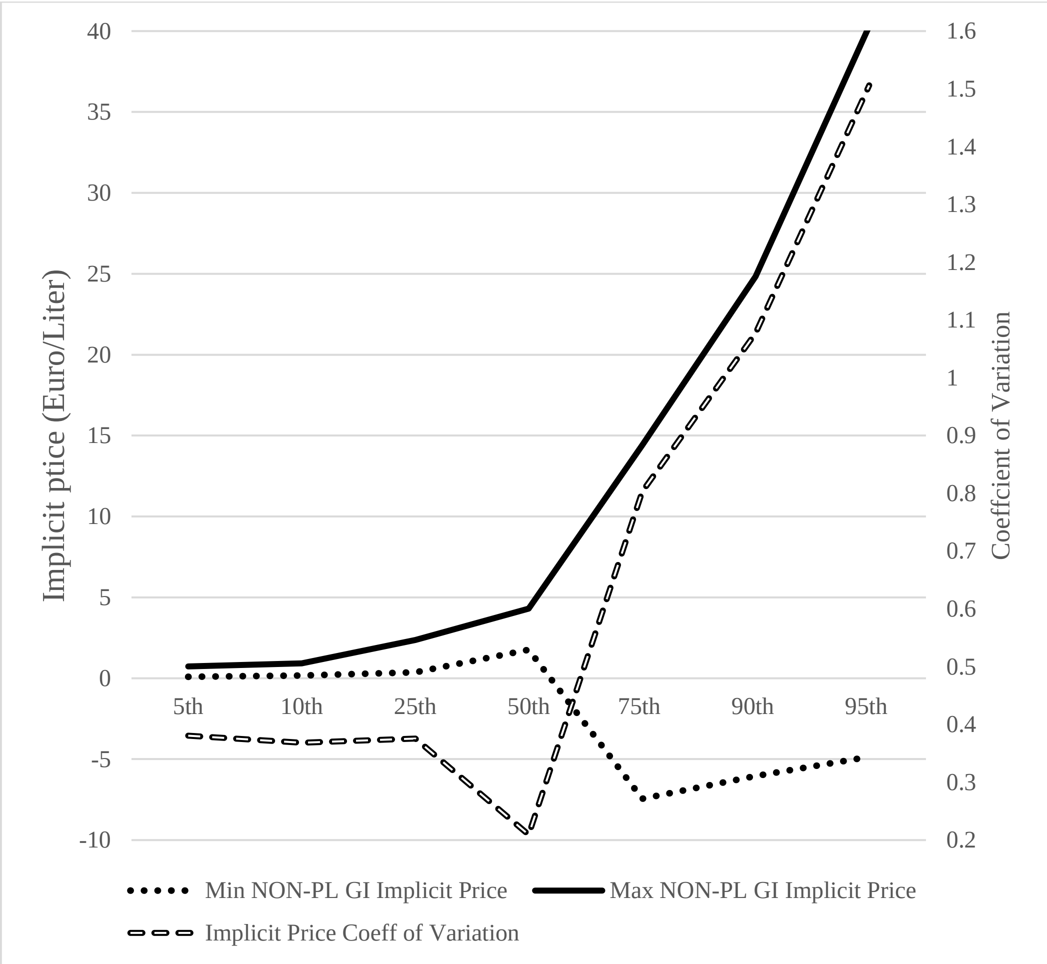

Table 1 – Summary Statistics (*N=114,136)*

| Variable | Mean | St Dev | Min | Max |
|---|---|---|---|---|
| Price | 7.457 | 3.888 | 0.336 | 25 |
| PDO | 0.189 | 0.392 | 0 | 1 |
| PDO*PL | 0.013 | 0.113 | 0 | 1 |
| Aprutino Pescarese | 0.003 | 0.058 | 0 | 1 |
| Brisighello | 0.001 | 0.036 | 0 | 1 |
| Bruzio | 0.002 | 0.047 | 0 | 1 |
| Canino PDO | 0.001 | 0.038 | 0 | 1 |
| Cartoceto | 0.000 | 0.021 | 0 | 1 |
| Chianti Classico | 0.003 | 0.056 | 0 | 1 |
| Cilento PDO | 0.003 | 0.058 | 0 | 1 |
| Colline Salernitane | 0.001 | 0.036 | 0 | 1 |
| Colline Teatine | 0.002 | 0.048 | 0 | 1 |
| Dauno Gargano | 0.009 | 0.097 | 0 | 1 |
| Favarello di Calabria | 0.001 | 0.030 | 0 | 1 |
| Garda PDO | 0.006 | 0.075 | 0 | 1 |
| GPI Toscano | 0.020 | 0.140 | 0 | 1 |
| Lucca PDO | 0.000 | 0.020 | 0 | 1 |
| Molise | 0.004 | 0.061 | 0 | 1 |
| Monte Etna | 0.000 | 0.020 | 0 | 1 |
| Monti Iblei | 0.001 | 0.037 | 0 | 1 |
| Multiple – Lombardy | 0.002 | 0.044 | 0 | 1 |
| Multiple – Sicily | 0.002 | 0.045 | 0 | 1 |
| Multiple – Tuscany | 0.005 | 0.070 | 0 | 1 |
| Multiple – various | 0.021 | 0.145 | 0 | 1 |
| Riviera Ligure | 0.013 | 0.112 | 0 | 1 |
| Sabina PDO | 0.002 | 0.043 | 0 | 1 |
| Sardegna PDO | 0.009 | 0.097 | 0 | 1 |
| Taggiasca | 0.001 | 0.034 | 0 | 1 |
| Terra di Bari | 0.026 | 0.160 | 0 | 1 |
| Terre di Siena | 0.000 | 0.021 | 0 | 1 |
| Tuscia | 0.003 | 0.054 | 0 | 1 |
| Umbria Colli Mar | 0.001 | 0.023 | 0 | 1 |
| Umbria PDO | 0.024 | 0.152 | 0 | 1 |
| Val di Mazzara | 0.011 | 0.104 | 0 | 1 |
| Valle del Belice | 0.001 | 0.029 | 0 | 1 |
| Valli Trapanesi | 0.003 | 0.057 | 0 | 1 |
| Valpolicella PDO | 0.004 | 0.061 | 0 | 1 |
| Veneto Euganei e | 0.000 | 0.021 | 0 | 1 |
| PL | 0.058 | 0.234 | 0 | 1 |
| 100% Italian | 0.265 | 0.441 | 0 | 1 |
| 100% Italian *PL | 0.019 | 0.136 | 0 | 1 |
| Organic | 0.105 | 0.307 | 0 | 1 |
| Organic*PL | 0.013 | 0.113 | 0 | 1 |
| Fruity | 0.076 | 0.264 | 0 | 1 |
| Flavored | 0.002 | 0.049 | 0 | 1 |
| 500 ml | 0.121 | 0.326 | 0 | 1 |
| 750 ml | 0.437 | 0.496 | 0 | 1 |

Source: Author's elaboration on Symphony IRI data

Table 2 – Equation 2 - Unconditional Quantile Regression – Selected estimated coefficients across quantiles.

| | 5th | | 10th | | 25th | | 50th | | 75th | | 90th | | 95th | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PDO | 0.383 | *** | 0.554 | *** | 1.501 | *** | 3.110 | *** | 7.276 | *** | 8.184 | *** | 7.321 | *** |
| | (0.009) | | (0.009) | | (0.023) | | (0.037) | | (0.111) | | (0.211) | | (0.244) | |
| PDO*PL | -0.460 | *** | -0.346 | *** | 0.381 | *** | 2.680 | *** | 4.847 | *** | 0.063 | | 0.596 | |
| | (0.027) | | (0.042) | | (0.063) | | (0.087) | | (0.216) | | (0.322) | | (0.449) | |
| PL | 0.520 | *** | 0.284 | *** | -0.774 | *** | -3.487 | *** | -3.882 | *** | -3.239 | *** | -3.470 | *** |
| | (0.027) | | (0.045) | | (0.066) | | (0.067) | | (0.107) | | (0.128) | | (0.190) | |
| 100% Italian | 0.571 | *** | 0.835 | *** | 1.743 | *** | 1.440 | *** | 0.213 | *** | -0.514 | *** | -0.415 | *** |
| | (0.010) | | (0.012) | | (0.025) | | (0.029) | | (0.042) | | (0.041) | | (0.060) | |
| 100% Italian* PL | -0.487 | *** | -0.441 | *** | -0.016 | | 0.587 | *** | -0.577 | *** | 0.313 | *** | 0.471 | *** |
| | (0.024) | | (0.043) | | (0.068) | | (0.112) | | (0.112) | | (0.102) | | (0.150) | |
| Organic | 0.231 | *** | 0.334 | *** | 0.997 | *** | 2.472 | *** | 2.338 | *** | 1.839 | *** | 2.167 | *** |
| | (0.008) | | (0.009) | | (0.017) | | (0.042) | | (0.098) | | (0.104) | | (0.171) | |
| Organic * PL | -0.157 | *** | 0.048 | | 0.646 | *** | 0.977 | *** | -4.395 | *** | -1.692 | *** | -0.722 | *** |
| | (0.021) | | (0.030) | | (0.058) | | (0.112) | | (0.196) | | (0.165) | | (0.253) | |
| Fruity | -0.006 | | 0.190 | *** | 0.629 | *** | 0.661 | *** | 0.247 | *** | 0.138 | | -0.346 | *** |
| | (0.016) | | (0.018) | | (0.033) | | (0.045) | | (0.075) | | (0.097) | | (0.111) | |
| Flavored | 0.526 | *** | 1.037 | *** | -0.382 | | 1.191 | *** | 2.408 | *** | 2.243 | *** | 2.472 | *** |
| | (0.045) | | (0.073) | | (0.260) | | (0.066) | | (0.103) | | (0.119) | | (0.175) | |
| 500 ml | 0.604 | *** | 0.845 | *** | 1.765 | *** | 3.284 | *** | 6.846 | *** | 8.192 | *** | 10.858 | *** |
| | (0.012) | | (0.014) | | (0.026) | | (0.040) | | (0.115) | | (0.230) | | (0.450) | |
| 750 ml | 0.527 | *** | 0.687 | *** | 1.113 | *** | 2.734 | *** | 3.731 | *** | 0.616 | *** | -0.929 | *** |
| | (0.012) | | (0.014) | | (0.022) | | (0.032) | | (0.060) | | (0.060) | | (0.058) | |
| Constant | 2.297 | *** | 2.560 | *** | 2.646 | *** | 3.590 | *** | 5.295 | *** | 10.482 | *** | 13.071 | *** |
| | (0.106) | | (0.105) | | (0.085) | | (0.206) | | (0.207) | | (0.165) | | (0.204) | |
| Adj R2 | 0.094 | | 0.168 | | 0.324 | | 0.491 | | 0.448 | | 0.319 | | 0.239 | |

Note: bootstrapped standard errors in parenthesis.

Table 3 – Equation 3 – Selected Unconditional Quantile Regression Coefficients for different PDO/PGI labels; average implicit price, standard deviations and coefficients of variation (CV)

| PDOs | 5th | 10th | 25th | 50th | 75th | 90th | 95th | Average | St. Dev | CV |
|---|---|---|---|---|---|---|---|---|---|---|
| Private Label | -0.075 | 0.211 | 1.891 | 5.800 | 12.067 | 8.100 | 7.697 | 5.099 | 4.578 | 0.898 |
| Aprutino Pescare | 0.579 | 0.817 | 2.017 | 3.864 | 7.972 | 2.505 | 0.327 | 2.583 | 2.684 | 1.039 |
| Brisighello | 0.359 | 0.467 | 1.026 | 2.977 | 10.530 | 21.657 | 39.358 | 10.911 | 14.753 | 1.352 |
| Bruzio | 0.646 | 0.890 | 2.142 | 3.349 | -2.696 | -2.056 | -1.122 | 0.165 | 2.220 | 13.489 |
| Canino | 0.409 | 0.618 | 1.812 | 3.867 | 11.571 | 4.702 | 3.785 | 3.823 | 3.803 | 0.995 |
| Cartoceto | 0.229 | 0.202 | 0.486 | 2.543 | 11.936 | 22.334 | 1.453 | 5.598 | 8.474 | 1.514 |
| Chianti Classico | 0.088 | 0.171 | 0.454 | 2.359 | 9.368 | 4.446 | 5.312 | 3.171 | 3.444 | 1.086 |
| Cilento | 0.476 | 0.648 | 1.789 | 3.462 | 7.018 | -0.276 | -0.420 | 1.814 | 2.655 | 1.464 |
| Colline Salernit | 0.411 | 0.540 | 1.673 | 2.946 | -3.063 | -2.225 | -0.572 | -0.041 | 2.105 | 50.979 |
| Colline Teatine | 0.506 | 0.751 | 2.005 | 4.297 | -2.536 | 0.610 | 1.468 | 1.015 | 2.044 | 2.014 |
| Dauno Gargano | 0.403 | 0.623 | 2.110 | 3.641 | 3.378 | 5.162 | 3.771 | 2.727 | 1.755 | 0.644 |
| Favarello | 0.456 | 0.643 | 1.803 | 3.545 | 0.025 | -1.997 | -0.560 | 0.559 | 1.759 | 3.144 |
| Garda | 0.479 | 0.668 | 1.585 | 3.705 | 12.723 | 24.840 | 37.100 | 11.586 | 14.333 | 1.237 |
| PGI Toscano | 0.399 | 0.592 | 1.345 | 3.229 | 9.545 | 4.492 | 4.578 | 3.454 | 3.201 | 0.927 |
| Lucca | 0.274 | 0.325 | 0.731 | 2.632 | 10.565 | 18.533 | 35.546 | 9.801 | 13.253 | 1.352 |
| Molise | 0.418 | 0.573 | 1.294 | 2.763 | 1.678 | 3.597 | -2.182 | 1.163 | 1.865 | 1.603 |
| Monte Etna | 0.734 | 0.929 | 2.363 | 4.301 | 6.965 | 2.029 | -0.772 | 2.364 | 2.569 | 1.086 |
| Monti Iblei | 0.281 | 0.413 | 1.146 | 2.156 | 7.942 | 7.091 | 2.406 | 3.062 | 3.155 | 1.030 |
| Multiple - Lomba | 0.169 | 0.269 | 0.640 | 1.765 | 7.130 | 7.697 | 15.269 | 4.706 | 5.655 | 1.202 |
| Multiple - Sicil | 0.541 | 0.878 | 2.143 | 3.514 | -3.668 | -0.206 | 1.488 | 0.670 | 2.257 | 3.370 |
| Multiple - Tusca | 0.227 | 0.377 | 1.022 | 3.636 | 12.286 | 18.552 | 10.796 | 6.699 | 7.211 | 1.076 |
| Multiple - vario | 0.320 | 0.464 | 1.380 | 2.835 | 9.936 | 12.142 | 9.945 | 5.289 | 5.156 | 0.975 |
| Riviera Ligure | 0.356 | 0.477 | 1.290 | 2.931 | 9.069 | 16.755 | 13.327 | 6.315 | 6.734 | 1.066 |
| Sabina DOP | 0.485 | 0.705 | 1.880 | 4.152 | 10.228 | 8.424 | -2.505 | 3.338 | 4.570 | 1.369 |
| Sardegna | 0.482 | 0.640 | 1.568 | 3.529 | 10.039 | 6.064 | 4.400 | 3.817 | 3.427 | 0.898 |
| Taggiasca | 0.436 | 0.620 | 1.785 | 3.745 | 14.412 | 23.374 | 14.758 | 8.447 | 9.038 | 1.070 |
| Terra di Bari | 0.513 | 0.684 | 1.728 | 2.565 | 3.585 | 4.286 | 1.318 | 2.097 | 1.442 | 0.688 |
| Terre di Siena | 0.275 | 0.327 | 0.754 | 2.475 | 10.596 | 19.662 | 19.478 | 7.652 | 8.900 | 1.163 |
| Tuscia | 0.250 | 0.384 | 1.084 | 2.337 | 9.042 | 10.211 | 6.755 | 4.295 | 4.270 | 0.994 |
| Umbria Colli Mar | 0.236 | 0.390 | 1.167 | 3.175 | -7.443 | -6.043 | -4.851 | -1.910 | 4.114 | 2.154 |
| Umbria | 0.220 | 0.380 | 1.182 | 2.952 | 10.574 | 12.987 | 10.646 | 5.563 | 5.590 | 1.005 |
| Val di Mazzara | 0.294 | 0.468 | 1.691 | 3.200 | 4.700 | 3.790 | 2.371 | 2.359 | 1.659 | 0.703 |
| Valle del Belice | 0.411 | 0.583 | 1.627 | 3.272 | 11.549 | 0.889 | -1.051 | 2.469 | 4.213 | 1.706 |
| Valli Trapanesi | 0.381 | 0.627 | 1.666 | 3.606 | 4.374 | -2.907 | -1.618 | 0.876 | 2.619 | 2.991 |
| Valpolicella | 0.320 | 0.410 | 0.883 | 2.719 | 10.746 | 22.005 | 40.306 | 11.056 | 15.150 | 1.370 |
| Veneto Euganei | 0.127 | 0.196 | 0.377 | 1.790 | 8.682 | 21.682 | 30.220 | 9.011 | 12.205 | 1.355 |