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ARTICLE

Trade uncorked: Genetic distance and taste-related barriers in wine trade

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Abstract

A nascent literature explores the impact of taste differences on trade. In gravity model estimations, the coefficient on geographic distance is large because it tends to capture such (usually unobservable) preference-related frictions. We examine this question in the context of French wine, that is, a cultural good characterized by a great variety of types (i.e. accommodating a large heterogeneity in wine tastes) and of quality levels (from cheap table wine to the finest *grands crus*). A series of gravity models are estimated using the universe of French bottled wine exports by detailed appellation between 1998 and 2015. We use genetic distance as a proxy for taste differences inherited from biology and culture. We show that this interpretation is not ruled out by other possible roles of genetic distance on trade (i.e., microgeography or non-gustatory cultural dimensions such as trust). We find that genetic distance has an independent effect on trade, explaining between 20% and 40% of the coefficient on geographic distance. Dynamic estimates confirm this result and establish both the persistent and contemporaneous effects of genetic differences. A heterogeneous analysis also corroborates previous findings in the literature showing that high-tier goods tend to escape gravity. In addition, we find that premium wines escape the home bias associated with taste differences, possibly illustrating that luxury wines have become global iconic products purchased for status and investment motives rather than for gustatory pleasure.

KEYWORDS
cultural/genetic distance, geographic distance, gravity model, PPML, wine trade

JEL CLASSIFICATION
F10, F14, L66, Q17

1 | INTRODUCTION

Although freight costs have declined over time thanks to innovation, trade costs can remain high and persistent if hidden frictions—for instance those pertaining to cultural differences (Disdier & Head, 2008) —are large and subject to slow changes. These sources of resistance to trade, belonging to "dark trade costs" (Head & Mayer, 2013), have been detected in the estimation of standard gravity models and tend to inflate the coefficients on variables such as distance and borders. Another aspect is that quality sorting makes high-end products more geographically diversified and more able to meet their demand in distant markets (see Crozet et al., 2012, in the case of Champagne producers and Fontagné & Hatte, 2013; Martin & Mayneris, 2015, for French luxury brands). If we bring both aspects together, the question then becomes whether hidden trade barriers, pertaining to heterogeneity in tastes and culture, matter differently for products of different quality.

We examine these questions in the context of wine, a good that presents several advantages for such an investigation. First, although wine drinking has become particularly common in the Western world, it is now widely available in most countries. Moreover, as an experience good, wine is an interesting candidate for the exploration of hidden costs related to taste heterogeneity: Its consumption is intimately linked to local preferences shaped by cultural and biological diversity. In this regard, we focus on French wine and capture the diversity of tastes around the world using the genetic distance between France and importing countries. Both dimensions, culture and biology, may transpire in this proxy of taste heterogeneity. The biological aspect is rarely explored in the context of international trade but potentially matters a lot for exports of food and beverage (Jäkel, 2019). Regarding culture, wine is precisely defined as a "cultural good," whose quality is a priori unknown but often proxied by its reputation or expert rating (Hadj Ali & Nauges, 2007). Focusing on French wines is useful for our investigation because these wines are exported to most parts of the world and have a wide variety of tastes and quality that can be exploited empirically.

Our primary objective is to estimate a one-exporter gravity model to disentangle the determinants of French wine exports and in particular the role of geographic distance (representing transportation costs, essentially) and genetic distance (representing taste heterogeneity). In this way, we aim to show that part of the distance puzzle is explained by the fact that geographic distance, in addition to trade costs, implicitly accounts for long-lasting barriers to trade due to taste diversity across countries. We adapt the standard gravity equation (Anderson & Van Wincoop, 2003, 2004) and adopt usual techniques to deal with heteroskedasticity and the presence of zero trade flows (Santos Silva & Tenreyro, 2006).

Our empirical investigation relies on a dataset recently assembled by the French federation of exporters of wine and spirit. We avail of trade data on the universe of wine shipments between 1998 and 2015 for bottled wine, which represents around 95% of the value of total French wine exports. These data comprise 158 French wine "appellations" (e.g. Saint-Emilion, Chateauneuf-du-Pape, etc.) from the different wine regions (e.g. Bordeaux, Rhone Valley, etc.) and covers 51 countries over 18 years. We combine this dataset with information on standard trade determinants that vary over time (annual gross domestic [roduct [GDP], real exchange rates, theoretically funded measures of multilateral resistance, importing countries' own wine production) as well as constant factors including geographic distance, common language, and genetic distance (as measured by Spolaore & Wacziarg, 2016, 2018).

We also attempt to derive heterogeneous effects of geographic and genetic distances along broad proxies for quality in order to test if premium wines escape gravity but also the influence of taste differences. In that respect, French wine presents a great variety that allows meeting different types of tastes (thanks to a broad diversity of grapes, regions, and *terroir*) and is also characterized by important differences in quality (from cheap table wine to the finest *grands crus*). We can exploit this strong vertical differentiation using variation across 158 appellations, combined with time variation over 18 years and the fact that several types of proxies for quality can be mobilized: regional reputation (Bordeaux and Burgundy), regional vintage ratings (by the wine expert Robert Parker), and average unit values.

The results can be summarized as follows. Genetic distance diminishes the effect of geographic distance by 20% to 40% (depending on the specification). Its independent effect on trade is interpreted as differences in tastes due to cultural/biological diversity. Although we cannot prove that this interpretation is correct, or the only possible one, we tend to rule out alternative explanations. Namely, whereas genetic distance might capture other types of barriers related to the microgeography or to the distance between countries in terms of non-gustatory cultural traits (such as trust and values), we still find a substantial remaining effect of genetic distance on exports when including proxies for these different factors. Finally, we use alternative ways to proxy wine quality in order to check whether premium wines defy both gravity and taste-related frictions. All the approaches lead to the same conclusion: High-end wines defy gravity but also tend to escape taste differences as captured by genetic distance.[1] A likely interpretation of the latter result may be related to the fact that premium varieties have become iconic luxury products on a global scale, increasingly disconnected from local taste identity and instead imported for conspicuous consumption or investment motives. Finally, although reputation is treated as a constant difference across regions or appellations in some of our heterogeneity analysis, we also introduce dynamic estimates of the gravity model, which may capture changes in both reputations and consumer tastes. We find a large persistent effect that may pertain to habit persistence in consumer preferences (Campbell, 2010) and long-lasting reputation effects. Despite the fact that consumer tastes for French wines may have changed slightly over the period, we find that differences in taste associated with cultural/biological diversity still play a significant contemporary role on French wine exports, and this immediate effect is greater than that of geographic distance.

The contribution of this paper is multifold. *First*, we add to the literature on the "new" sources of trade friction, linked to localized preferences and taste differences across nations as explained by historical paths of cultural and biological evolutions (see Appendix A1 for an overview of the literature). Specifically, the impact of bilateral cultural "affinity" on trade patterns has been examined through traditional gravity variables such as language or new variables such as trust, homophily, and bilateral values or opinions (see e.g. Felbermayr & Toubal, 2010; Melitz & Toubal, 2014; 2019). The present paper completes this literature by interpreting genetic distance as a measure of biological/cultural diversity in taste. *Second*, it provides extensive checks showing that in our context, genetic distance is not a mere proxy for trust (as in Guiso et al., 2009) or microgeography (Giuliano et al., 2014). *Third*, we insist on the fact that genetic proximity is not only interpreted as a proxy for cultural links but also relates to biological explanations for taste proximity. A growing literature describe the genes and molecular receptors responsible for food and beverage preferences (Reed et al., 2006). Our results complement the biological research that examines the relationship between genetics and taste/olfactory perceptions explaining wine preference (e.g. Carrai et al., 2017; Pirastu et al., 2015). *Fourth*, our work also pertains to the literature on quality sorting. Exports of high-end products are less sensitive to geographic distance than other products (Fontagné & Hatte, 2013; Martin & Mayneris, 2015). We confirm this trend for the wine sector (see also Chen & Juvenal, 2016; Crozet et al., 2012), meaning that top wine producers are better equipped to meet demand in distant markets such as Eastern Asia. Additionally, we investigate whether the role of cultural/biological distance also varies with wine quality, bringing further information on the ability of high-end producers to conquer markets that are not only far away but also culturally different. *Finally*, we suggest one of the few attempts to estimate a dynamic gravity model, along the lines of Anderson and Yotov (2020), and disentangle persistent from contemporary effects of both geographic and genetic distances.

2 | EMPIRICAL APPROACH

2.1 | Main gravity model

To empirically analyze the impact of geographic and genetic distances on French wine exports, we rely on a theory-consistent estimation of the gravity model of trade (Anderson & Van Wincoop, 2003, 2004). The most frequent model used in the empirical literature is the log-linearized form of the gravity equation (Head & Mayer, 2014; Yotov et al., 2016). Given that there is only one exporter (France), the model is written as follows:

$$\begin{aligned} ln\left(X_{irjt}\right) = {} & \gamma_0 + \gamma_1 ln\left(GDP_{jt}\right) + \gamma_2 ln\left(Pop_{jt}\right) + \gamma_3 ln\left(RER_{jt}\right) + \gamma_4 ln\left(AVE_{jt}\right) + \gamma_5 \ln\left(Prod_{jt}\right) \\ & + \gamma_6 Language_j + \gamma_7 ln\left(Geo_j\right) + \gamma_8 ln\left(Gen_j\right) + \gamma_9 MR_{Geo,j,t} + \gamma_{10} MR_{Gen,j,t} + \mu_t + \theta_{rt} + \lambda_i + \varepsilon_{irjt} \end{aligned} \tag{1}$$

where X_{irjt} represents French wine exports (in volume) of appellation i and region r to country j at time t. Trade determinants varying with trading partner and time include the log GDP of the partner, the log of its population size (it is equivalent, in logs, to use GDP and GDP per capita), the log bilateral real exchange rate (*RER*) between the French Franc or Euro and the partner's local currency, and the log of one plus the average tariff level with partner j in ad valorem equivalent (*AVE*). We also add factors pertaining to cultural dimensions, including the log of local wine production and a dummy for common language. We will focus particularly on the geographic distance (*Geo*) and the genetic distance (*Gen*) between France and destination countries. We associate multilateral resistance (*MR*) terms that are theoretically funded. We control for several types of fixed effects. Year dummies μ_t account for a variety of common time factors: the overall quality of the new vintage (e.g. general weather conditions), the quantity and quality of (unsold) older vintages, exogenous factors affecting trade (business climate, trade policy, etc.), and factors affecting demand globally (such as the Great Recession years). Region × year dummies θ_{rt} proxy local climate conditions that may affect the production level and the average quality in one of the wine regions of France (8 regions × 18 years - 1 = 143 dummies). At the most disaggregated level, appellation dummies λ_i reflect the long-term characteristics of each appellation; they also absorb regional characteristics. Crozet et al. (2012) insist on the possibility to interpret firm heterogeneity in trade levels as due to variation in quality as much as in productivity (i.e. the original interpretation of the seminal paper of Melitz, 2003, linking firm heterogeneity and trade). In our setting, our disaggregation at the appellation level leads to a similar interpretation about appellation fixed effects (long-term heterogeneity in actual quality). For estimation, we reply mainly on the Poisson Pseudo Maximum Likelihood (PPML) estimator proposed by Santos Silva and Tenreyro (2006), which allows dealing with usual difficulties: (i) the heteroscedasticity deriving from the log-linearization and (ii) the problem of having numerous zero-value observations when estimating the log of trade, as further described in Appendix A2.

2.2 | Data sources

We present the main datasets used in the empirical analysis. Note that the different variables, the link to data sources and detailed descriptive statistics are presented in Appendix Table A1.

Export data

We exploit a dataset assembled by the French federation of exporters of wine and spirit (*Fédération des Exportateurs de Vins et Spiritueux de France, FEVS*). It represents the universe of French wine shipments for the period 1998–2015. We focus on bottled wine. Other alcoholic drinks (spirits, liquors) and other wine packaging (i.e. bulk wine) correspond to different types of products and markets. In particular, bulk wine accounts for a very small share of total exports (less than 5%) and is not assessed by wine experts, so it could not be used in our heterogeneity analysis. Thus, out of 291 exported appellations, we select the 158 appellations corresponding to bottled wine. They represent 95% of total French wine exports in value over the period (94% for the year 2015, i.e., €7.43 billion). This leads to a sample covering 18 years, 51 countries, and 158 appellations, hence a total of 145,044 observations. Exported bottles are essentially produced in the seven main wine regions of France.[2] Among the 51 importing countries, the top 10 represents 74.4% of total exports of French bottled wine.[3] On average over the period, 80% of the appellations export nonzero volumes to an average of 36 destinations. The evolution of French wine exports is presented in Appendix A3.

Note that export data are available at appellation-level only. This potential limitation is due to the specificity of the wine industry in France, namely the fact that wineries rarely sell wine themselves but use intermediaries (see Cardebat & Figuet, 2019).[4] Our estimations at appellation level are still valuable. Indeed, we do not focus on factors that matter at product level (e.g. tariffs and nontariff measures). Moreover, even if firm-level data are increasingly used, the gravity model has traditionally been estimated mostly with aggregate data, and there is a lot of robust evidence on the impact of traditional trade determinants including what we are interested in, that is, measures of bilateral distance (Head & Mayer, 2014). Finally, as described above, there is a lot of variation in export destinations across the numerous wine appellations in France, as well as much variation in quality and reputation that we can exploit hereafter. We nonetheless provide robustness checks in the result section.

Trade determinants

We combine this dataset with other sources on trade determinants. For standard gravity variables (geographic distance, common language, etc.) we use the database provided by the Centre d'Etudes Prospectives et d'Information Internationales (CEPII). Data on GDP, population size, and real exchange rates are taken from the World Bank's *World Development Indicators*. Bilateral exchange rates are expressed in real terms using the French and the foreign country's consumer price index (CPI). Tariffs are taken from the World Integrated Trade Solution of the World Bank. Multilateral resistance (MR) is accounted for using the method of Baier and Bergstrand (2009).[5]

Genetic distance

Genetic distance is measured as the difference in the distribution of gene variants, providing an approximate time because two populations have shared common ancestors (Spolaore & Wacziarg, 2009). First introduced by Cavalli-Sforza et al. (1996), these data are more comprehensively available in Pemberton et al. (2013). We exploit the new database by Spolaore and Wacziarg (2016, 2018), which extends this measurement of genetic distance between ethnic pairs to that between country pairs.[6] It can be interpreted as the expected genetic distance between two randomly selected individuals in two different countries. To get an order of its scale magnitude, note that the genetic distance between France and wine-importing countries ranges from five (countries like Belgium) to 160 (the UK) in Europe; worldwide, it goes up to 510 (Ivory Coast).

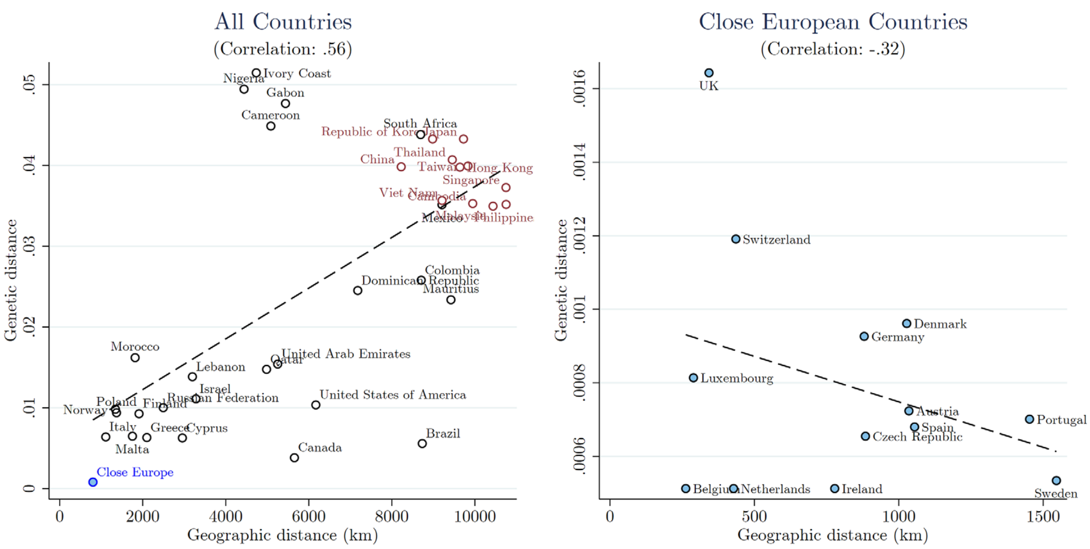

FIGURE 1 Correlation between genetic and geographic distances. Author's graphs based on geographic distance (from trade indicators provided by CEPII, Paris) and genetic distance (coancestry measure, provided by Spolaore and Wacziarg, 2016)

The main objective of the paper is to show that part of the distance puzzle is explained by the fact that geographic distance does not only capture trade costs but also taste differences across countries, inherited from biology and culture and proxied by using genetic distance. Thus, because both geographic and genetic distances are time invariant, much collinearity between these measures could be a concern for the identification of the taste effect. It turns out that the global correlation rate between geographic and genetic distances is "only" 0.56 and mainly driven by Asian countries, as illustrated in the first graph of Figure 1. In the set of French wine importers, Asian countries are among the most distant from France and also geographically distant. Otherwise, the association between geographic and genetic distances is limited. If we zoom on European countries, the correlation is actually negative, as shown in the second graph of of Figure 1. In our empirical analysis, we will simply check how our results change when controlling for an "Asian countries" dummy.

In Figure 2, we provide the basic intuition for our results. We observe the usual negative relationship between geographic distance and trade flows (left-side graph). We also distinguish a similar relationship between genetic distance and trade (right-side graph). Estimates will take into account both distances as well as the standard determinants of trade. We will also include additional variables to attempt to control for alternative interpretations of the bias attached to genetic distance, notably microgeography and non-gustatory cultural traits such as trust and values.

Microgeography

For other types of goods, Giuliano et al. (2014) show that genetics essentially capture microgeographic barriers to trade. Terrain variability can affect the construction and maintenance costs of surface transport networks, hence the costs to use these networks, whereas an increase in the road gradient also increases fuel consumption. Thus, as these authors, we will control for the existence of a common sea/ocean between France and its trading partner as well as for topographical variability or *ruggedness*. The most frequent measure is the Terrain Ruggedness Index developed by Riley et al. (1999). It is measured in hundreds of meters of elevation difference at very thin grid points and averaged at the country level. To capture the possibility that ruggedness may be more important in areas that are more densely populated, we will also use a population-weighted measure of ruggedness (see

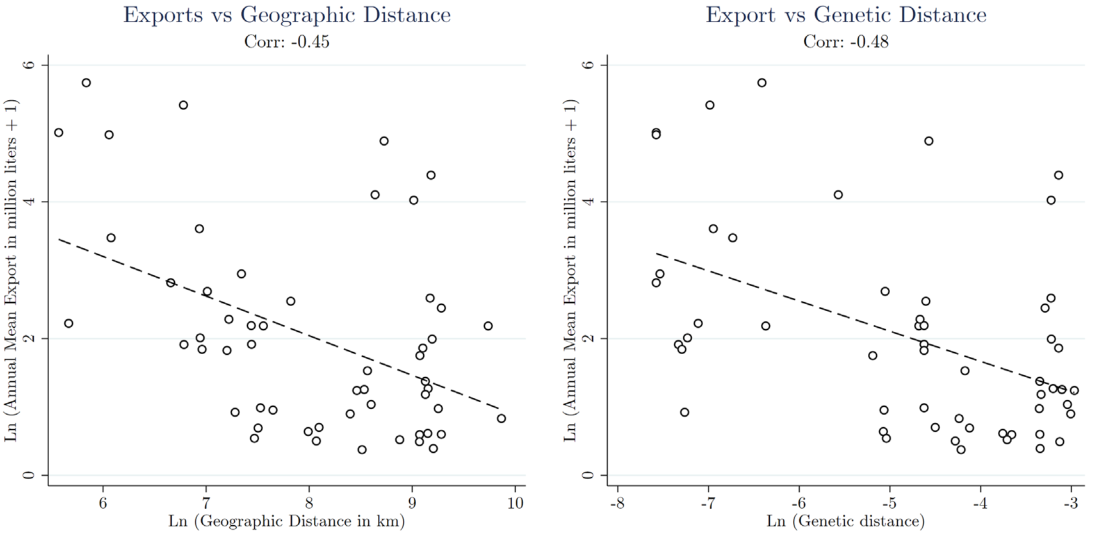

FIGURE 2 Export flows vs geographic and genetic distances. Author's graphs based on trade data from the French federation of exporters of wine and spirit (FEVS), geographic distance form CEPII (Paris) and genetic distance (coancestry measure) from Spolaore and Wacziarg (2016)

more details on the construction of both indices in Nunn & Puga, 2012). Not surprisingly, a very flat country like the Netherlands gets the lowest value for both indices in our data, namely 0.03 for the main ruggedness measure and 0.04 for the population-weighted measure. The highest level is reached by Switzerland for the former measure (4.76) and Lebanon for the latter (2.17).

Non-gustatory cultural proximity

We shall check whether the role of genetic proximity on wine trade corresponds to close connections between nations—in terms of nongustatory cultural traits such as trust, language proximity and common values—rather than on culturally and biologically determined proximity in tastes. In the empirical literature, trust is mainly calculated on the basis of answers to particular questions that reflect the ability of individuals to trust each other. Most empirical studies rely on the World Value Survey (WVS) and average the responses to obtain a country's level of trust in others (Ahern et al., 2015; Guiso et al., 2009; La Porta et al., 1997; Sapienza et al., 2013). Yet, this measure does not allow providing interpretations on bilateral trust, for instance if French exporters are trusted by Italian importers. Guiso et al. (2009) have proposed a bilateral measure of trust based on the Eurobarometer survey. Conducted on a representative sample of total populations of age 16 and over (around 1000 individuals per country), it asks the question on trust in people from various countries ("*For each country, please tell me whether you have a lot of trust, some trust, not very much trust, or no trust at all*"). Based on the answers, they provide a bilateral measure of trust for 15 European countries that ranges from 0 (no trust at all) to 4 (a lot of trust). We extract such a measure of bilateral trust between France and EU importing countries. Regarding language and values, we rely again on Spolaore and Wacziarg (2016). For linguistic distance, these authors adopt the approach based on language trees. For values, as Guiso et al. (2009), they make use of survey questions about individual values from the World Value Survey 1981–2010 Integrated Questionnaire. Their final dataset contains 98 questions that can be used to measure cultural distance between France and 74 countries, of which only 36 are present in our sample of French wine importers. For each question, Spolaore and Wacziarg compute the standardized Euclidian distance between the shares of respondents, in two countries, who give a specific answer to the question. For the global measure of cultural distance between countries, they simply sum the standardized indices for all the 98 questions. They also provide some measures aggregating questions on specific cultural topics such as life perception, work perception, family perception, politics and society, and religion and morale, which we shall also use.[7]

Proxies for quality: Expert rating and unit values

Our analysis includes the estimation of heterogeneous effects of geographic and genetic distances on exports by quality levels. There are no perfect proxies for quality, and we use alternative strategies. In particular, we follow Crozet et al. (2012)'s idea to use expert ratings, and we primarily rely on the scores given by the wine expert Robert Parker. We use the scores attributed to French regions and subregions each year ("local vintage scores"), as broad proxies for local quality. Parker has been a leading US wine critic who has assessed wines based on blind tastings published as consumer advice in a bimonthly publication, the *Wine Advocate*. The rating system employs a 50–100 point scale where wines are usually rated according to their name, type, grape, and vintage. His evaluation is one of the largest coverage of wine ratings that exists for French wines. Nevertheless, his ratings (or other expert's scores) do not cover all wine producers or appellations. This is the reason why our heterogeneity analysis hinges on summary scores attributed to local vintages by Parker. In total, this rating covers 18 regions or subregions over 18 years, hence 291 points of observation for our heterogeneity analysis (324 points minus 33 missing observations, i.e., 10.2%).[8] Among rated wines, the lowest rate is 58 and the highest is 99. The distribution across wines is symmetric as the mean and the median are equal (at a value of 88.5). We use Parker's score as a broad proxy for quality. We define four broad categories including the three terciles of the score distribution and a fourth group corresponding to ungraded wines.[9] Note that Parker's scores for Tercile 1 range from 58 to 86, those of Tercile 2 from 87 to 90, and those of Tercile 3 from 91 to 99. We also rely on a dichotomous measure of subregions $\times$ year receiving a score above 90. This threshold is known as a symbolically high score in Parker's scaling, and it also corresponds to the cutoff of the upper tercile. Thus, it is supposed to capture wines of particularly high reputation and quality. We alternatively use terciles of unit values as broad proxies for wine quality.[10]

3 | RESULTS

3.1 | Standard determinants and the role of genetic distance

Estimation results for various specifications of the gravity model are presented in Table 1. In Column (1), we start with a set of standard gravity variables. Geographic distance has a significant and large effect. The coefficient of −0.716 [−0.800; −0.632] is of a similar order of magnitude as the mean and median distance effects calculated by Head and Mayer (2013) over a large number of surveyed studies. In particular, it corresponds well to the geographic distance coefficient found in the most recent studies based on PPML estimates (see Head and Mayer's Figure 5). The other trade determinants give the expected results. The income elasticity, captured by the coefficient on the log of GDP, is close to 1. The coefficient on the real exchange rates is positive (i.e. an appreciation of the foreign currency increases trade flows). Tariffs depress the export flows.[11]

The following specifications introduce usual *culture-related variables* in a stepwise way. Model (2) adds a common language dummy: French speaking countries tend to significantly import French wine more than other regions of the world. Model (3) includes the log of local wine production: Its coefficient potentially reflects opposing forces. Wine producing countries are characterized by higher preferences for wine consumption, which would make them more likely to import wine if they seek

TABLE 1 PPML estimation of the gravity model: Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)
Log geogr. distance	−0.716***	−0.678***	−0.551***	**−0.395*****	**−0.427*****	**−0.348*****
	(0.0427)	(0.0432)	(0.0455)	**(0.0486)**	**(0.0493)**	**(0.0482)**
Log GDP	0.932***	0.967***	1.081***	1.072***	1.041***	1.120***
	(0.0704)	(0.0699)	(0.0622)	(0.0628)	(0.0633)	(0.0537)
Log pop.	−0.154**	−0.0514	0.0221	0.134*	0.184***	0.0738
	(0.0721)	(0.0740)	(0.0674)	(0.0709)	(0.0708)	(0.0606)
Log real exch. rate	0.117***	0.180***	0.0560*	0.0971***	0.106***	−0.0360
	(0.0265)	(0.0268)	(0.0312)	(0.0339)	(0.0349)	(0.0392)
Log (tariffs +1)	−0.0825***	−0.228***	−0.173***	−0.110***	−0.126***	−0.154***
	(0.0281)	(0.0292)	(0.0319)	(0.0349)	(0.0355)	(0.0348)
Common language		0.831***	0.939***	0.890***	0.874***	1.038***
		(0.0931)	(0.0801)	(0.0869)	(0.0882)	(0.0905)
Log local production			−0.112***	−0.129***	−0.133***	−0.126***
			(0.0148)	(0.0133)	(0.0137)	(0.0130)
Log genetic distance				**−0.278*****	**−0.288*****	**−0.375*****
				(0.0571)	**(0.0579)**	**(0.0540)**
Log (unit value +1)					0.317***	
					(0.0271)	
Asia dummy						1.269***
						(0.207)
Constant	−16.50***	−18.26***	−18.88***	−22.82***	−22.86***	−22.86***
	(1.614)	(1.565)	(1.486)	(1.622)	(1.570)	(1.570)
Observations	145,044	145,044	145,044	145,044	145,044	145,044
Pseudo R-squared	0.627	0.622	0.621	0.636	0.637	0.664
Multilateral resistance variables	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
Region-Year dummies	YES	YES	YES	YES	YES	YES
Appellation FE	YES	YES	YES	YES	YES	YES

Note: PPML estimations of export volume in level. Standard errors, clustered at country-appellation level, in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

diversity. At the same time, their own wines are competitors/substitutes to imported wines, and national preferences do not necessarily include French wines in their demand for variety. The latter effect seems to prevail because the coefficient is negative.

Most importantly, model (4) adds the *log genetic distance* (and the associated multilateral resistance variable) to the other covariates. Its inclusion does not fundamentally affect the interpretation and magnitude of the coefficients on GDP, exchange rate, tariffs, common language, or local wine production. As expected, it substantially diminishes the effect of geographic distance, namely by 28% compared to Model (3). Nonetheless, genetic distance has a negative and significant coefficient, which happens to be relatively similar in magnitude to the coefficient on geographic distance. These results, and robustness checks hereafter, suggest that genetic distance plays an independent role on trade flows, possibly related to cultural and biological determinants of wine preferences.[12]

3.2 | Robustness checks

Additional controls

The rest of Table 1 contains a few sensitivity checks. First, Model (5) shows that adding log unit values does not change the previous conclusions nor the magnitude of the coefficients on the key variables. The role of unit values could be that of a price, so a negative sign is expected. At the same time, they may also reveal quality and thus be a positive driver of export flows. The latter mechanism seems to prevail as the coefficient on unit values is positive and significant.[13] Second, we have seen that most of the international correlation between genetic and geographic distances is driven by the cluster of Asian countries (cf. Figure 1). Hence, an interesting check consists of adding an Asian dummy in the model, which would capture much of the commonalities between geographic and genetic distances.[14] In Model (6), we see that the results are qualitatively similar. The effect of genetic distance increases slightly and that on geographic distance decreases a little (i.e. a change of about a quarter in both cases).

Estimation methods and specification

Our results are not dependent on the estimation method. We have experimented with several alternative approaches, which lead to the same conclusions, including basic Tobit estimations or a Heckman two-step procedure using religious alcohol prohibition as an instrument. In unreported estimations, we have also tried alternative specifications including hub dummies (to denote the particular role of re-exporting countries such as the Netherlands, Belgium, Hong Kong, and Singapore), adding the per-capita consumption of alcoholic drinks in destination country or directly introducing the prohibition dummy (equal to 1 for a trade partner in which alcohol consumption is in principle forbidden due to religious motives, cf. Bouët et al., 2017). Adding these variables makes very little difference overall and, in particular, on the coefficients on geographic and genetic distances.

Discussion on appellation-level estimations

Using export flows at the appellation-level may mask some heterogeneity, with stronger effects in some regions than in others. We carry out a detailed heterogeneity analysis hereafter but can already provide additional information and checks. *First*, we avail of a lot of variation in both French wine appellations and export destinations in the data (the 158 appellations involved in the export of bottled wine $\times$ 51 destination countries $\times$ 18 years). This sample also captures much heterogeneity in quality that we shall exploit. *Second*, quality is often relatively homogenous within appellations, and the fact that we use thin appellation classifications (see Online Appendix Figure B1) helps better dissociate quality levels, for instance between communal appellations (higher quality) and regional appellations (lower quality). *Third*, we re-estimate the gravity model without the appellations (or regions) showing the highest heterogeneity in price and quality. We find relative stability in the key estimates compared to baseline results, suggesting that the aggregation implicit in our data does not bias our main conclusions.[15]

Wine characteristics and time-varying conditions

Although we attempt to measure taste heterogeneity between consumers due to their genes, another important dimension is the variety in wine characteristics (including grapes and strength, i.e., alcohol content) and how it interacts with wine preferences. These depend on the region, the wine-making process and the year-specific weather conditions mainly. One would expect that consumers from countries that produce full-bodied and strong wines (more likely to be found in Australia, Chile, Argentina, and the US for example) have developed a taste for such wines and, hence, are more likely to be attracted by red wines from Bordeaux or Côtes du Rhône rather than wines from Loire or Burgundy. These factors may matter if unobserved wine characteristics are correlated with both Parker's scores (as used later) and volumes exported to specific countries, for instance (for a discussion on endogeneity issues related to unobserved wine quality, see Dubois & Nauges, 2010). In fact, the long-term wine characteristics (grapes, terroir, etc.) are to a large extent taken into account by the appellation FE. Regarding time-varying conditions and how they interact with wine characteristics, we could use records from the national weather forecast agency, but we already control for region-by-year fixed effects, which capture local weather conditions that affect yields, quality, alcohol content, and so on, and hence traded volumes.

3.3 | Alternative interpretations of the role of genetic distance

Our reading of genetic distance as a marker of taste heterogeneity can be challenged by other interpretations. It may pick up nongustatory cultural traits that affect trade in general (e.g. trust) or other correlates (e.g. micro-geographic factors). Thus, in what follows, we filter out the informational content of the genetic distance variable by adding proxies for these variables.

Microgeography

Geographic factors possibly contributed to the genetic drift by having determined past migration routes or by having separated populations. For this reason, genetic distance could simply proxy how the microgeography affects land/sea transportation and the related trade costs, as shown in Giuliano et al. (2014). Following these authors, we check how the coefficient on genetic distance varies when controlling for two additional variables, namely the presence of a common sea/ocean and the measure of topographical variability or *ruggedness*. Giuliano et al. (2014)'s results—that is, the effect of genetic distance fully disappears when controlling for these factors—are particularly strong in the case of bulky goods for which geographic barriers are more of an impediment to trade. We do not necessarily expect the same result here. First, we do not focus on bulk wine but on bottled wine. Second, Giuliano et al. (2014) focus on trade within Europe, whereas we study the *global* trade of French wine. Third, and most importantly, their study relies on the older genetic data from Cavalli-Sforza et al. (1996). Recent evidence based on the new data from Spolaore and Wacziarg (2018), which we use, shows that genetic distance is more strongly associated with economic outcome than previously thought. This is particularly true with trade, as demonstrated by Melitz and Toubal (2019).

Results are reported in Table 2. We see that compared to the baseline (Column 1), our measure of genetic distance is reduced by a half when ruggedness is included (Column 2). Adding the presence of shared seas/oceans barely changes the estimates for gravity and genetics (Column 3). Although smaller, the effect of genetic distance remains significant at the 1% level (i.e., an estimate of -0.190 $[-0.300; -0.081]$). These results suggest that genetic distance may be a trade factor per se: Although it cannot be subsumed by geographic distance nor by geographic factors, it possibly reflects trade frictions that pertain to the existence of localized tastes inherited from cultural/biological diversity.

Our findings are possibly different from Giuliano et al. (2014) and similar to Melitz and Toubal (2019), mainly because of the use of the new genetic database. The other reason discussed above is the fact that they focus on Europe. Transportation costs are mainly associated with land routes in their case, so the presence of mountain chains may matter. This is less the case here: Half of France's trading partners are located on a different continent; moreover, the global wine trade increasingly

TABLE 2 PPML estimation of the gravity model: Adding geographic controls

	(1)	(2)	(3)	(4)	(5)
Log geogr. distance	−0.348***	−0.515***	−0.511***	−0.454***	−0.449***
	(0.0482)	(0.0468)	(0.0473)	(0.0478)	(0.0483)
Log genetic distance	−0.375***	−0.187***	−0.191***	−0.285***	−0.290***
	(0.0540)	(0.0545)	(0.0558)	(0.0566)	(0.0580)
Ruggedness		−0.260***	−0.253***		
		(0.0401)	(0.0414)		
Pop-weighted ruggedness				−0.267***	−0.254***
				(0.0546)	(0.0570)
Common sea			0.0852		0.156*
			(0.0881)		(0.0919)
Observations	145,044	145,044	145,044	145,044	145,044
R-squared	0.664	0.661	0.660	0.660	0.659
Standard trade determinants	YES	YES	YES	YES	YES
Multilateral resistance variables	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
Region-year dummies	YES	YES	YES	YES	YES
Appellation FE	YES	YES	YES	YES	YES

Note: PPML estimations of export volumes. Standard errors, clustered at country-appellation level, in parentheses.
Significance level: ***$p < 0.01$.

relies on sea and air transportation (Candau et al., 2017), whereas the containerization allows multiple modes of freight transport (Emlinger & Lamani, 2020). Nonetheless, in unreported estimations, we have also added the presence of mountains chains, which have virtually no impact on our results. Similarly, ruggedness is not so much used to capture the topographic variability that lies between France and the destination country but rather the implicit costs of transporting wine *within* the importing country. In that respect, a population-weighted measure of ruggedness seems to be an interesting alternative. As shown in Table 2, it diminishes the coefficient on genetic distance but only by around a quarter (from −0.375 [−0.481; −0.269] to −0.285 [−0.396; −0.174] in Column 4 and to −0.290 [−0.403; −0.176] in column 5).[16] Finally, additional estimations convey that in the most complete specifications, namely Models 3 and 5, genetic distance still reduces the effect of geographic distance, by 23% and 31% respectively.

Nongustatory cultural proximity

We also need to check alternative interpretations in terms of cultural proximity. Genetic proximity may capture close connections between nations that are associated with trust, homophily, and common values. These values tend to enhance the intensity of international trade between culturally close countries, as shown for instance by Guiso et al. (2009) and Melitz and Toubal (2019).[17] Thus, the positive effect of genetic distance on trade may just reflect the role of nongustatory cultural mechanisms, associated with trust and common values, rather than the effect of taste differences. Admittedly, we cannot perfectly clean genetic distance from these cultural traits, but we nonetheless try account for reasonable proxies of trust and values in additional estimations. Note that the next estimations also control for microgeography factors.

TABLE 3 PPML estimation of the gravity model: Adding trust and cultural distance

	Trust (European sample, Guiso et al., 2009)		Cultural distance (Spolaore & Wacziarg, 2016)			
	Baseline (on sample with trust) (1)	Incl. trust (2)	Baseline (on sample with linguistic dist.) (3)	Incl. linguistic dist. (pop. weighted) (4)	Baseline (on sample with values distance) (5)	Incl. total values distance (6)
Log geogr. distance	−0.844***	−0.652***	−0.504***	−0.502***	−0.559***	−0.517***
	(0.172)	(0.175)	(0.0487)	(0.0508)	(0.0555)	(0.0591)
Log genetic distance	−0.461***	−0.283***	−0.171***	−0.171***	−0.376***	−0.352***
	(0.113)	(0.107)	(0.0514)	(0.0516)	(0.0668)	(0.0658)
Trust or log (cultural Distance)		2.366***		−0.265		−0.0792**
		(0.356)		(0.713)		(0.0360)
Observations	39,816	39,816	130,824	130,824	102,384	102,384
Pseudo R-squared	0.741	0.750	0.669	0.668	0.669	0.669
Standard trade determinants	YES	YES	YES	YES	YES	YES
Microgeography	YES	YES	YES	YES	YES	YES
Multilateral resistance variables	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
Region-year dummies	YES	YES	YES	YES	YES	YES
Appellation FE	YES	YES	YES	YES	YES	YES

Note: PPML estimations of export volume in level. Standard errors, clustered at country-appellation level, in parentheses.
Significance levels: *** $p < 0.01$, ** $p < 0.05$.

We start with trust, using the bilateral measure suggested by Guiso et al. (2009) and previously defined in the data section. Because it is collected for European countries only, our sample size is considerably reduced. We first replicate our baseline specification on this sample to check the impact of the sample size reduction. Results are reported in Model (1) of Table 3. Both geographic and genetic distances are still significant. Their magnitudes are larger here, but the standard errors are also multiplied by 3.5. We then add trust in model (2). As expected, it has a strong positive effect on trade. Importantly, the coefficient on genetic distance is reduced by 38% (from −0.461 [−0.682; −0.240] to −0.283 [−0.493; −0.073]) but remains statistically significant. Note that the coefficient on geographic distance also decreases. Given the very small sample used here, these results are only suggestive.[18] Nonetheless, we share the views of Melitz and Toubal (2019) about the fact that genetic distance does not only measure the level of trust between nations but possibly embodies other trade factors such as local tastes. Finally, note that with this specification adding genetic distance to the model reduces the effect of geographic distance by 40%, which is more than what we have previously found.

We move to linguistic and cultural distances using the data from Spolaore and Wacziarg (2016). We first report the estimation based on our usual specification (the only difference here is that "common language" is taken out). We use the subsample for which linguistic distance is available (Model 3). Adding the log linguistic distance does not change the relative effects of geographic and genetic distances (Model 4): Both remain highly significant. Similar conclusions are obtained in Models (5) and (6) where we add a measure of log cultural distance, calculated as the average distance over different types of values, namely perceptions about life, work, family, politics/society, and religion/morale. In Table A2, we test each of these values separately. Two of them, the log distances in work values and in religion/morale, significantly reduce the intensity of wine trade with France. In all cases, adding these nongustatory cultural measures does not dramatically affect the estimates of geographic and genetic distances. These results are suggestive of the fact that genetic distance captures other dimensions possibly related to tastes inherited from gustatory culture and biology (Table A3).

3.4 | Quality sorting and heterogeneity

Previous results implicitly account for the diversity in wine types and how it interacts with preference heterogeneity in explaining trade flows. We now exploit this diversity more explicitly by sorting our observations according to different quality measures. Our aim is to test whether export flows of high-quality wines are less sensitive to transportation costs (as proxied by geographic distance, cf. Martin & Mayneris, 2015) but also less dependent on local preferences (as proxied by genetic distance).[19]

Regional heterogeneity

We start using regional reputation as a broad proxy for quality. Consumers rely on the overall reputation of a wine's origin—the region it comes from—to indicate the wine's quality (see e.g. Castriota & Delmastro, 2015; Costanigro et al., 2010; Landon & Smith, 1998; Oczkowski & Doucouliagos, 2015; and the review by Lockshin & Corsi, 2012). In the case of French wines, two regions of world renown stand out: Bordeaux and Burgundy. Table 4 shows that these two regions export to a greater number of destinations, to the most distant geographically, but also to the countries most genetically different from France. The last row also shows that for two criteria, the number of destinations and genetic distance, the gap with other regions is even larger for premium wines of Bordeaux and Burgundy (identified using a high expert score, as explained below).

Our heterogeneity analysis is consistent with these observations. We estimate the interaction of the log geographic and genetic distances with dummies for Bordeaux wines, Burgundy wines, and other regions. Results are reported in Figure 3 where we plot the heterogeneous effects of geographic distance (left) and genetic distance (right) for each region against the mean unit value of the wines exported by the region (mean values over all years). The negative effects of both geographic and genetic distances are significantly dampened for the two famous wine regions. Whatever the other region we compare them to, Bordeaux and Burgundy produce wines that are more expensive, less dependent on freight and transportation costs (proxied by geographic distance), and not sensitive to taste heterogeneity (as captured by genetic distance).[20]

Figure 3 actually suggests that the distance coefficients are reduced especially in the case of Burgundy. Bordeaux is a more heterogeneous region that mixes both renowned appellations and simpler wines. Burgundy is characterized by a much smaller area—hence a smaller production level—almost entirely dedicated to fine wines. These factors contribute to less variation in price and quality compared to Bordeaux, which may explain the observed pattern regarding distance effects.[21] When testing the equality of coefficients between Bordeaux or Burgundy and other French wines, we reject equality in all specification, but, consistently with the discussion above, the rejection is stronger for Burgundy (p-values close to zero) than for Bordeaux (p-values between 0.05 and 0.10).[22]

Heterogeneity within and across regions

We turn to a more detailed heterogeneity analysis in Table 5. For both geographic and genetic distances, we estimate heterogeneous effects between regions as well as within Bordeaux and Burgundy regions. We suggest two ways of extracting premium Bordeaux and Burgundy wines. The first approach is simply based on reputation: We focus on the observations that correspond to the *Grands Crus* of the Côte d'Or for Burgundy and, for Bordeaux, we select *Communales du Médoc* (which includes Margaux, Saint-Julien, Saint-Estèphe, and Pauillac), Graves, Saint-Emilion and Sauternes. The second approach relies on appellation and time variation in Parker scores: We characterize as top Bordeaux and Burgundy those wines with a grade above 90.

Results go in the same direction with both approaches. Top wines from Bordeaux and Burgundy tend to escape both gravity and trade barriers associated with genetic distance. Other Bordeaux and Burgundy wines are in an intermediary situation between premium wines and wines from other French regions. Note that these results are consistent with the descriptive statistics of Table 4: Top wines tend to be exported to more countries, more geographically distant countries, and more genetically distant countries, compared to other wines. The tests reported at the end of Table 5 highlight the differences already mentioned between Bordeaux and Burgundy regions. Whatever the approach used, the geographic and genetic distances affect top Bordeaux significantly less than other Bordeaux, whereas statistical differences do not emerge within the Burgundy region. This is probably due to the reason suggested above, namely the fact that there is less dispersion and an overall higher average quality among Burgundy wines.[23] In the last two rows of Table 5, we additionally test the "other" Burgundy and Bordeaux wines against wines from other regions. We consistently find that the gap is significantly different from zero for Burgundy but not for Bordeaux: The "small" wines from Bordeaux are similar to that of other regions.[24]

Note that our heterogeneity analysis above partly relies on regional reputation (Bordeaux and Burgundy) or appellation reputation (using renowned wines such as Margaux, Saint-Emilion, etc.). This means that, as a first approximation, we treat reputation as a constant factor, which is reasonable for this type of wines. More generally, reputation depends on the quality standards applied in the different French regions and on historical factors the 19th century ranking of French *grands crus* or the creation of the appellations in the 1930s (cf. Humbert, 2011; Mérel et al., 2021). Reputation is also a dynamic and cumulative phenomenon (see for instance Winfree & McCluskey, 2005). In At

TABLE 4 Average geographic or genetic distance by wine region

	Average number of export destinations	Average weighted geogr. distance to export markets (km)[a]	Average weighted genetic distance to export markets[b]
	(1)	(2)	(3)
Burgundy	33	3422	0.0095
Bordeaux	33	2649	0.0079
Other regions	28	2530	0.0068
Top Bordeaux/Burgundy[c]	40	3300	0.0096

Note: A complement to this table showing the distribution of number/distance of export markets by broad region groups is provided in the online appendix.
[a]For each appellation × year, we calculate the mean geographical distance over all export destinations, weighted by the normalized volumes exported to these destinations.
[b]For each appellation × year, we calculate the mean genetic distance over all export destinations, weighted by the normalized volumes exported to these destinations.
[c]Top Bordeaux/Burgundy are appellation × year receiving a Parker score above 90.

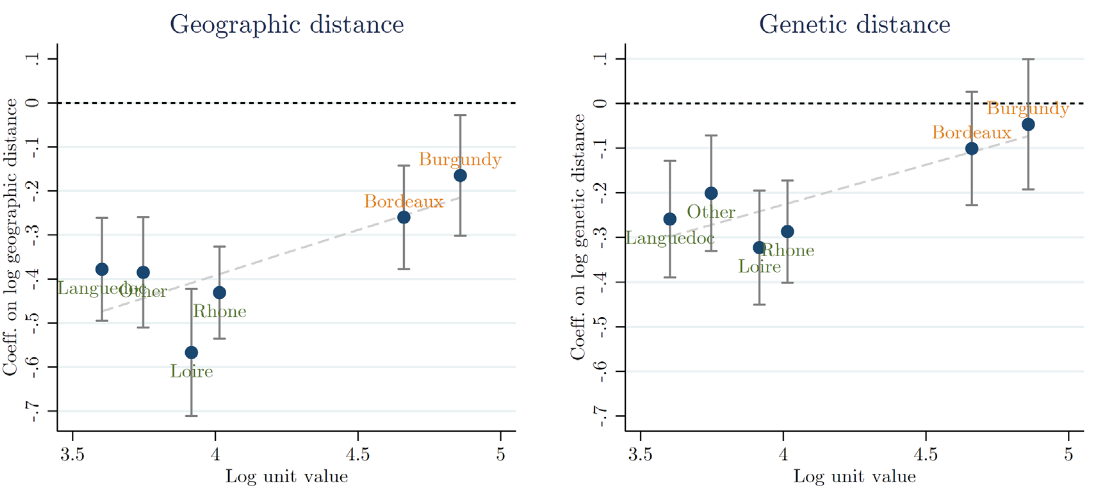

FIGURE 3 Effects of geographic and genetic distances by main regions. Estimated coeff. for geographic or genetic distance with 95% confidence interval, controlling for the other distance index and usual trade determinants

the end of the paper, we shall try to integrate some dynamics within our framework that may capture this process.

Quality heterogeneity proxied by expert rating and unit value

Another way of sorting regions according to quality is to rely on expert judgment. As extensively described in the data section, Parker's scores are an international reference that helps individuals and professionals assess the quality of all sorts of wine. As discussed in the data section, we avail of Parker's local vintage scores, namely ratings for 18 sub-regions × 18 years, hence 324 points of observation for the heterogeneity analysis.[25] We group them in four broad categories: the three terciles of the score distribution and the group of "ungraded" wines. We interact distance measures with the dummies for this four categories.

Results are presented in Table 6. An almost monotonic pattern appears in the baseline results of Column (i). Ungraded wines turn out to be more sensitive to geographic and genetic distances than Terciles 1–2 (which show no difference between each other), whereas top-tercile wines are less

TABLE 5 Geographic and genetic distance effects by quality levels: Regional variation and heterogeneity within Bourgogne and Bordeaux

	Top Bordeaux: Communales du Médoc, Graves, Saint-Emilion, Sauternes; Top Burgundy: Grands Crus of Côte d'Or			Top Bordeaux and Burgundy: Parker's grade above 90		
	Geographic distance (1)	Genetic distance (2)	Genetic distance (3)	Geographic distance (4)	Genetic distance (5)	Genetic distance (6)
Log Distance						
× Top Bordeaux	−0.0530	−0.0237	0.143	−0.197***	−0.208***	−0.0254
	(0.124)	(0.104)	(0.108)	(0.0693)	(0.0697)	(0.0709)
× Top Burgundy	−0.0151	−0.0503	0.126	−0.158**	−0.224***	−0.0431
	(0.165)	(0.129)	(0.130)	(0.0772)	(0.0753)	(0.0783)
× Bordeaux (others)	−0.267***	−0.291***	−0.109*	−0.300***	−0.332***	−0.151**
	(0.0615)	(0.0655)	(0.0663)	(0.0565)	(0.0630)	(0.0633)
× Burgundy (others)	−0.167**	−0.227***	−0.0482	−0.170**	−0.226***	−0.0475
	(0.0704)	(0.0721)	(0.0750)	(0.0682)	(0.0702)	(0.0729)
× Loire	−0.568***	−0.509***	−0.323***	−0.568***	−0.509***	−0.322***
	(0.0737)	(0.0625)	(0.0652)	(0.0736)	(0.0623)	(0.0650)
× Languedoc	−0.379***	−0.444***	−0.259***	−0.378***	−0.443***	−0.258***
	(0.0597)	(0.0680)	(0.0666)	(0.0596)	(0.0678)	(0.0663)
× Rhone	−0.432***	−0.473***	−0.287***	−0.432***	−0.472***	−0.286***
	(0.0534)	(0.0545)	(0.0583)	(0.0534)	(0.0543)	(0.0580)
× Others	−0.385***	−0.383***	−0.200***	−0.385***	−0.383***	−0.200***
	(0.0640)	(0.0631)	(0.0662)	(0.0640)	(0.0629)	(0.0659)
Observations	145,044	145,044	145,044	145,044	145,044	145,044
Standard trade determinants	YES	YES	YES	YES	YES	YES
Multilateral resistance variables	YES	YES	YES	YES	YES	YES
Microgeography variables	NO	NO	**YES**	**NO**	**NO**	**YES**
Year dummies	YES	YES	YES	YES	YES	YES
Region-year dummies	YES	YES	YES	YES	YES	YES
Designation FE	YES	YES	YES	YES	YES	YES

(Continues)

TABLE 5 (Continued)

	Top Bordeaux: Communales du Médoc, Graves, Saint-Emilion, Sauternes; Top Burgundy: Grands Crus of Côte d'Or			Top Bordeaux and Burgundy: Parker's grade above 90		
	Geographic distance (1)	Genetic distance (2)	Genetic distance (3)	Geographic distance (4)	Genetic distance (5)	Genetic distance (6)
Test equality of heterogeneous effects (p-value):						
Top Bordeaux versus other Bordeaux	0.09	0.01	0.02	0.01	0.00	0.00
Top Burgundy versus other Burgundy	0.37	0.18	0.18	0.72	0.93	0.85
Other Bordeaux versus other wines	0.07	0.13	0.14	0.16	0.36	0.38
Other Burgundy versus other wines	0.00	0.02	0.02	0.00	0.02	0.02

Note: PPML estimations of export volume in level. Region dummies are absorbed by appellation dummies. Standard errors, clustered at country-appellation level, in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 6 Geographic and genetic distance effects by quality level (proxy: Parker's rating)

	(i)	(ii)	(iii)	(iv)	(v)
Log geographic distance (interacted with terciles of Parker grades)					
× No grade	−0.398***	−0.396***	−0.389***	−0.366***	−0.290***
	(0.0549)	(0.0955)	(0.0550)	(0.0629)	(0.0503)
× 1st tercile	−0.311***	−0.312***	−0.297***	−0.327***	−0.237***
	(0.0531)	(0.0768)	(0.0536)	(0.0641)	(0.0556)
× 2nd tercile	−0.310***	−0.316***	−0.288***	−0.303***	−0.232***
	(0.0484)	(0.0755)	(0.0484)	(0.0568)	(0.0474)
× 3rd tercile	−0.273***	−0.275***	−0.244***	−0.308***	−0.195***
	(0.0522)	(0.0818)	(0.0532)	(0.0569)	(0.0551)
Observations	145,044	145,044	144,594	122,094	142,200
Test equality of heterogeneous effects (p-value):					
No grade = 3rd tercile	0.00	0.03	0.00	0.14	0.07
1st tercile = 3rd tercile	0.14	0.00	0.08	0.04	0.25
Log genetic distance (interacted with terciles of Parker grades)					
× No grade	−0.423***	−0.421***	−0.424***	−0.386***	−0.388***
	(0.0562)	(0.0939)	(0.0561)	(0.0610)	(0.0544)
× 1st tercile	−0.342***	−0.343***	−0.339***	−0.352***	−0.331***
	(0.0590)	(0.0852)	(0.0590)	(0.0706)	(0.0596)
× 2nd tercile	−0.348***	−0.351***	−0.339***	−0.337***	−0.335***
	(0.0561)	(0.0846)	(0.0556)	(0.0652)	(0.0542)
× 3rd tercile	−0.288***	−0.289***	−0.275***	−0.320***	−0.271***
	(0.0562)	(0.0853)	(0.0557)	(0.0651)	(0.0562)
Observations	145,044	145,044	144,594	122,094	142,200
Test equality of heterogeneous effects (p-value):					
No grade = 3rd tercile	0.00	0.05	0.00	0.14	0.01
1st tercile = 3rd tercile	0.05	0.12	0.03	0.20	0.07
Standard trade determinants	YES	YES	YES	YES	YES
Multilateral resistance variables	YES	YES	YES	YES	YES
Region-year FE	YES	YES	YES	YES	YES
Appellation FE	YES	NO	YES	YES	YES
Exclusing Bordeaux × USA	NO	NO	YES	NO	NO
Excluding Bordeaux	NO	NO	NO		NO
Exclusing USA	NO	NO	NO	NO	YES

Note: PPML estimations of export volume in level. Region dummies are absorbed by appellation dummies. Standard errors, clustered at country-appellation level, in parentheses. Significance level: *** $p < 0.01$.

sensitive. The difference is highly significant between ungraded and top wines. Coefficient equality between Terciles 1 and 3 cannot be rejected at standard levels for geographic distance, but the results go in the direction of past studies showing that high-end products defy gravity. Interestingly, the difference between Terciles 1 and 3 is strongly rejected in the case of genetic distance.

We provide some robustness checks for these results. Even if Parker's scores are just used as a broad proxy for quality variation, they might be biased. Indeed, Parker's ratings are known to impact prices beyond the pure quality/reputational information they convey (see Dubois & Nauges, 2010;

Hadj Ali et al., 2008; or Carayol & Jackson, 2019), and some French producers may have changed their wine style to meet the preferences of critics like Parker. This "Parkerization effect" must affect our analysis in a limited way because we use broad regional/subregional grades, and only as a broad source of heterogeneity (terciles). Nonetheless, we suggest sensitivity checks in Table 6. If some producers/appellations are characterized by Parkerization in the long run, this should be captured in appellation FE. Thus, Column (ii) provides results from a regression without these FE. We also highlight the fact that even though the *Wine Advocate* is distributed in 37 countries, this review is in English and the main readership, for the period considered in our data, was at 80% in the United States. Moreover, the Parkerization phenomenon was relatively marginal and known to be geographically limited (it essentially affected Saint-Emilion and Pomerol producers in Bordeaux). We then report the results of estimations where we remove the trade flows from Bordeaux to the US (Column iii), those from Bordeaux in general (Column iv), and those to the US (Column v). All these specifications show the same pattern as the basic results.

We also suggest a similar set of estimations where quality is now proxied by terciles of unit values. Price is an imperfect measure of quality, and so are expert ratings, but both strategies point to the same results. Indeed, in Appendix Table A4, distance effects are significantly smaller for the most expensive wines, in general and for all the alternative specification discussed above.

Interpretations

Regarding geographic distance, our results corroborate firm-based evidence by Fontagné and Hatte (2013) and Martin and Mayneris (2015), who study luxury goods in general. We confirm that high-end wines suffer less from trade costs. We additionally find that premium wines are not affected by genetic distance, which possibly denotes a limited dependence on taste differences. There are at least three possible explanations for this, which are not mutually exclusive and which may actually reinforce each other. *First*, cultural globalization may have pervaded local authentic preferences and facilitated the export of some of the luxury goods, which are now iconic and known by a large majority of people worldwide.[26] *Second*, luxury goods such as top wines are used by some people to achieve social status and signal their wealth through conspicuous consumption (Bagwell & Bernheim, 1996). This type of Veblen effect is relevant today, at a global scale, as much as it was centuries ago among the bourgeois of Europe (Hori, 2008).[27] *Third*, luxury wines have also become an investment good (Dimson et al., 2015; Masset & Henderson, 2010; Storchmann, 2012). Interestingly, these interpretations are compatible with the bias discussed above about Parker's ratings. Indeed, expert scores have possibly become focal points for collectors and wine investors who purchase highly rated wines in the hopes that the scores will increase the value of the wine. With the interpretations above, expensive and highly rated wines are expected to defy persistent trade barriers that pertain to taste differences because they are likely demanded as prestige/investment goods.

3.5 | Dynamic model

Trade flows may show some persistence due to the role of different historical factors (Eichengreen & Irwin, 1998). Yet, the bulk of the empirical trade literature uses static gravity equations. The reason is that, although some theoretical foundations for dynamic gravity models have been suggested (Anderson & Yotov, 2020; Olivieiro & Yotov, 2012),[28] the estimation of such models raises issues. We nonetheless suggest a dynamic model estimation along the lines of Anderson and Yotov (2020). Results are reported in Table A5 in the appendix. For comparisons, Column (1) shows baseline PPML estimates of the static model on the full sample.

A first difficulty with dynamic models pertains to the use of PPML estimators. As shown in Blundell et al. (2002), the functional form of the lagged dependent variable in the exponential function can potentially lead to explosive series and raises serious issues in terms of convergence. One way to overcome the problem is to use a logarithmic transformation of the lagged dependent variable. In this case, we lose all the zero-value observations (40% of our sample). Column (2) reports PPML estimates of the static model on this sample to assess if previous conclusions change. Reassuringly, we find significant effects of both geographic and genetic distances of similar magnitudes as in the static baseline. Because we shall rely on OLS estimators for our main dynamic estimates, as explained below, we also report OLS static estimations of the log exports in Column (3). Coefficients are now smaller, but relative effects remain fairly balanced.

We then move to dynamic specifications and include the lagged dependent variable $ln\left(X_{irjt-1}\right)$ in the model. Estimates on the reduced sample are reported in Columns (4) and (5) when focusing on geographic distance only, and in Columns (6) and (7) when both distances are included, using PPML and OLS respectively. Our results highlight the strong persistence of trade flows, with a coefficient on lagged exports that ranges from 0.75 [0.745, 0.761] to 0.87 [0.853, 0.891]. These "naïve" estimates are useful as they represent an upper bound of the coefficient associated with the lagged dependent variable and a lower bound for our explanatory variables including distances.[29] Importantly, even in this polar case, both distances still have a significant deterring effect on French wine exports. Their coefficients are much lower—they represent 18% and 28% of the static elasticities in the OLS estimations for geographic and genetic distances respectively —but the proportions by which they are reduced are in line with Anderson and Yotov (2020).

These results provide a double explanation of the "distance puzzle." The first one is the reduction effect discussed above. It reveals that most of the negative effect of geographical distance on trade in static gravity models comes from "past trade costs." Then, our results additionally show that genetic difference is an important factor that explains part of the geographic distance effect, as can be seen by comparing estimates of Columns (4) and (6) (for PPML), or (5) and (7) (for OLS). We also calculate persistent effects as the short-run estimate of distance divided by one minus the lag coefficient. The persistent geographic distance effect is reduced by around a half after inclusion of genetic distance.

Interestingly, dynamic estimations show that genetic distance matters for wine trade through its impact on both current and past trade. Despite the large persistent component, consumer preferences and taste for French wines may have changed slightly over the period, due to the penetration of French imports into destination countries. We find that differences in taste associated with cultural/biological diversity still play a significant contemporary role on French wine exports, and this immediate effect is greater than that of geographic distance.

Finally, we address another issue with dynamic models known as the Nickell's (1981) bias, that is, the existence of a positive correlation between the lagged dependent variable and the unobservable FE in the error term. Roodman (2009) suggests that the use of sufficiently long time span may eliminate this bias when relying on OLS. In our case, even with a time span of 18 years, some bias could remain. Therefore, we implement an instrumental variable (IV) approach. Following Anderson and Yotov (2020), we construct an instrument for lagged trade by using a reduced form gravity specification that only includes the standard gravity variables (exogenous by definition) plus importer population and GDP. We use the second and third lags of this newly constructed trade variable as instruments for the lagged dependent variable.[30] Note that the IV estimation is carried out by OLS because, in this case, the PPML estimator is subject to the incidental parameter problem. Results are reported in Column (8) for a model with geographic distance only and Column (9) with both distances. Previous conclusions are preserved.

4 | CONCLUSION

We exploit a rich dataset on French wine exports worldwide at the appellation level over the period 1998–2015. Estimation of static gravity models allows us to disentangle the effects of geographic distance and genetic distance. We show that the latter cannot be subsumed by microgeographic factors nor does it capture the standard cultural factors that foster trade (trust, linguistic proximity or common values). Our favorite interpretation is that (i) a genuine effect of genetic distance exists and (ii) it possibly reflects trade frictions pertaining to cultural/biological differences in gustatory and olfactory tastes derived from French wines. It is important to isolate this effect because preference heterogeneity can be long-lasting and thus represents a persistent trade barrier.

Dynamic estimations confirm these results and indicate that taste differences play a significant contemporaneous role, which is more important than the role of trade costs represented by geographic distance. Heterogeneity analyses also show that trade barriers related to taste differences do not apply uniformly to all wines. Using alternative proxies for quality (region/appellation reputation, expert ratings, unit values), we find that top wines tend to escape gravity but are also less sensitive to taste differences captured by genetic distance. This last point indicates that global demand for high-end wines is less dependent on a country's average preferences maybe because high-profile consumers have different preferences, seek social status, or buy premium wines more as an investment. In any case, high-end variety exporters have the incentive to export to more distant markets and to more heterogeneous consumers, that is, features that we consistently observe in our data. Specialization towards high-end varieties remains a strategy that allows reaping the benefits from globalization, notably from higher growth rates in emerging economies.

Related aspects are left for future research. First, further work could investigate the effects of genetic distance on different outputs including prices, proxied by unit values, to test our interpretation in terms of reputational effect of high-quality wines against more classic mechanisms. In particular, theoretical channels through which genetic distance affects wine trade can be explored, starting with mechanisms as modeled in Chen and Juvenal (2016). Second, exploiting country heterogeneity along other dimensions (such as endowments, GDP per capita, growth prospect and income inequality) to investigate how different types of wines are exported to different markets seems a promising avenue. In particular, it is possible that prices vary with the wealth of the importing country (Candau et al., 2017). The quantity allocated to each market may also vary with country characteristics (such as the expected growth, for Asian markets for instance). The French wine sector lends itself to this type of analysis because of a relatively fixed production. Finally, one should also consider destination country's characteristics such as income inequality and how demand varies across social/income groups or with genetic diversity within a country. Addressing these questions would require better data, notably more disaggregated information about wine consumption within destination countries.

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ENDNOTES

[1] Taste differentiation can be related to the home bias puzzle (Bronnenberg et al., 2012; Head & Mayer, 2013; Lopez & Matschke, 2012; Trefler, 1995).

[2] The French appellation system is made up of three tiers, including *Vin de France*, IGP (*Indication géographique protégée*) and AOP (*Appellation d'origine protégée*), with increasingly stringent requirements. Export wines correspond essentially to AOC and IGP wines (48% and 10% of bottle exports respectively) and Champagne (34%).

[3] Additional information is provided in Online Appendix II: detailed exports by top importing countries and top exporting regions (Tables B1 and B2); the lists of appellations grouped by region with export levels (Figure B1); the list of destination countries with region export shares by country (Figures B2 and B3).

[4] An exception is the Champagne region: firm-level data exists for Champagne and is exploited in Crozet et al. (2012).

[5] Tariffs correspond to Most Favored Nation (MFN). Countries do not apply different tariffs to different types of wines, only by degree of alcoholic content across types of alcoholic drinks. Regarding MR, see additional information in Online Appendix I.

[6] For that, Spolaore and Wacziarg use the ethnic composition by country gathered by Alesina et al. (2003) and construct a comprehensive set of weighted genetic distance between countries. See detailed descriptions in Online Appendix I.

[7] See detailed presentations in Online Appendix I.

[8] These "local vintage scores" are documented on the site: https://www.robertparker.com/resources/vintage-chart. We report the scores used in this paper in the Online Appendix Table B3.

[9] Treating missings as an additional category of "ungraded wines" when interacting distance with quality measures aims to acknowledge the fact that unrated subregions × year may be specific, and also to keep the same sample size as in baseline estimations.

[10] Parker's ratings might be biased because of their influence on prices and wine making. We discuss the potential role of 'Parkerization' below. Yet, the literature also tends to show that Parker's scores are reasonable proxies for true quality. Expert ratings reveal at least the quality variation due to rainfall and temperature (Ashenfelter, 2008). Several papers estimate the unobserved quality of wine, including Dubois and Nauges (2010) or Carayol and Jackson (2019). The latter show that the correlation between estimated quality and experts' scores ranges from 0.69 to 0.89 across all experts. Parker is in the median, with a correlation of 0.81 between his scores and the quality measure.

[11] Note that for tariffs (mean value: 21) or unit values (mean value: 43), we use the log of the variable plus one (results change marginally if we use a tiny value). The objective is to avoid creating missings when tariffs or unit values (calculated as export value divided by export volume) are zero.

[12] A regression of genetic distance on all the variables of the model including geographic distance and MR variables (resp. without MR variables) gives a variance inflation factor of 4.6 (resp. a VIF of 3.9), which is not extremely worrying regarding excessive multicollinearity.

[13] Further checks on the way we control for unit values are presented in Online Appendix III.

[14] Our conclusions are not fundamentally altered when adding a dummy for China instead, despite the specificities of this country (Liu & Song, 2021).

[15] See detailed results in Online Appendix III.

[16] Note that the correlation between the main ruggedness index and the population-weighted index is 0.78 (0.94 when weighted by exported volumes).

[17] Genetic distance has been used as a proxy of vertical transmission of cultural traits in many studies (see the discussion in Spolaore & Wacziarg, 2009, 2016, 2018).

[18] We must assume that the measure of trust is strongly correlated with the trust between wine importers and wine makers in the industry. This approximation also concerns individual values hereafter, and genetics before: The genetic distance variable does not specifically correspond to the distance between wine producing regions and wine drinking populations in destination countries.

[19] For the sake of comparability, we will extract detailed coefficients for regions producing both red and white wines. This means that we exclude Champagne (it receives much attention in Crozet et al., 2012) and Alsace (which produces essentially white wine).

[20] Estimates corresponding to Figure 3 are reported in appendix Table A3. Controlling for microgeography variables diminishes all the genetic-distance coefficients, as expected, but does not change our conclusion: Wines from reputed regions tend to be less affected by genetic distance than other regions. Microgeographic factors affect the distance coefficients by the same magnitude for Bordeaux, Burgundy, and other regions: Even if top regions export further, the microgeography of their global trade is not fundamentally different and does not affect our interpretations.

[21] When trimming the top 5% and excluding zeros, log unit values show a larger standard deviation among Bordeaux wines (0.80) than among Burgundy wines (0.71), as well as more density at lower unit values. This is illustrated in Figure B5 in the online appendix.

[22] See the last rows of Table A3.

[23] See the online appendix Figure B5.

[24] For Bordeaux, these results tend to indicate that the appellation reputation of premium wines is more important than the overall regional reputation effect and help them escape gravity. Similarly, Costanigro et al. (2010) point out that for most expensive wines, winery-level reputation matters more than collective reputation.

[25] In comparison, Crozet et al. (2012) use data on expert rating for 284 champagne firms. Chen and Juvenal (2016) use wine-specific rating from the *Wine Spectator* for Argentinian wines.

[26] A few studies look at cultural convergence during the globalization process (Aizenman & Brooks, 2008) and how overall bilateral trade tends to reduce cultural distance (Maystre et al., 2014).

[27] Beyond social status, people may also genuinely respond to higher prices: neuroscience experiments such as Plassmann et al. (2008) show that increasing the price of a wine can effectively change people's experiences with it, namely to increase subjective reports of flavor pleasantness.

[28] Persistent pattern of trade flows are theoretically justified by habit persistence in consumer tastes and learning-by-doing production (Campbell 2010) or through theories of capital accumulation (Anderson & Yotov, 2020; Olivero & Yotov, 2012).

[29] This is explained by positive correlation between the lagged dependent variable and country-appellation FE in the error term. If we purge the country-appellation FE out of the error term as suggested by Roodman (2009), we obtain a coefficient of 0.363 [0.349; 0.376] for the lagged dependent variable, which establishes a lower bound for this coefficient. In this case, however, all the time invariant variables, such as distances, are absorbed by the FE.

[30] Table A5 also reports a F-statistic of the null hypothesis that the instruments are weak as well as the effective F-statistic developed by Montiel Olea and Pflueger (2013) when errors are not conditionally homoscedastic and serially uncorrelated. With both tests, we reject the null hypothesis that our instruments are weak.

[31] Some of these factors are slow-moving and strongly associated with conventional transaction costs (Guiso et al., 2006). Yet, cultural ties may also provide some resilience in trade during crises (Carrère & Masood, 2018) or benefit from a certain degree of convergence due to bilateral trade itself (Maystre et al. 2014) or more generally during the globalization process (Aizenman & Brooks, 2008).

[32] Admittedly, there are possibly cultural aspects that are missing in our analysis, like the general food culture of destination countries. However, it does not mean that genetic distance itself—accounting for deeply rooted differences in taste—does not play a role, or that this role is overstated. This is especially true if genetic distance is seen as a relatively exogenous factor, considering the short period under study (18 years). If anything, the discussion above suggests that genetic factors influence food/drink habits (and in particular the demand for French wine of different regions) and not the other way around.

[33] Martin and Mayneris (2015) use French firm-level data and focus on heterogeneity across firms in terms of variety-type within a country. Fontagné and Hatte (2013) use product-level data and focus on this heterogeneity across countries. To define quality, both studies rely on information from the main French luxury brands, that is, the Colbert group, and identify high-end variety exporters as firms selling the same product at least at the same price as Colbert firms.

[34] While several studies show that exporting firms are more likely to ship high-quality goods to more distant markets (Crozet et al., 2012; Fontagné & Hatte, 2013; Johnson, 2012; Martin & Mayneris, 2015), recent evidence also indicate that firms exporting to wealthier and more distant countries apply higher markups due to quality differentiation (Bellone et al., 2016).

[35] They assume that this industry conforms well to the assumption of heterogeneous firms and monopolistic competition of the Melitz (2003)'s model and focus on the quality interpretation of the latter.

[36] Recent evidence based on field experiment shows that consumers value expert opinion labels on wine as a form of reducing asymmetric information about product quality (Villas-Boas et al., 2021).

[37] Note also that export volumes appear in levels rather than in log with the PPML estimator, but coefficients can still be interpreted as in the log specification of Equation (1).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A1: LITERATURE ON CULTURAL AND BIOLOGICAL FACTORS SHAPING DEMAND AND TRADE

Hidden Trade Factors

The international trade literature usually highlights foreign demand (determined by country income and tastes) and price-competitiveness (determined by relative prices and nominal exchange rates) as key determinants of exports, whereas the more recent literature adds other factors: non-price competitiveness—and particularly the quality of goods (Hallak, 2006; Melitz, 2003)—trade costs and frictions, which include transportation costs, tariffs and nontariffs barriers. However, in standard gravity models of trade, the coefficients on geographic distance is usually too large to be explained by traditional variables such as tariffs or transportation costs (Grossman, 1998). Head and Mayer (2013) argue that behind the estimated coefficient associated with geographic distance, hidden sources of resistance are of greater importance. These "dark trade" costs (for the analogy to astrophysics) would account for 50%–85% of the effect of geographic distance on trade flows, according to their estimation based on the data of Feyrer (2021). These "new" sources of frictions could be linked to spatial decay of information, localized tastes, colonial legacies, and long-run impacts of conflicts. They may especially relate to differences in tastes and preferences across nations, as explained by historical paths of cultural and biological evolutions.

Culture Factors Shaping Trade

The impact of bilateral cultural "affinity" on trade patterns has been examined in three streams of the trade literature. The first one corresponds to the exploration of traditional gravity variables that pertain to cultural dimensions, such as sharing a common language (e.g. Boisso & Ferrantino, 1997; or Melitz & Toubal, 2014), colonial ties (e.g. Head et al., 2010; or Rose, 2000), religion, or the legal system (Glaeser & Shleifer, 2002; Mayer & Zignago, 2011). More recently, another branch of the literature has focused on variables that further explain affinity, notably the role of bilateral trust (Guiso et al., 2009; Yu et al., 2015; Spring & Grossman, 2016), homophily (Melitz & Toubal, 2019), bilateral opinions (Disdier & Mayer, 2007), or bilateral values (Ahern et al., 2015; Maystre et al., 2014). Finally, original indicators of taste proximity have also been suggested. Felbermayr and Toubal (2010) construct affinity measures based on an international song contest. Disdier et al. (2010) use trade in cultural goods as a proxy for countries' cultural proximity. Jäkel (2019) examines export performance of Danish chocolate producers depending on taste proximity based on information on the average ingredients of chocolate and confectionery sold in different countries.[31]

Genetic Diversity and Trade

Genetic variation has been investigated in a few studies on trade. In Giuliano et al. (2014), it essentially captures trade barriers due to the geography. In Guiso et al. (2009), it relates to frictions due to trust and values. We will check for the role of these other pathways in our empirical analysis. Note that genetic distance has rarely been used as a direct determinant of trade. Guiso et al. (2009) use it only as an instrument for trust. Quite inversely, we want to extract from genetic distance what is unrelated to either geographic distance or common values and trust, that is, what purely pertains to preference heterogeneity due to culture and biology. Closer to us, Melitz and Toubal (2019) test the direct role of somatic distance and co-ancestry, two different aspects of genetic distance, on trade. Focusing on a cultural interpretation, they find that both of them impact trade flows whether trust measures are controlled for or not. Bove and Gokmen (2017) also use gravity models and genetics to revisit Spolaore and Wacziarg (2009), suggesting that trade is a possible channel through which cultural differences delay the diffusion of development. Gokmen (2017) also demonstrates the deterring effect of cultural gaps on trade and how they have progressively replaced other barriers such as geopolitical divides.

Genetic Diversity and the Role of Biology in Tastes and Trade

In our case, genetic proximity is not only interpreted as a proxy for *cultural affinity* in tastes. It may also directly relate to *biological explanations* for this proximity in tastes. For most food and beverage goods, the role of genetics in explaining tastes has been highlighted for years. In a review of the biological literature, Reed et al. (2006) describe the genes and molecular receptors responsible for taste preferences. Birch (1999) reveals how the interaction between environmental factors (culture) and the genetic predispositions produces food preferences. These genetics-based preferences have been analyzed in the context of different ethnic groups and nationalities, showing significant differences in food tastes in general (Bertino & Chan, 1986) and in tastes for alcoholic beverages in particular (Duffy et al., 2004). More specifically in the context of wine preferences, the current biological research is trying to understand the mechanisms that relate genetics and taste/olfactory perceptions. In particular, Lanier et al. (2005) show that genes changing perceptions of bitterness and sweetness also affect alcohol consumption. Pirastu et al. (2015) reveal the genes responsible for white or red wine preferences on a large sample of three different populations from Italy, Central Asia, and The Netherlands. Muñoz-González et al. (2015) analyze how oral microbiota, that is, the bacteria living in the human mouth, produce aromatic volatile compounds from grape and wine. They find that individual (and country) differences in oral microbial make-up have profound implications on how people understand wine tasting and the perception of aromas and flavors. Carrai et al. (2017) find a direct relationship between variability of taste receptors' genes and wine perception (namely sensations such as astringency and bitterness). They show that even small genetic variation matters. Focusing on Mediterranean versus Central European populations, which are similar in allelic frequencies for taste receptors, they find that the country of origin is an important factor, indicating that genetics alongside cultural factors (dietary habits) play a significant role in individual liking of wine and wine varieties. We will show how genetic proximity, possibly accounting for cultural but also such biological factors, matters for wine trade.[32]

Quality Sorting and Trade Patterns

Our work also pertains to the literature on quality sorting. Developed countries tend to specialize, within products, in the production of high-end varieties. The normative prescription that they should do so is also common in the literature (Schott, 2004), but actual implications of specializing in high-end varieties are rarely studied. Martin and Mayneris (2015) and Fontagné and Hatte (2013) show that exports of high-end products are less sensitive to geographic distance—and more sensitive to destination country wealth—than other products.[33] This question is important in countries like France, whose economy crucially depends on a few export sectors, notably the luxury sector and the wine industry that generate trade surplus and create employment. As discussed in the introduction, France produces fine wines but also wines of lower quality, so the question of whether further specialization is a winning strategy is still pending. If the pattern found in the aforementioned studies applies to the wine sector, it means that high-end variety exporters are better equipped to meet demand in distant markets and notably in Eastern Asia, which remains the major source of global growth.[34] The present study aims to verify this point using data on French wine exports. It completes the investigation of Crozet et al. (2012), who focus on the Champagne industry.[35] Using firm-level exports, these authors find that high-quality Champagne producers have a higher likelihood of exporting, export higher volumes, and charge higher prices. Chen and Juvenal (2016) conduct a similar analysis on Argentinian wines using detailed firm information on wine types. As we do, both studies use expert ratings as a possible proxy for product quality.[36] Additionally, we investigate whether the role of cultural or biological distance also vary with wine quality.

APPENDIX A2: ESTIMATION METHODS

Estimating the log-linearized form of the gravity model of trade by fixed effects ordinary least squares (FE-OLS) raises several issues. Heteroscedasticity derives from the log-linearization (Santos Silva & Tenreyro, 2006). Disaggregated data entail a large number of zero-value observations: If the latter are not randomly distributed, dropping them from the sample by log-linearizing the equation leads to a selection bias (Westerlund & Whilhelmsson, 2011). In the empirical literature of trade, several methods have been introduced to deal with these issues, including Tobit models (Eaton & Tamura, 2004), two-step Heckman models (Helpman et al., 2008), or Poisson family estimators

(Martínez-Zarzoso, 2013; Santos Silva & Tenreyro, 2006). Yotov et al. (2016) recommend using the Poisson Pseudo Maximum Likelihood (PPML) estimator proposed by Santos Silva and Tenreyro (2006) to estimate the structural gravity model of trade. This method has the advantage of dealing with both problems and of performing better than OLS and Tobit in the presence of heteroscedasticity. The PPML remains consistent under overdispersion in the data (Head & Mayer, 2014) and under high frequency of zeros (Santos Silva & Tenreyro, 2011).[37]

APPENDIX A3: DESCRIPTIVE STATISTICS AND EXPORT TRENDS

Descriptive Statistics

TABLE A1 Descriptive statistics and data sources

	# obs.	Mean	Std. dev.	Min	Max	Source
Exports						
in value (1000 $)	145,044	718	7933	0	581,981	FEVS
in volume (hl)	145,044	1314	9494	0	498,849	
Gravity variables and country characteristics						
Geogr. distance (km)	145,044	5306	4443	262	19,264	CEPII
Genetic distance	145,044	0.0187	0.0172	0.0005	0.0515	Spolaore and Wacziarg (2016)
GDP (B$ 2010 PPP)	145,044	875	2150	3	18,037	World Bank indicators
Population (M.)	145,044	65	185	0.4	1371	World Bank indicators
Real exch. rate (ad valorem equivalent)	145,044	789	3656	1	32,207	World Bank indicators
Tariffs (French franc or euro/LCU)	145,044	21	41	0	414	World Bank, WITS
Common language (0/1)	145,044	0.196	0.397	0	1	CEPII
Local production (hl)	145,044	3094	8105	0	50,809	IOVW
Microgeography						
Ruggedness	145,044	1.377	1.114	0.016	4.761	Nunn and Puga (2012)
Common sea	145,044	0.510	0.500	0	1	Nunn and Puga (2012)
Culture						
Trust[a]	39,816	2.77	0.20	2.32	3.04	Giuso et al. (2009)
Linguistic distance	145,044	0.95	0.06	0.80	1.00	Spolaore and Wacziarg (2016)
Values: total distance	102,384	64.50	31.67	1.00	148.14	Spolaore and Wacziarg (2016)
Values: life perception	102,384	20.87	9.19	1.00	43.25	Spolaore and Wacziarg (2016)
Values: work perception	102,384	13.77	8.70	1.00	45.11	Spolaore and Wacziarg (2016)
Values: family perception	102,384	6.22	2.78	1.00	10.71	Spolaore and Wacziarg (2016)
Values: politics and society	102,384	18.84	11.24	1.00	59.85	Spolaore and Wacziarg (2016)
Values: religion and morale	102,384	13.45	7.69	1.00	33.60	Spolaore and Wacziarg (2016)

(Continues)

TABLE A1 (Continued)

	# obs.	Mean	Std. dev.	Min	Max	Source
Proxy of quality						
Parker grades	70,941	88.5	4.6	58	99	Wine advocate
Unit value ($/l)	145,044	4.3	12.0	0	1300	FEVS

[a]Bilateral trust between France and importing countries, EU only.

Source: Authors' calculations based on data from the *Fédération des Exportateurs de Vins et Spiritueux de France (FEVS)* on the universe of French wine shipments for exports in value and volume over the period 1998–2015 (as well as for unit value calculations), data from the Centre d'Etudes Prospectives et d'Information Internationales (CEPII) for standard gravity variables (geographic distance, common language, common sea) (www.cepii.fr/CEPII/en/bdd_modele/bdd.asp), additional microgeography data (population-weighted measure of ruggedness) from Nunn and Puga (2012) (http://diegopuga.org/data/rugged), data from the World Bank's World Development Indicators (databank.worldbank.org/data) for country characteristics (GDP, population size, real exchange rate, and the bilateral exchange rates, expressed in real terms using the French and the foreign country's Consumer Price Index CPI) and from the World Integrated Trade solution of the World Bank for tariffs (https://wits.worldbank.org/), local wine production from the International Organization of Vine and Wine (http://www.oiv.int/en/), data from Spolaore and Wacziarg (2016, 2018) for genetic distance and cultural distance (www.anderson.ucla.edu/faculty_pages/romain.wacziarg/papersum.html), trust information from Guiso et al. (2009) based on the Eurobarometer survey, regional scores from Robert Parker's *Wine Advocate*.

Evolution of French wine exports

Figures A1–A3 Present the evolution of French wine exports by broad groups of destination countries, for top importing countries and for top exporting French regions, respectively, both in value and in volume. EU countries (particularly the UK and Germany) represent the main export market of French wine, followed by Asia (mainly Japan and China) and North America (mainly the US). European customers tend to import less wine over time but of higher quality (exports in value are constant). We observe an acceleration of exports to Asia, mainly driven by China, in both volume and value. Bordeaux and Languedoc-Roussillon are the main exporting regions in volume, whereas Bordeaux and Champagne are the main regions in terms of export value.

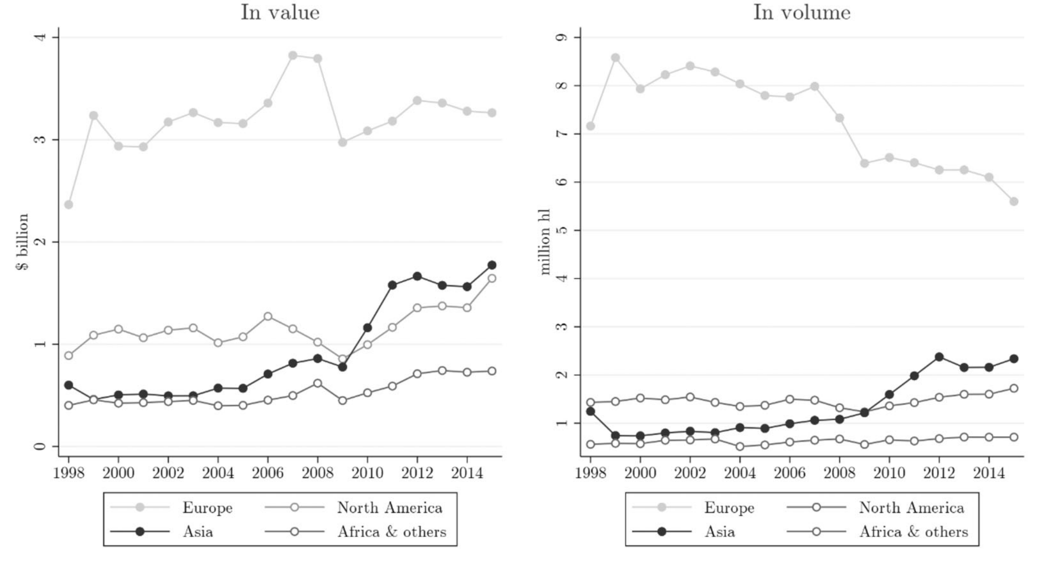

FIGURE A1 Evolution of exports by main groups of country

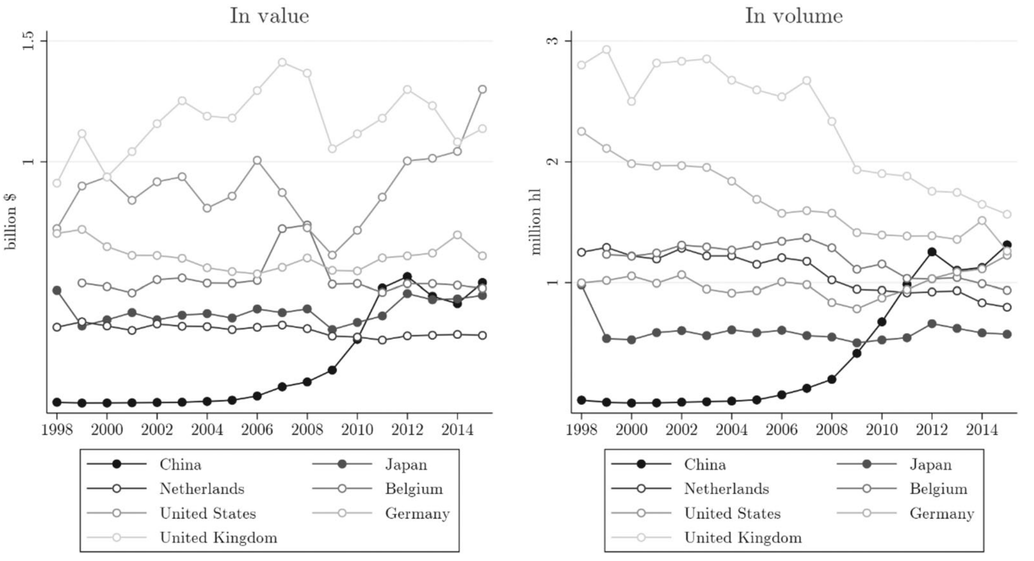

FIGURE A2 Evolution of exports for the top importing countries

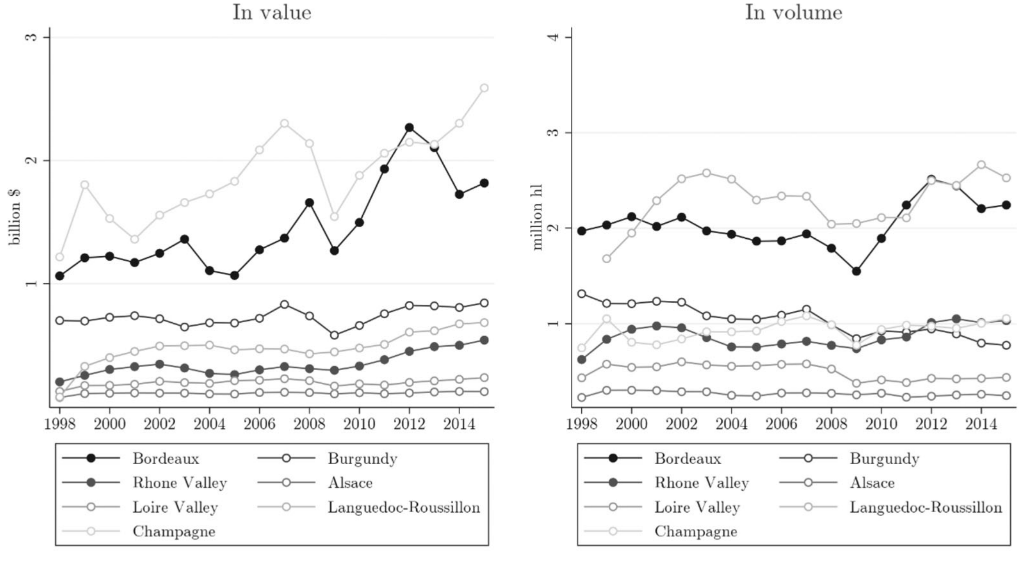

FIGURE A3 Evolution of exports by top French exporting regions

APPENDIX A4: ESTIMATION RESULTS

TABLE A2 PPML estimation of the gravity model: Adding specific non-gustatory cultural distances

	Cultural distance (Spolaore & Wacziarg, 2016):				
	Life perception	Work perception	Family perception	Politics and perception	Religion and morale
Log geogr. distance	−0.571***	−0.452***	−0.567***	−0.556***	−0.348***
	(0.0576)	(0.0658)	(0.0610)	(0.0565)	(0.0665)
Log genetic distance	−0.380***	−0.324***	−0.382***	−0.376***	−0.299***
	(0.0683)	(0.0619)	(0.0668)	(0.0670)	(0.0576)
Log cultural distance (values)	0.0316	−0.297***	0.0325	−0.00854	−0.669***
	(0.0462)	(0.0606)	(0.0828)	(0.0529)	(0.0912)
Observations	102,384	102,384	102,384	102,384	102,384
Pseudo R-squared	0.665	0.665	0.665	0.664	0.682
Standard trade determinants	YES	YES	YES	YES	YES
Microgeography	YES	YES	YES	YES	YES
Multilateral resistance variables	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES
Region-year dummies	YES	YES	YES	YES	YES
Appellation FE	YES	YES	YES	YES	YES

Note: PPML estimations of export volume in level. Standard errors, clustered at country-appellation level, in parentheses. Significance level: *** $p < 0.01$.

TABLE A3 Geographic and genetic distance effects by region

	Geographic distance	Genetic distance	Genetic distance
Log Distance			
× Bordeaux	−0.260***	−0.283***	−0.101
	(0.0599)	(0.0642)	(0.0649)
× Burgundy	−0.165**	−0.226***	−0.0468
	(0.0699)	(0.0716)	(0.0744)
× Loire	−0.567***	−0.510***	−0.323***
	(0.0736)	(0.0625)	(0.0652)
× Languedoc	−0.378***	−0.444***	−0.259***
	(0.0596)	(0.0680)	(0.0665)
× Rhone	−0.431***	−0.473***	−0.287***
	(0.0534)	(0.0545)	(0.0582)
× Others	−0.385***	−0.384***	−0.201***
	(0.0640)	(0.0631)	(0.0661)
Test equality of heterogeneous effects	(p-value):		
Bordeaux = Others	0.05	0.08	0.09
Burgundy = Others	0.01	0.02	0.02

(Continues)

TABLE A3 (Continued)

	Geographic distance	Genetic distance	Genetic distance
Observations	145,044	145,044	145,044
Standard trade determinants	YES	YES	YES
Multilateral resistance variables	YES	YES	YES
Microgeography variables	NO	NO	**YES**
Year dummies	YES	YES	YES
Region-year dummies	YES	YES	YES
Appellation FE	YES	YES	YES

Note: PPML estimations of export volume in level. Region dummies are absorbed by appellation dummies. Standard errors, clustered at country-appellation level, in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$.

TABLE A4 Geographic and genetic distance effects by quality level proxies by terciles of unit value

	(i)	(ii)	(iii)	(iv)	(v)
Log geographic distance (interacted with terciles of unit value)					
× 1st tercile	−0.263	−0.266***	−0.256***	−0.237***	−0.193***
	(0.0499)	(0.0714)	(0.0502)	(0.0581)	(0.0447)
× 2nd tercile	−0.217***	−0.262***	−0.208***	−0.202***	−0.153***
	(0.0482)	(0.0674)	(0.0486)	(0.0565)	(0.0442)
× 3rd tercile	−0.197***	−0.193***	−0.188***	−0.175***	−0.153***
	(0.0511)	(0.0688)	(0.0514)	(0.0598)	(0.0488)
Observations	81,742	81,742	81,382	66,080	79,566
Test equality of heterogeneous effects (p-value):					
1st tercile = 3rd tercile	0.00	0.01	0.00	0.00	0.05
Log genetic distance (interacted with terciles of unit value)					
× 1st tercile	−0.352***	−0.330***	−0.351***	−0.327***	−0.325***
	(0.0520)	(0.0765)	(0.0520)	(0.0567)	(0.0509)
× 2nd tercile	−0.193***	−0.243***	−0.187***	−0.261***	−0.176***
	(0.0540)	(0.0817)	(0.0540)	(0.0641)	(0.0549)
× 3rd tercile	−0.186***	−0.201**	−0.184***	−0.178**	−0.190**
	(0.0689)	(0.0838)	(0.0690)	(0.0848)	(0.0745)
Observations	81,742	81,742	81,382	66,080	79,566
Test equality of heterogeneous effects (p-value):					
1st tercile = 3rd tercile	0.00	0.04	0.00	0.02	0.02
Standard trade determinants	YES	YES	YES	YES	YES
Multilateral resistance variables	YES	YES	YES	YES	YES
Region-year FE	YES	YES	YES	YES	YES
Appellation FE	YES	NO	YES	YES	YES
Exclusing Bordeaux × USA	NO	NO	YES	NO	NO
Excluding Bordeaux	NO	NO	NO	YES	NO
Exclusing USA	NO	NO	NO	NO	YES

Note: PPML estimations of export volume in level. Region dummies are absorbed by appellation dummies. Standard errors, clustered at country-appellation level, in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$.

TABLE A5 Static versus dynamic gravity models (estimations on strictly positive trade flows in columns 2–9)

	Static model, baseline (1)	Static model, on a sample excluding 1998 (2)	Static model, on a sample excluding 1998 (3)	Dynamic model with only geog. Distance (not instrumented) (4)	Dynamic model with only geog. Distance (not instrumented) (5)	Dynamic model (not instrumented) (6)	Dynamic model (not instrumented) (7)	Dynamic model (instrumented by lags two and three) only on geogr. distance (8)	Dynamic model (instrumented by lag two and three) (9)
Log trade t-1				0.872***	0.753***	0.867***	0.751***	0.729***	0.729***
				(0.00964)	(0.00409)	(0.0100)	(0.00413)	(0.0322)	(0.0320)
Log geographic distance	−0.348***	−0.349***	−0.219***	−0.0506***	−0.0736***	−0.0252***	−0.0390***	−0.0760***	−0.0393***
	(0.0482)	(0.0484)	(0.0272)	(0.00846)	(0.00527)	(0.00849)	(0.00762)	(0.0127)	(0.0110)
Log genetic distance	−0.375***	−0.361***	−0.177***			−0.0441***	−0.0504***		−0.0521***
	(0.0540)	(0.0554)	(0.0232)			(0.00881)	(0.00651)		(0.00901)
Observations	145,044	73,629	73,629	73,629	73,629	73,629	73,629	66.781	66.781
R-squared (or Pseudo R-squared)	0.664	0.688	0.629	0.922	0.840	0.923	0.840	0.840	0.840
Post estimation calculations:									
Short-run effect as % of static effect									
Log geog.						*7%*	*18%*		*19%*
Log genetic						*12%*	*28%*		*29%*
Persistent effect									
Log geog.				*−0.395*	*−0.298*	*−0.189*	*−0.157*	*−0.280*	*−0.145*
Log genetic						*−0.332*	*−0.202*		*−0.192*
Estimator	PPML	PPML	OLS	PPML	OLS	PPML	OLS	OLS	OLS
Dep. variable in	Level	Level	Log	Level	Log	Level	Log	Log	Log
F-test of excluded instruments								80.003	80.540
Montiel-Pflueger robust weak instrument test								132.223	132.994
Standard trade determinants	YES	YES	YES	YES	YES	YES	YES	YES	YES
Multilateral resistance variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region-year dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Appellation FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors, clustered at the country-appellation level, in parentheses. Significance levels: *** $p < 0.01$.