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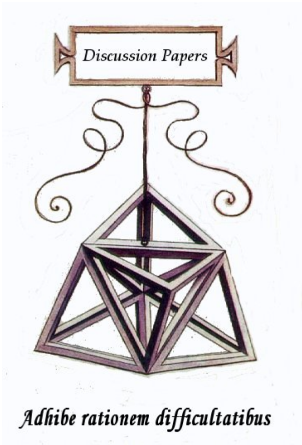

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Identifying the collective reputation premium: a spatial discontinuity approach

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JEL CLassification: L14; L15

Identifying the collective reputation premium: a spatial discontinuity approach

Stefano Castriota [a]
Paolo Frumento [b]
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Abstract

In competitive markets, reputation building is considered an important tool to reduce price competition and increase profits. However, from an empirical point of view, identifying the contribution of collective reputation on price net of other confounding variables such as quality, firm reputation and horizontal differentiation, is not trivial. In this work, using an extensive database on Italian geolocalized wineries, we exploit spatial discontinuity at the borders of the wine appellation areas in Piedmont and Tuscany to investigate the impact of collective reputation on price. Results show that collective reputation carries an important price premium for well-known appellations, while the effect is not significant or even negative for weaker ones. This suggests that an excessive proliferation of collective brands might not be useful and could even turn out being harmful as it can confuse buyers.

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1 Introduction

In markets characterized by a large number of products and strong differentiation, reputation has been identified as a valuable tool to reduce asymmetric information between producer and consumer, increase prices, and boost sales (Shapiro, 1983; Höner, 2002; Fedele and Tedeschi, 2014). Firm reputation has been proved to be important in several markets, such as airlines (Borenstein, 1989), the hotel industry (Anagnostopoulou et al., 2019), and electronic sales (Cabral and Hortacsu, 2010; Elfenbein et al., 2015; Fan et al., 2016). However, firm reputation – defined as the expectation about quality (Bar-Isaac et al., 2008) based on the average quality delivered in the past – is difficult to achieve for small firms and start-ups. In fact, building a famous brand requires time, money, and repeated purchases, all prerogatives of well-established firms (Grossman and Horn, 1988; Fombrun and Shanley, 1990; Martinelli, 1997; Rob and Fishman, 2005; Mailath and Samuelson, 2015).

In such a context, collective reputation – defined as an aggregate of individual reputations (Tirole, 1996) – is another tool that can increase firm revenues. Collective brands are commonly used in the agri-food sector where producers establish the geographical borders of the coalition, the minimum quality standards, and the production techniques, like in the European Union's Protected Denominations of Origin (PDOs) and Protected Geographical Indications (PGIs). The reputation of a group depends on the age and size of the coalition, the minimum quality standards, social norms, the frequency of controls, and the intensity of penalties in case of violations of rules (Winfree and McCluskey, 2005; Saak, 2012; Castriota and Delmastro, 2015; Fishman et al., 2018). Collective reputation is determined by the joint effort of members. However, it can be damaged by the misbehavior of a single member that can negatively affect the demand, as shown by Bai et al. (2022) using data from a large-scale scandal that affected the Chinese dairy industry in 2008 and by Nosko and Tadelis (2015) with data on eBay auctions.

The empirical literature has shown the existence of price premia attached to some production regions, like for Galician veal (Loureiro and McCluskey, 2000) and Zagora Greek apples (Fotopoulos and Krystallis, 2003). The wine market has been particularly studied to measure the return of collective reputation because of the presence of many wine appellations and the abundance of available data. Researchers usually rely on hedonic price models where the price of a standardized bottle of 0.75 Liters is regressed over a set of controls, which include dummy variables for the wine appellations considered. The literature has shown the positive price premium of collective brands using data from Australian wine areas (Oczkowski, 1994; Schamel and Anderson, 2003), French sub-appellations (Landon and Smith, 1998), California and Oregon (Haeger and Storchmann, 2006), California (Costanigro et al., 2010), and Mosel Valley (Frick and Simmons, 2013).

From the theoretical point of view, the mechanism through which collective reputation should produce benefits is clear as it reduces the asymmetric information problem. However, from the empirical point of view, the size of the premium is not easy to measure. In terms of identification strategy, the ideal empirical setting would be having two identical wines randomly assigned to two labels – one with a collective brand like Barolo and the other without – like in an experiment.

Unfortunately, conducting a large-scale experiment with this approach is not viable, and the hedonic price models described above present serious issues that can undermine the results. The first is omitted variable bias. Most studies do not have (proper) measures for product quality, firm reputation, firm size, and horizontal differentiation (e.g. grape varieties, soil characteristics or climate conditions). All these variables have been shown to be important drivers of prices, therefore omitting one of them can lead to biased results.

A related problem is the effect of the so-called “terroir”, defined by Bartlett (2009) as “the almost mystical combination of soil, aspect, microclimate, rainfall, and cultivation that the French passionately believed gave the wine from each region - and indeed, each vineyard - its unique character”.

Due to unknown or unmeasured soil or climate characteristics, the same grape could yield different wines depending on the area in which it is cultivated (Cross et al., 2011). For example, Pinot Noir grapes planted in Bourgogne have different characteristics from the same grapes planted in Bordeaux, California, or Australia. Furthermore, the same choice of grapes to be planted could endogenously depend on soil and climate characteristics.

Unfortunately, controlling for the terroir is an almost impossible task, due to the multifaceted nature of this variable. A partial solution is to include area fixed effects in a regression model and, possibly, interaction terms between the grape and the area or between the grape and some other features of the area. This allows to account for systematic, unexplained differences between areas. However, it requires formulating models with large number of coefficients, resulting in poor identification and low statistical efficiency. Moreover, if the grape varieties were perfectly correlated with appellations, it would be impossible to disentangle the price differences due to the grapes from those due to the appellations themselves. Imagine, for example, comparing Bordeaux wines made with Merlot-Cabernet Sauvignon-Cabernet Franc blends and Bourgogne wines made with Pinot Noir grapes.

Some studies have tried to mitigate these issues by restricting the analysis to single-grape wines. To attenuate the above problems, Haeger and Storchmann (2006) focus on Pinot Noir produced in California and Oregon; in their analysis, however, wineries are dispersed in two huge States where soil and climate can differ dramatically. Therefore, the problems mentioned above are still present. Benfratello et al. (2009) compare prices of Barolo and Barbaresco wines produced in Piedmont with 100% Nebbiolo grapes. However, they do not control for firm size, they do not consider more basic appellations that use the same grape varieties, and do not use geolocalized data to build the ideal counterfactual. Frick and Simmons (2013) refine the analysis by considering only wines produced with Riesling grapes in the Mosel Valley in Germany, a small area where wineries have similar soil and climate conditions. In their empirical work, the authors measure the collective reputation premium of belonging to two different consortia. Nonetheless, participation in the two professional associations is not random, as wineries must be invited by at least one member and approved by the others. This process creates selection bias, the opposite of random assignment. Cross et al. (2011) use a different strategy and rely on data on vineyards’ sales to estimate the collective reputation’s price premium. However, the same authors acknowledge the complication of vineyards differing in grape varietals planted.

In our study, we propose a spatial discontinuity approach to overcome these problems and obtain unbiased estimates of the collective reputation premium. We focus on small geographical areas with similar soil and climate conditions and wines produced with only one grape variety. Using geolocalized data, we then compare – net of other confounding variables such as firm reputation and size and wine quality – the price of virtually identical wines produced with the same grape varieties inside and outside the borders of the wine appellation. The perimeters of the appellations are not intentionally designed to include the best wineries but closely follow the administrative borders of the municipalities. Therefore, having vineyards inside or just outside them is random.

2 Data

The dataset used in this analysis comes from the 2024 wine guide *Vitae* of the Italian Association of Sommeliers (AIS). The guide is the most complete in Italy, with information on more than 10,000 wines produced by over 2,000 wineries. To carry on the spatial discontinuity analysis described above, we need to exclude blends – thereby considering only wines produced with 100% single grapes – and wines with insufficient observations. In Italy, there are 407 wine PDOs and 118 PGIs (Federdoc, 2024), but most of them do not impose the use of a single grape variety. For example, Verdicchio dei Castelli di Jesi is a white wine from the Marche region made with at least 85% Verdicchio grapes.We do not consider these appellations since producers can (quite) freely choose the remaining 15% of grapes. Furthermore, many wines made with single grapes have insufficient observations for a meaningful statistical inference. After a careful analysis, the two wines that fit our requirements – single grape and a sufficient number of observations – are those made with 100% Nebbiolo grapes in Piedmont and those made with 100% Sangiovese grapes in Tuscany.

Concerning the first one, we focus on the eastern part of the province of Cuneo in Piedmont (see Figure 1)[1]. This province has five appellations, all produced with different minimum percentages of Nebbiolo grapes (see Table 1). Barolo, Barbaresco, and Nebbiolo d'Alba are the most rigorous, imposing 100% Nebbiolo grapes, while Roero requires a minimum of 95%. The appellation Langhe has the lowest minimum percentage of Nebbiolo (85%) and includes all the colored areas: not only the light blue but also all the others. This appellation is the counterfactual of the other appellations since, in all these areas, winemakers can produce wines with Nebbiolo grapes and label them as Langhe. Wineries whose vineyards lie within the borders of the four stricter appellations (Barolo, Barbaresco, Nebbiolo d'Alba, and Roero) can produce both one of the four and Langhe. Our sample of wines from Piedmont consists of 698 bottles of wine produced in the eastern part of the province of Cuneo and made of 100% Nebbiolo grapes (see Table 1); Barolo and Barbaresco are the most represented in the guide (63% and 20% of the sample respectively), while the counterfactual (Langhe 100% Nebbiolo grapes) consists of 56 observations (8% of the sample).

Concerning the second wine considered, we focus on the provinces of Siena and Grosseto in Tuscany since Montalcino - where the famous Brunello appellation is produced - lies at the border between the two areas (see Figure 2)[2]. In these provinces, there are seven appellations all based on Sangiovese grapes: Brunello di Montalcino, Rosso di Montalcino, Nobile di Montepulciano, Chianti Classico, Chianti[3], Morellino di Scansano, and Montecucco (see Table 2). Furthermore, in the entire Tuscan region, winemakers can produce the PGI Tuscany by using one (or many, as a blend) of the 87 grape varieties established by law. The counterfactual of the seven appellations using Sangiovese is the wines produced with 100% Sangiovese grapes in the provinces

[1] It is possible to produce PDO Langhe within the entire Langhe area shown in the figure. Additionally, in the Roero area, it is also possible to produce PDO Nebbiolo d'Alba.

[2] In the figure, the light rose and light blue areas represent the provinces of Siena and Grosseto, respectively. It is possible to produce the PGI Tuscany (our counterfactual) across all of Tuscany.

[3] The Chianti appellation can be produced in various areas within the province of Siena.

of Siena and Grosseto and labeled as PGI Tuscany. Our sample of Tuscan wines consists of 281 bottles of wine, all made with 100% Sangiovese grapes produced in the provinces of Siena and Grosseto. Brunello di Montalcino (34.3% of the sample), Rosso di Montalcino (13.3%), and Chianti Classico (26.5%) are the most represented (see Table 2). The counterfactual - PGI Tuscany 100% Sangiovese - consists of 34 observations (12%). In the appendix, two tables provide the main descriptive statistics and brief descriptions of the variables used in the regression analyses for both Nebbiolo and Sangiovese wines (see Table A1 and Table A2, respectively).

Figure 1: Wine appellations using Nebbiolo grapes in Piedmont

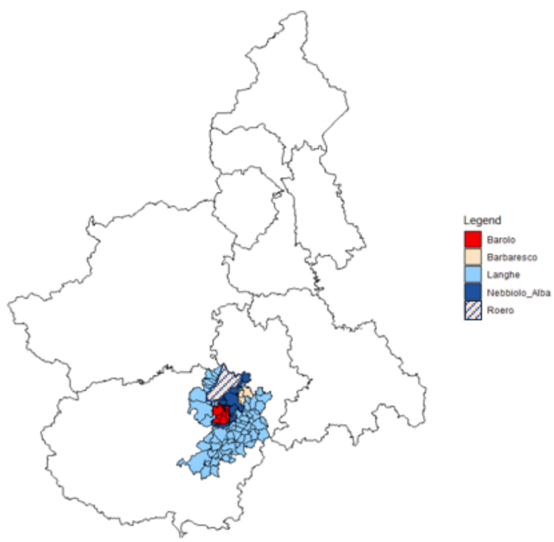

Table 1: Distribution and minimum percentage of Nebbiolo required in the wine appellations in Piedmont

Appellations	**N°**	**(%)**	**Min % Nebbiolo**
Barolo	440	63	100
Barbaresco	142	20.3	100
Nebbiolo d'Alba	27	3.9	100
Roero	33	4.7	95
Conterfactual (PDO Langhe)	56	8	85
Total	698	100	

Figure 2: Wine appellations using Sangiovese grapes in Tuscany (shades of red: province of Siena; shades of blue: province of Grosseto)

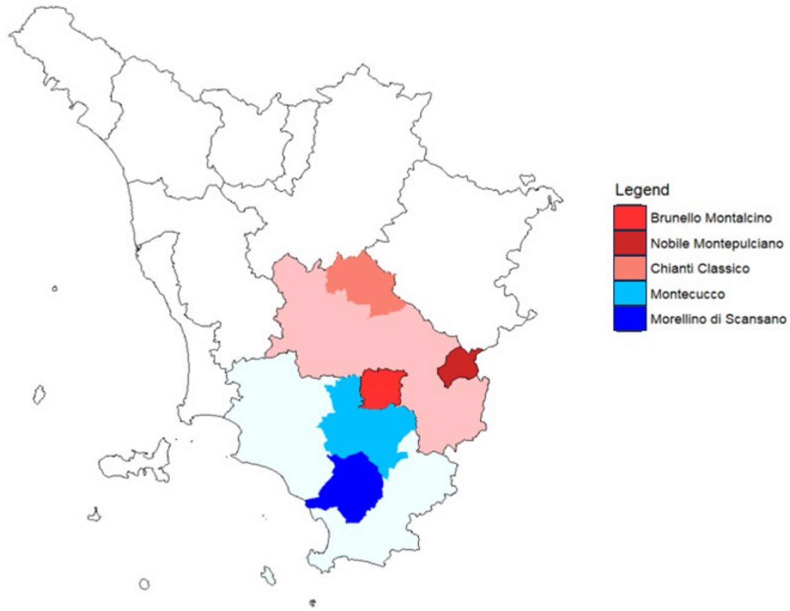

Table 2: Distribution and minimum percentage of Sangiovese required in the wine appellations in Tuscany

Appellations	**N°**	**(%)**	**Min % Sangiovese**
Brunello di Montalcino	106	34.3	100
Rosso di Montalcino	41	13.3	100
Vino Nobile di Montepulciano	19	6.1	70
Chianti Classico	82	26.5	80
Chianti	6	1.9	70
Morellino di Scansano	5	1.6	85
Montecucco	13	4.2	85
Counterfactual (PGI Tuscany)	37	12	0
Total	281	100	

3 Empirical Analysis

3.1 Nebbiolo

We start the analysis by considering all the wines and appellations in Table 3, and we refine the analysis with geolocalized data by restricting the sample around the Barolo appellation in Table 4. In Table 3, we formulate three regression models to describe the effect of predictors on log-price. In Column (1), we include only dummies for Barolo, Barbaresco, Nebbiolo d'Alba, and Roero. The first two appellations have remarkably higher prices, while Nebbiolo d'Alba does not differ significantly from the reference (100% Nebbiolo PDO Langhe). In contrast to Tuscany, the Langhe region does not have a PGI Langhe, neither a PGI Piedmont. Therefore, we are compelled to choose a PDO wine as the reference. The selected PDO Langhe is produced throughout the whole Langhe territory and has the lowest minimum requirement for Nebbiolo grapes. Although this model is quite simple, it already provides a reasonably good fit, with $R^2 = 0.358$. In Column (2), we add firm-level predictors. Compared with Column (1), the coefficients associated with the collective brands remain essentially unchanged. In line with the literature (e.g., Castriota, 2020) we find a significant positive effect on log-price for firm reputation, size, and the organic dummy, while firm age has no significant effect. The predictive ability is much higher than in regression 1, with $R^2 = 0.509$. In Column (3), we also include predictors that reflect the characteristics of the wine and achieve $R^2 = 0.671$. By adjusting for wine quality, age, and the number of bottles of the specific label produced, the coefficient associated with firm reputation becomes, as expected, smaller than in Column (2).

The most relevant insight, however, is provided by the coefficients associated with the wine dummies. Intuitively, suppose the price differences were explained only by differences in quality, and no reputation premium existed. In this case, the coefficients of the dummies of the appellations should tend towards zero and become insignificant. Instead, the coefficients associated with Barolo and Barbaresco remain strongly significant, although smaller in magnitude, suggesting that a reputation premium is present. Moreover, with respect to column 2, Roero is now significantly underpriced compared to the reference. With equal quality, Roero is a lesser-known wine and is 'overshadowed' by its more prestigious neighbors.

In Table 4 we refine the analysis and re-estimate Regression (3) of Table 3 with two important changes. First, we exclude Barbaresco, Nebbiolo d'Alba, and Roero, thereby comparing only Barolo with the reference (Langhe). Second, we introduce a geographical dimension[4]. In Column (1), we use data from the whole Langhe region. In Column (2), we only consider wines produced in the Barolo area and within 10 km from its border. Finally, in Column (3) of Table 4, we only focus on the Barolo area. Results are very similar to those reported in the last Column of Table 3. Again, an average reputation premium of about 0.45 in terms of log-price is found for Barolo compared with the reference. This corresponds to a 57% difference[5] in price between two otherwise identical wines.

[4]A map indicating the region under analysis and the location of the counterfactual wineries is available in the appendix (see Figure A1).

[5]We calculated $e^{0.45} \approx 1.57$. Actually, this is likely an under-estimate, due to the fact that, for any random variable X, $E[e^X] > e^{E[X]}$.

Table 3: OLS Regressions Nebbiolo

	Dependent variable: log_Wine_Price		
	(1)	(2)	(3)
Barolo	1.152***	1.068***	0.463***
	(0.053)	(0.053)	(0.069)
Barbaresco	1.012***	0.923***	0.381***
	(0.073)	(0.070)	(0.064)
Nebbiolo_Alba	0.103	0.115	−0.011
	(0.072)	(0.077)	(0.073)
Roero	0.243***	0.265***	−0.252***
	(0.074)	(0.077)	(0.080)
log_Total_Bottles		0.053***	0.101***
		(0.018)	(0.016)
Firm_Reputation		0.201***	0.081***
		(0.017)	(0.020)
log_Firm_Age		0.016	−0.010
		(0.024)	(0.020)
Organic		0.088**	0.073**
		(0.041)	(0.034)
log_Label_Bottles			−0.115***
			(0.021)
Wine_Quality			0.086***
			(0.010)
Wine_Age			0.092***
			(0.023)
Constant	3.025***	1.814***	−4.947***
	(0.047)	(0.190)	(0.934)
Observations	698	697	677
R^2	0.358	0.509	0.671
Adjusted R^2	0.354	0.503	0.666

*Note:**p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis. In this regression, we have exclusively selected wine bottles made from 100% Nebbiolo grapes produced in the eastern part of the Cuneo province in Piedmont (see Figure 1). The reference base for the coefficients of the wine appellations is PDO Langhe which can be produced in the whole area.

Table 4: Barolo vs Langhe

	Dependent variable: log_Wine_Price		
	(1)	(2)	(3)
	Langhe	10KM	Barolo area
Barolo	0.459***	0.449***	0.453***
	(0.069)	(0.074)	(0.081)
log_Total_Bottles	0.114***	0.117***	0.112***
	(0.017)	(0.018)	(0.018)
Firm_Reputation	0.089***	0.089***	0.084***
	(0.022)	(0.023)	(0.023)
log_Firm_Age	−0.027	−0.030	−0.019
	(0.023)	(0.023)	(0.023)
Organic	0.059*	0.058	0.059*
	(0.035)	(0.035)	(0.035)
log_Label_Bottles	−0.128***	−0.130***	−0.130***
	(0.022)	(0.022)	(0.022)
Wine_Quality	0.077***	0.077***	0.077***
	(0.008)	(0.008)	(0.008)
Wine_Age	0.103***	0.105***	0.106***
	(0.020)	(0.021)	(0.021)
Constant	−4.127***	−4.183***	−4.147***
	(0.713)	(0.728)	(0.726)
Observations	477	467	454
R^2	0.684	0.666	0.643
Adjusted R^2	0.678	0.661	0.636

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis. In this regression, we have exclusively selected wine bottles made from 100% Nebbiolo grapes produced in the eastern part of the Cuneo province in Piedmont (see Figure 1). The reference base for the coefficient of the Barolo appellation is PDO Langhe which can be produced in the whole area. With respect to Table 3, we have excluded the bottles belonging to the following appellations: Barbaresco, Nebbiolo d'Alba, and Roero.

3.2 Sangiovese

Our analysis of Sangiovese presents various similarities with that of Nebbiolo.

Column (1) in Table 5 shows that the average log-price is significantly higher than the reference (PGI Tuscany) for Brunello, Chianti Classico, and Nobile di Montepulciano. Instead, Chianti's prices are significantly lower. The wine dummies maintain very similar coefficients in Column (2), which includes firm-level predictors.

Next, the coefficients of the wine dummies shrink in magnitude but remain significant in model 3, where wine characteristics are included. This evidence suggests that a reputation premium might be present, as the wine characteristics do not entirely explain the price differences. A large premium is found for Brunello, followed by Morellino di Scansano, Nobile di Montepulciano, Chianti Classico, and Rosso di Montalcino. The price premium for Chianti is still negative but becomes insignificant, while Montecucco is virtually indistinguishable from the reference. Interestingly, the premium exhibited by Nobile di Montepulciano is essentially the same in models (1)-(3), suggesting that other variables, possibly including the catchy name, could be responsible for the extra price. Another interesting exception is Rosso di Montalcino, which only has a small premium in Column (1) but presents a larger, significant premium in Column (3). This might suggest that this wine is slightly overpriced for its quality. A role could be played by the presence of "Montalcino" in its name, which potentially makes it more appealing, especially to foreign buyers [6].

Finally, in Table 6, we exclude Chianti, Chianti Classico, Nobile di Montepulciano, Morellino di Scansano and Montecucco, and only compare Brunello di Montalcino and Rosso di Montalcino with the reference (PGI Tuscany 100% Sangiovese)[7]. Moreover, we add a spatial dimension: in Column (1), we consider the whole provinces of Siena and Grosseto; in Column (2), we restrict to an area with a 10 Km radius around the Montalcino region; and in Column (3) we only use wineries from the area of Montalcino. Also in this case, results are qualitatively comparable with those obtained in previous analyses, with some minor changes in the magnitude of the coefficients. In the Montalcino area, Brunello enjoys an estimated average premium of 0.779 in terms of log-price, which corresponds to a 118% price increase compared with the reference[8].

It is important to note that the coefficients observed for Brunello should not be directly compared to the coefficients found for Barolo. In the case of Sangiovese, our counterfactual consists of 100% Sangiovese PGI Tuscany wines. In contrast, in the analysis of Nebbiolo, due to the absence of a PGI Langhe or Piedmont denomination, the reference is 100% Nebbiolo PDO Langhe, a more prestigious denomination than PGI Tuscany. Therefore, the two price premiums are not exactly comparable.

[6] In Table A3 in the appendix, we report the same regression analysis restricted to the province of Siena, thus excluding Grosseto. The results are qualitatively similar to those presented earlier.

[7] A map indicating the region under analysis and the location of the counterfactual wineries is available in the appendix (see Figure A2).

[8] See note 5.

Table 5: OLS Regressions Sangiovese (Siena & Grosseto)

	Dependent variable: log_Wine_Price		
	(1)	(2)	(3)
Brunello_Montalcino	1.137***	1.074***	0.904***
	(0.107)	(0.105)	(0.125)
Rosso_Montalcino	0.112	0.023	0.209**
	(0.124)	(0.108)	(0.099)
Nobile_Montepulciano	0.502***	0.471***	0.427***
	(0.145)	(0.157)	(0.146)
Chianti_Classico	0.395***	0.398***	0.295***
	(0.107)	(0.111)	(0.105)
Chianti	−0.391**	−0.306**	−0.107
	(0.156)	(0.147)	(0.145)
Morellino_Scansano	0.439	0.585*	0.573**
	(0.321)	(0.305)	(0.273)
Montecucco	0.025	0.092	−0.004
	(0.120)	(0.122)	(0.120)
log_Total_Bottles		−0.067***	−0.004
		(0.020)	(0.017)
Firm_Reputation		0.238***	0.231***
		(0.033)	(0.029)
log_Firm_Age		−0.022	−0.025
		(0.032)	(0.023)
Organic		0.006	−0.031
		(0.057)	(0.046)
log_Label_Bottles			−0.178***
			(0.020)
Wine_Quality			0.040***
			(0.011)
Wine_Age			0.042*
			(0.025)
Constant	3.107***	3.525***	0.692
	(0.094)	(0.227)	(1.013)
Observations	308	306	294
R^2	0.462	0.568	0.710
Adjusted R^2	0.449	0.552	0.695

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis. In this regression, we have exclusively selected wine bottles made from 100% Sangiovese grapes produced in the provinces of Siena and Grosseto in Tuscany (see Figure 2). The reference base for the coefficient of the Brunello appellation is PGI Tuscany 100% Sangiovese which can be produced in the whole area.

Table 6: Montalcino vs PGI Tuscany

	Dependent variable: log_Wine_Price		
	(1)	(2)	(3)
	Siena-Grosseto	10KM	Montalcino
Brunello_Montalcino	0.688***	0.971***	0.779***
	(0.182)	(0.176)	(0.207)
Rosso_Montalcino	0.211**	0.403***	0.289**
	(0.096)	(0.096)	(0.114)
log_Total_Bottles	−0.013	−0.040**	−0.044**
	(0.024)	(0.020)	(0.020)
Firm_Reputation	0.246***	0.232***	0.232***
	(0.035)	(0.035)	(0.034)
log_Firm_Age	−0.040	−0.036	−0.039
	(0.034)	(0.034)	(0.033)
Organic	−0.046	−0.038	−0.034
	(0.060)	(0.055)	(0.057)
log_Label_Bottles	−0.138***	−0.135***	−0.135***
	(0.026)	(0.026)	(0.027)
Wine_Quality	0.048***	0.035**	0.038***
	(0.015)	(0.014)	(0.014)
Wine_Age	0.112**	0.101**	0.123**
	(0.050)	(0.049)	(0.056)
Constant	−0.412	0.871	0.635
	(1.321)	(1.267)	(1.308)
Observations	177	158	153
R^2	0.743	0.773	0.762
Adjusted R^2	0.729	0.759	0.747

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis. In this regression, we have exclusively selected wine bottles made from 100% Sangiovese grapes produced in the provinces of Siena and Grosseto in Tuscany (see Figure 2). The reference base for the coefficient of the Brunello appellation is PGI Tuscany which can be produced in the whole area. We have excluded the bottles belonging to the following appellations: Vino Nobile di Montepulciano, Chianti Classico, Chianti, Morellino di Scansano and Montecucco.

4 Conclusions

In markets characterized by asymmetric information and product differentiation, reputation is crucial to increase the price and sales volume, since it is difficult for small and young companies to build a solid firm reputation. Therefore, collective reputation has emerged as a useful (alternative or additional) marketing tool. From the theoretical point of view, the reasons why collective reputation should benefit producers are clear, but from the empirical one, it is complicated to isolate its effects from those of other confounding variables. Large-scale experiments through random assignment of labels – with and without a famous collective brand – are impossible. In order to measure the collective price premium, the literature has usually relied on hedonic price models with control variables, including dummy variables for the different geographic areas. However, this approach presents several issues, from omitted variable bias to endogeneity and selection bias.

To circumvent these problems, we propose an approach based on geographical discontinuity around the border of the Italian wine appellations. Using geolocalized data, we compare prices of virtually identical wines – made with 100% Nebbiolo grapes in Piedmont and 100% Sangiovese grapes in Tuscany – whose firms are located inside or outside the borders of the wine appellations. Since the borders of the appellations are not intentionally built to include the best wineries but rather follow the administrative borders of the municipalities (e.g., Barolo and Montalcino), having the vineyards just inside or outside them is random. Results show that controlling for wine (e.g., quality, aging, and additional features) and other firm characteristics (e.g., size and reputation), the price premium of different appellations varies dramatically and can achieve as much as +118% for Brunello di Montalcino versus the reference PGI Tuscany, and +57% for Barolo versus the reference PDO Langhe.

However, for some appellations, the price premium is null, while for one - Roero in Piedmont - it is even negative. This latter result is crucial because it shows that the proliferation of geographic appellations is not necessarily profitable as it can confuse buyers. Therefore, some new appellation might be perceived as an inferior product. Our analysis is a picture taken with data from the 2024 wine guide of the Italian Sommelier Association. However, life is a movie, not a picture. As shown by Castriota and Delmastro (2015) using dynamic data on Italian wine appellations, collective reputation depends on time and on the size of the coalition, while investments in marketing campaigns are not directly tested in the same work but surely matter. Therefore, nothing will prevent this negative reputation premium from turning positive in the future.

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Appendix

Figure A1: Barolo region and its counterfactual

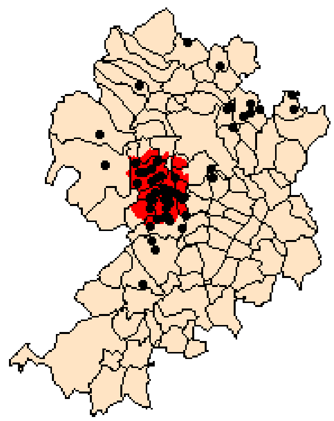

Figure A2: Montalcino within the provinces of Siena and Grosseto

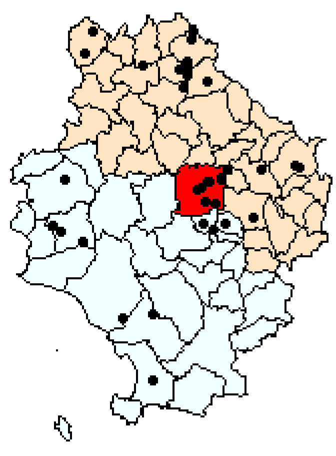

Table A1: Summary Statistics Nebbiolo

Variable	**Description**	**Observations**	**Mean**	**Median**	**Min**	**Max**	**Sd**
Wine_Price	Price of the wine in €	698	68	50	10	750	73
Barolo	Dummy variable for Barolo	698	0.63	1	0	1	0.48
Barbaresco	Dummy variable for Barbaresco	698	0.2	0	0	1	0.4
Roero	Dummy variable for Roero	698	0.05	0	0	1	0.21
Nebbiolo_Alba	Dummy variable for Nebbiolo d'Alba	698	0.04	0	0	1	0.19
Counterfactual	Dummy variable for the counterfactual case	698	0.08	0	0	1	0.27
Total_Bottles	Total number of bottles produced	697	252,007	100,000	4,000	8,000,000	773,186
Firm_Reputation	Reputation score of the firm (1 to 4)	698	2.8	3	1	4	1.1
Firm_Age	Age of the firm in years	698	83	64	3	684	71
Organic	Dummy variable for organic production	698	0.35	0	0	1	0.48
Label_Bottles	Number of bottles for the specific label	678	9,305	5,600	500	200,000	14,890
Wine_Quality	Quality score of the wine (out of 100)	698	90	89	81	98	3
Wine_Age	Age of the wine (in years)	698	5.5	5	2	11	14

Table A2: Summary Statistics Sangiovese

Variable	**Description**	**Observations**	**Mean**	**Median**	**Min**	**Max**	**Sd**
Wine_Price	Price of the wine in €	308	50	40	10	490	48
Brunello	Dummy variable for Brunello di Montalcino	309	0.34	0	0	1	0.48
Rosso_Montalcino	Dummy variable for Rosso di Montalcino	309	0.13	0	0	1	0.34
Chianti	Dummy variable for Chianti	309	0.02	0	0	1	0.14
Chianti_Classico	Dummy variable for Chianti Classico	309	0.27	0	0	1	0.44
Nobile_Montepulciano	Dummy variable for Nobile di Montepulciano	309	0.06	0	0	1	0.24
Morellino_Scansano	Dummy variable for Morellino di Scansano	309	0.02	0	0	1	0.13
Montecucco	Dummy variable for Montecucco	309	0.04	0	0	1	0.20
Total_Bottles	Total number of bottles produced	307	714,428	100,000	10,000	28,000,000	3,095,211
Firm_Reputation	Reputation score of the firm (1 to 4)	309	2.1	2	1	4	0.96
Firm_Age	Age of the firm in years	309	109	47	8	981	197
Organic	Dummy variable for organic production	309	0.58	1	0	1	0.49
Label_Bottles	Number of bottles for the specific label	298	26,306	11,000	700	450,000	47,455
Wine_Quality	Quality score of the wine (out of 100)	309	90	90	80	96	2.6
Wine_Age	Age of the wine in years	308	5	5	2	16	1.7

Table A3: OLS Regressions Sangiovese (Siena)

	Dependent variable: log_Wine_Price		
	(1)	(2)	(3)
Brunello_Montalcino	1.062***	1.035***	0.789***
	(0.130)	(0.126)	(0.148)
Chianti	−0.466***	−0.352**	−0.181
	(0.172)	(0.162)	(0.157)
Chianti_Classico	0.320**	0.355***	0.208*
	(0.131)	(0.130)	(0.119)
Rosso_Montalcino	0.037	−0.017	0.145
	(0.144)	(0.130)	(0.115)
Nobile_Montepulciano	0.428***	0.436**	0.338**
	(0.163)	(0.173)	(0.160)
log_Total_Bottles		−0.072***	−0.012
		(0.020)	(0.017)
Firm_Reputation		0.238***	0.225***
		(0.033)	(0.029)
log_Firm_Age		−0.012	−0.022
		(0.033)	(0.024)
Organic		0.023	−0.019
		(0.062)	(0.051)
log_Label_Bottles			−0.171***
			(0.021)
Wine_Quality			0.044***
			(0.012)
Wine_Age			0.056*
			(0.033)
Constant	3.181***	3.577***	0.395
	(0.120)	(0.255)	(1.096)
Observations	280	278	267
R^2	0.441	0.559	0.710
Adjusted R^2	0.431	0.544	0.697

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis. In this regression, we have exclusively selected wine bottles made from 100% Sangiovese grapes produced in the provinces of Siena and Grosseto in Tuscany (see Figure 2). The reference base for the coefficient of the Brunello appellation is PGi Tuscany which can be produced in the whole area. We have excluded the bottles belonging to the following appellations: Vino Nobile di Montepulciano, Chianti Classico, Chianti, Morellino di Scansano and Montecucco.