Assessing Production Functions and Technical Efficiency in Quality-Differentiated Agri-Food Products: Evidence from Argentine Wineries

Nicolás Depetris-Chauvin[1], Gustavo Ferro[2], Nicolás Gatti[3], and Emiliano Villanueva[4]

Abstract

This study examines the production technology and technical efficiency of Argentine wineries producing high-quality versus low-quality wines for both domestic and export markets. Using data from a survey of 230 Argentine wineries, we estimate production functions with Ordinary Least Squares and assess technical efficiency through Stochastic Frontier Analysis. We differentiate between above-average and below-average quality wine producers and further segment these into exporters and non-exporters. Our findings highlight distinct production technologies and input intensities between high-quality and low-quality wine producers. High-quality wine producers show no economies of scale, unlike their low-quality counterparts. Additionally, exporters, particularly those with higher export intensity, exhibit greater efficiency and quality levels compared to lower-intensity exporters and non-exporters. These results offer valuable insights for emerging market policymakers and agribusinesses, illustrating how strategic quality differentiation and export focus can enhance competitiveness and productivity in the global wine industry.

Keywords: Efficiency, Stochastic Frontier Analysis, Wineries, Argentina

1. Introduction

The global agri-food industry is increasingly recognized for its potential in technological advancement and value addition, particularly through product differentiation and quality enhancement. The wine industry, where quality and origin command a premium, exemplifies how emerging markets can enhance the value of their exports through strategic innovation and quality upgrading. Since the 1970s, latecomers in the global wine market have transformed how wine is produced, sold, and consumed, highlighting the role of consistent investments in innovation (Villanueva et al., 2023). Argentina's wine industry, known for producing both high-quality and low-quality wines, serves as an illustrative case of how emerging markets can successfully compete internationally by focusing on quality differentiation.

Competition in international markets increasingly centers on product quality, compelling firms to secure high-quality inputs and adhere to stringent production and marketing standards to gain market access (Amodio and Martinez-Carrasco, 2018; Atkin et al., 2017; Bas and Strauss-

[1] HES-SO, Haute École de Gestion de Genève, Geneva, Switzerland. E-mail: nicolas.depetris-chauvin@hesge.ch
[2] Universidad del CEMA (UCEMA) and CONICET, Buenos Aires, Argentina. E-mail: gaf97@ucema.edu.ar
[3] Universidad del CEMA (UCEMA) and Centro de Investigación en Economía y Prospectiva CIEP-INTA. Buenos Aires, Argentina. Email: nicolasgatti1987@gmail.com
[4] Eastern Connecticut State University, Willimantic, CT, United States. E-mail: villanuevae@easternct.edu

Kahn, 2014; Bastos et al., 2018; Hallak and Sivadasan, 2013; Halpern et al. 2015; Kugler and Verhoogen, 2012). Argentine wineries, particularly those that export, have responded by investing in better-trained human capital, advanced physical capital, and refined marketing practices (Depetris-Chauvin and Villanueva, 2024). This aligns with the broader literature on international trade and firm heterogeneity, which consistently shows that exporting firms tend to be more productive, larger, and more efficient than their non-exporting counterparts (Melitz, 2003; Bernard and Jensen, 1999; Crozet et al., 2012; Brambilla et al. 2017). The productivity advantage of exporters often stems from their ability to leverage superior resources, adopt advanced technologies, and engage in learning-by-exporting processes, thereby enhancing their competitive edge (Clerides et al., 1998; Lileeva and Trefler, 2010; Golovko and Valentini, 2011).

Despite the growing importance of quality in global trade, there is limited evidence on whether the production functions of high-quality wines differ from those of lower-quality wines, particularly in the context of an emerging market economy like Argentina. This paper aims to address this gap by assessing the differences in production functions between Argentine wineries producing high-quality wines and those focused on lower-quality products. We hypothesize that producers of above-average quality wines employ distinct techniques and input mixes compared to those producing below-average quality wines, which could have significant implications for their competitiveness in both domestic and export markets. Additionally, we explore the relative technical efficiency within these groups, with a particular focus on the differences between exporters and non-exporters, reflecting the established link between export status and firm productivity (Head and Ries, 1999; Baldwin and Gu, 2004; Wagner, 2007).

The primary contributions of this study are twofold. First, we characterize the differences in production technology across diverse types of wineries, which is crucial for understanding how product differentiation strategies impact performance in international markets. Numerous studies have emphasized the importance of differentiation strategies in enhancing competitiveness, particularly in the wine industry, where the ability to manage quality differentiation is key to success (Chen et al., 2014; Cavusgil and Knight, 2015; Depetris-Chauvin and Fernández-Olmos, 2024; Knight et al., 2020). Second, we estimate the technical efficiency of these wineries using Stochastic Frontier Analysis (SFA), providing insights into how quality differentiation influences efficiency within the Argentine wine sector. Given the importance of studying comparable goods in efficiency assessments, we design meaningful subsamples containing well-differentiated producers of wines of different quality. Although quality is an unobservable characteristic, we employ a methodology that establishes a cardinal measure for wine quality through an index, enabling the construction of these subsamples.

This analysis is based on a new representative sample of 230 Argentine wineries, covering topics such as production, inputs, processes, quality, export destinations, and commercial practices. Following the modern theory of heterogeneous firms in trade, which highlights the distinct dynamics of exporters and non-exporters (Chaney, 2008; Helpman et al., 2008; Bernard and Jensen, 1995; Melitz, 2003), we distinguish in our analysis between exporting and non-exporting wineries.

This paper is structured as follows. Section 2 reviews the literature on technical efficiency in wineries. Section 3 presents the data, methodology, and models used in the analysis. Section 4 discusses the results, and Section 5 concludes with implications for the broader agri-food sector in emerging markets.

2. Literature review

Technical efficiency in wineries has been widely studied using Data Envelopment Analysis (DEA) and SFA. A non-exhaustive list of research articles using DEA includes Barros and Santos (2007), Sellers and Alampi-Sottini (2016), and Conradie et al. (2018). Another set of studies used SFA, such as Kallas and Lehnhardt (2011), Moreira et al. (2011), Vidoli et al. (2016), Piesse et al. (2018), Faria et al. (2021), and Santos et al. (2021). Lastly, Tóth and Gál (2014), Marta-Costa et al. (2017), Rebelo et al. (2018), and Urso et al. (2018) estimated and compared results from both types of models.

Table 1 summarizes the approach, data, and variables used in the analyzed studies, and in the paragraphs below, we discuss the details of each contribution and relate them to our goals.

An empirical efficiency study determines the relative position of each producer within a sample, comparing the input-output results of each observation to the group's best practices. There is no ambition to establish a theoretical or ideal efficiency level. Instead, the objective is to determine how efficiency varies within the sample and to identify the reasons for the difference, providing results useful for managerial and policy purposes.

Differences in productivity and efficiency are often related to wineries' characteristics. For instance, Barros and Santos (2007) compare the efficiency of cooperatives and private enterprises in the Portuguese wine industry, employing DEA, and conclude that, on average, Portuguese wine cooperatives are more efficient than their private counterparts. Sellers and Alampi-Sottini (2016) analyze the influence of firm size on the economic performance of wineries, employing different traditional profitability and productivity measures and a non-parametric technique to estimate efficiency as an indicator of performance. They find that size has a positive influence on the economic performance of wineries. Urso et al. (2018) investigate, using a DEA model, the technical efficiency of Italian wineries. They then estimate the determinants of the estimated levels of efficiency through an econometric model, aiming to understand which farm and area characteristics affect the differences in efficiency levels. In this set of contributions, the motivation is related to different organizational forms and the scale. In our sample, there are diverse types of firms (cooperatives and limited liability firms) and different scales of production (from familiar firms, "boutique" wineries, to industrial establishments). Our interest is to study efficiency in groups of different quality wines.

Efficiency could differ by region and change over time. For instance, Marta-Costa et al. (2017) analyze the productive efficiency of the viticulture sector for the Portuguese regions from 1989 to 2007, using both deterministic and stochastic approaches. Their results show increased technical efficiency in all regions when using SFA. Further, the DEA approach through the Malmquist index suggests a stabilization of technical efficiency during this period. Conradie et al. (2018) compare long-established and more recently developed wine regions in South Africa. DEA frontiers produce measures of technical efficiency and technical change over time. The results for scale efficiency are close to unity and switch from increasing to decreasing returns frequently over the period. The Malmquist TFP index shows limited technological change and efficiency improvements. The differences between the old and new districts are minimal, but growth was slightly higher in the newer regions. Faria et al. (2021) investigate the presence of spatial spillovers in firms' productive (in)efficiency, employing a spatial SFA model, which accounts for spatial dependence and persistent and transient (in)efficiency. The novelty of this study is the inclusion of information on the firms' exact location, which allows the incorporation of the neighboring dependence in the productive efficiency analysis. In our case, we do not differentiate wineries by origin, although above-average quality wine exporters are clustered in the primary producer region of Argentina, Mendoza. Our sample includes wineries from this wine region mainly, but our separation of the sample is not necessarily geographical but by quality. Also, since our database is a cross-section, we are not concerned with the evolution of efficiency over time.

Differences could drive comparisons of technical efficiency at the farm level. Moreira et al. (2011) estimate and analyze the technical efficiency component of productivity for a sample of wine grape producers in Chile. They used a Cobb-Douglas model to estimate an SFA model and obtain technical efficiency scores at the individual block and farm level. The results suggest a 77 percent average farm-level technical efficiency and nearly constant returns to size. Our sample is at the winery level; we do not have detailed information on farms or parcels within each winery.

Kallas and Lehnhardt (2011) assess the determinant factors that drive the wine and meat industries in Catalonia (Spain) to abandon their activities and the timing of their decision. They estimate technical efficiency using SFA. Results show a significant impact of technical efficiency and other economic factors on exit duration. Again, our sample is a cross-section; we cannot perform dynamic analysis.

There is evidence of differences in efficiency by country. Tóth and Gál (2014) estimate a Cobb-Douglas production function and technical inefficiency using SFA, showing a significant difference in technical efficiency between the major Old and New World countries, higher in the latter. In the study, inefficiency is related, in a second stage estimate, to the development of the financial system, the quality of human capital, and per capita wine consumption. Our database is of one New World producer. We could be interested in differences in efficiency at the regional level; however, even when the industry in Argentina is geographically distributed across 2,400 kilometers from North to South, wineries, production, exporting activity, and above-average quality are very concentrated in the primary producer province (Mendoza).

Contextual and structural factors may play a role. Vidoli et al. (2016) estimate the efficiency of a representative sample of Italian wine producers using a spatial SFA framework that allows isolating the spatial dependence among decision-making units (DMU) and evaluating the role of intangible local factors in firm performance. The study shows that specific territorial patterns cannot be explained solely by contextual factors. According to the study, in most localities, an embedded community stimulates local learning that thrives on the diffusion of tacit knowledge through continuous interaction among actors. The effect differs across firm sizes and has a more significant impact on small firms. Santos et al. (2021) analyze the productive efficiency of wine-growing farms and the structural factors that make wine grape farms more efficient in a sample of 154 wine-growing farms with specific input-output information from 2017. Many of the discrepancies among wineries and regions may be due to structural factors, such as the type of wine grapes and the specific characteristics of the region. In our study, we use some characteristics as controls, not based on regional differences but in practices related to wine quality. We find that some of these characteristics help explain efficiency in producing above-average quality wines, while they are not essential for producing below-average quality wines.

Inexperience in wine production could be a driver of inefficiencies. Piesse et al. (2018) apply an SFA model to wine grape farms in South Africa, comparing the efficiency levels for the old established wine regions with those of newer entrants. Thus, they investigate whether experience plus the first choice of location matters more than the follower's advantage of newer technology. We have information on several attributes of the firm's human capital, such as years of experience of their oenologists or marketers. However, these variables are not statistically significant in our model estimations.

In summary, precedent studies employed DEA, SFA, or both methods to estimate technical efficiency. The studies used cross-sectional or panel data. In a few cases, they use two-stage methods (DEA and econometrics to assess efficiency determinants) or spatial models (to assess differences due to the territorial position of the wineries). The dependent variable from these studies is either wine production or wine value, and some authors used sales instead of production. In addition, grape production is used as an independent variable (the raw material of the production process. The main explanatory variables included for production and sales functions are inputs, proxies of land, capital, labor, and raw materials. Moreover, some studies incorporated environmental (contextual or non-discretionary inputs) and qualitative variables to explain efficiency. We did not find studies that explicitly addressed quality, our main concern. Our contribution is to apply a method to separate production by quality when studying production technology and efficiency, recognizing that input mix and practices differ when producing high- or low-quality wines.

Table 1: Characterization of wineries technical efficiency studies.

Study	Method	Sample (type, DMUs, years, place)	Outputs	Inputs, quality, and environmental factors considered
Barros and Santos (2007)	DEA	Panel, five years, 27 wineries (DMUs), Portugal	sales, the value of production, and gross value added	Labor (workers), cost of labor, capital (book value of non-depreciated assets), cost of capital
Moreira et al. (2011)	SFA	Cross section, 263 observations (blocks) of 38 DMUs (farms), Chile	Wine	Labor cost, Machinery cost, other inputs, Block size Age of plantation, red wine, Premium, Single cordon, Double cordon, Pergola, and regions of Aconcagua and Cachapoal, Casablanca, Maipo, Colchagua and Rapel, Curicó, and Maule
Kallas and Lehnhardt (2011)	SFA	231 active and 20 inactive firms, (Catalonia) Spain	Deflated total sales of wine	Labor (wages), cost of intermediate inputs, capital
Tóth and Gál (2014)	SFA, two stages	Panel, 12 years, 16 countries (DMUs), Cross Country (11 Old-World and 5 New World producers)	wine production	land (area of vineyards), capital (agricultural capital stock), and labor force (employment in agriculture); four macroeconomic elements, and per capita wine consumption and belonging either to the Old or the New Wine World

Vidoli et al. (2016)	Spatial SFA	Cross section, 853 wineries (DMUs), Italy	Wine	labor, machinery, water-energy-fuel, and land capital; the spatial effect includes endogenous factors linked to the productive process or the corporate characteristics, exogenous physical factors, and exogenous economic indicators related to the local supply factors.
Urso et al. (2018)	DEA, two stages	Panel, six years, Italy	Gross marketable output	the value of the land capital, the value of labor, and the value of the working capital
Piesse et al. (2018)	SFA	Panel, 77 farms (DMUs) for 11 years, South Africa	Value of wine production	land, labor (wages), pesticide and herbicide costs, and fertilizer, fuel, and electricity costs (the two latter to proxy machinery and irrigation). Additionally, labor supervision costs, the proportion of permanent to total labor costs, the share of inorganic fertilizers in total fertilizer costs, the ratio of modern to old trellising, the proportion of total area on which drip irrigation or no irrigation was in place; the share of total planting that is on old vines; and the proportion of total planting allocated to red varieties.
Faria et al. (2021)	Spatial SFA	Panel, 304 wineries (DMUs) for six years, Portugal	Value of total sales	number of employees, the value of the fixed assets' depreciation and amortizations as a proxy for the capital input, cost of raw materials, and the cost of supplies and services
Santos et al. (2021)	SFA	Cross section, 154 wineries for 2017, Portugal.	Grape production	land, labor capital, and intermediate consumption costs); geographical location and type of wine produced

Source: Authors' elaboration.

3. Data, methodology and models

3.1 Data

Our data, collected from a diverse range of wineries, is a representative sample of producers distributed among all wine-producing regions of Argentina between September 2019 and May 2021. The survey was answered by 230 wineries (representing 26 percent of total Argentine wineries). Of these, 164 exported part of their production (71 percent), while 66 were non-exporting wineries (almost 29 percent of the sample). Two-thirds of the non-exporting wineries are in Mendoza, the main wine-producing region, which accounts for more than four-fifths of national production.

The survey was designed to gather comprehensive data, ranging from the winery characterization (age, size, ownership, location, sales, price segments, and employment) to the winery's production, qualities, inputs, marketing, and sales practices. It also provides data and information regarding technological and human resources and their participation in export markets (Depetris-Chauvin and Villanueva, 2024). Some observations are lost due to missing data in critical variables (outputs and inputs).

Table 2 presents the variables we use in our models, defining them and establishing the measurement units. As outputs, we have information on the wine production of each winery -in million liters-. The inputs are surface (hectares), labor (number of workers), capital index (as an indication of the capital stock, built adding several dummies of capital equipment that the wineries reported, see below), the grape yield (in tones by a hectare of the entry-level product of each winery). Some contextual ("environmental" in the efficiency literature jargon) variables address the proportion of temporary workers relative to total workers and the proportion of wine produced with own harvested grapes.

The table presents three partial productivity ratios (of land, labor, and capital) that will later be useful for characterizing the wineries within each subsample, comparing them, and correlating them with the efficiency measures determined by the estimates.

Table 2: Definition of the variables

Name	Variable label	Type of variable
ProdinL	Wine production (M liters)	Output
Surface	Surface (hectares)	Input
Labor	Number of workers	Input
capital_index	Capital Index	Input
Entryyield	Entry yield (tons per hectare)	Input
prop_temp	The proportion of temporary workers relative to total workers	Environmental
perc_ownharvest	Percentage of production that is from own harvest	Environmental
outputHa	= ProdinL/surface	Productivity of land
outputK	= ProdinL/capital_index	Productivity of capital
outputL	= ProdinL/Labor	Productivity of labor

Source: Authors' elaboration.

We use information on each firm's capital goods to create an index to obtain a capital measure. It is an unweighted sum of eighteen dummy variables of capital goods. This approximation behaves better than an alternative index built using a Principal Component Analysis (PCA) of the different physical capital measures. The capital index goes from 0 to 1.

Capital index = (Grapesortingtable + Grapecrusher + Presser + Tanks + Pumps + Filters + Bottlingequipment + Automatedwinerycontrol + Undervineweeders + Prepruners + Trimmers + Sprayers + Shredder + Pickingmachine + Tractors + irrigation_eq + Automatedvineyardcontrol + Cropscover)/18 (1)

The survey does not provide a direct indication of wine quality and there is no single definition of quality in the wine industry (Charters and Pettigrew, 2007). Some authors use prices as an indication of wine quality (Schnabel and Storchmann, 2010; Oczkowski and Doucouliagos 2015). The respondents of the survey were asked to inform the percentage of four price categories of wines they sell: value, premium, luxury, and iconic. However, due to some missing data, we cannot use this criterion as a proxy for quality. We also lack data on production value, and even when prices could yield a proxy of quality, high prices could also reflect high relative costs (Nerlove, 1995; Oczkowski, 1994; Combris et al., 1997, 2000). Export unit values are sometimes used as a proxy for quality in international trade (Schott, 2004; Hallak, 2006; Kugler and Verhoogen, 2012). We do not have that information. We do not have scores given by experts either, which can be another proxy of quality (Ferro and Benito-Amaro, 2018). Instead, we built an index of quality with information from the survey. Our index captures a winery's aim to reach a certain level of (sensory) quality rather than the actual quality achieved. There are two advantages to this approach. First, there is substantial agreement among winemakers that performing certain actions, ceteris paribus, enhances sensorial quality (see Reynolds 2010, Ch. 11, and Van Leeuwen and Darriet 2016). Second, since our measure is linked to the physical attributes of wines, it is more closely connected to the production function of the wineries. Thus, following Depetris-Chavin et al. (2023), we call this measure "pursued quality". The variable adds five equally weighted dichotomous variables, each associated with a winemaking or agricultural practice that leads to higher organoleptic quality. Since the quality index comprises five dichotomous variables, it ranges from a minimum score of 0 to a maximum score of 5.

Pursued quality index = (below_average_yield + greenharvest + egrapesorting + oak + enaturalcork) (2)

Decreasing the number of grapes allows the remaining to concentrate polyphenols, enhancing the wine's sensory attributes. Fruit thinning and grape sorting favor the polyphenolic concentration of the wine, and discarding damaged and diseased grapes before fermentation allows one to make wine from the best grapes of each vintage. Using oak barrels (French or American) to age the wine is a non-invasive practice highlighting each terroir singularity. The use of natural cork prevents the passage of external oxygen to the wine, which would damage its quality, allowing for better aging (Depetris-Chauvin et al., 2023).

Table 3 presents six combinations of above- or below-average quality and the conditions of exporter or non-exporter. The criteria for dividing the samples were taking first the average of the "pursued quality" variable for the whole sample. It is 2.36. Since the variable can take the values 0, 1, 2, 3, 4, and 5, and since the integer more proximate to 2.36 is 2, we take that value to split the samples. We determine two samples with no intersections: Sample A comprehends 142 observations of Above-average quality (pursued quality >= 2, on average 3.06), and Sample B includes 59 observations of Below-average quality (pursued quality < 2, on average 0.68). We called them Sample A and B for Above- and Below-Average Pursued Quality.

In both samples, there are exporters (both above and below the export intensity sample averages) and non-exporters. We estimate separate production functions using OLS and separate SFA functions using ML for Samples A and B, grouping the results within the six subsamples.

Table 3: Sampling and subsampling criteria

Quality level / Market	Pursued_quality = or >2	Pursued_quality <2
	Whole	**Sample**
Exporters and non-exporters	Sample A - Model A N = 142	Sample B - Model B N = 59
	Exporters	
Higher Intensity Exporters (above sample averages)	Subsample A1 Prop-exports >= 0.394 n = 72	Subsample B1 Prop-exports >= 0.365 n = 30
Lower Intensity Exporters (below sample averages)	Subsample A2 0 < Prop-exports < 0.394 n = 27	Subsample B2 0 < Prop-exports < 0.365 n = 18
	Nonexporters	
Non-exporting at all	Subsample A3 Prop-exports = 0 n = 43	Subsample B3 Prop-exports = 0 n = 11

Source: Authors' elaboration

Table 4 presents the descriptive statistics of the variables. Firstly, we present the whole dataset. The size of the set of observations (not considering missing values) is 201. The average winery of the sample produces 4.6 million liters annually. However, this number masks a variety of winery sizes, being the largest producer of 312 million liters. The average winery of the sample has a surface of 204 hectares (and a maximum of 7,000) and employs an average of 108 persons (60 percent temporary). The yield for the entry category of wine is 1.21 tons per hectare for the whole sample. The percentage of exported production is 37 percent on average. After the descriptive statistics for the whole sample, we present the same information for the two subsamples for which we are performing the efficiency analysis. From the observation and comparison of the data, the subsamples are different.

For the subsamples, we added the average productivity for each one of the three factors of production (land, labor, and capital). These three pairs of ratios allow us to characterize the samples. Sample A, for the Above-average "pursued quality index," has lower average labor and capital productivity, denoting the intensity of factors needed to produce the highest quality products. The exception is the output (wine) on the surface (hectares) ratio. The pursued quality index differs significantly on average between samples. However, the average export intensity is almost the same in both subsamples.

Table 4: Descriptive statistics of the variables

Variable	Obs	Mean	Std. dev.	Min	Max
Whole Sample					
ProdinL (million liters)	201	4.5846	26.5203	0.0003	312.0000
Surface (ha)	201	203.8831	645.8972	1.0000	7000.0000
Entryyield (tons/ha)	201	1.2117	0.6678	0.2000	4.0000
Capital_index	201	0.5807	0.1798	0.0556	1.0000
Labor	201	107.8706	348.5515	1.0000	3000.0000
prop_ownharvest	201	0.7606	0.2981	0.1250	1.0000
prop_temp	201	0.5980	0.2246	0.0000	1.0000
pursued_qualityy	201	2.3632	1.3937	0.0000	5.0000
prop_exports	201	0.3739	0.3513	0.0000	1.0000
Variable	Obs	Mean	Std. dev.	Min	Max
Above average quality subsample					
ProdinL (million liters)	142	1.2977	4.7203	0.0003	36.0000
Surface (ha)	142	109.2479	286.9861	1.0000	2410.0000
Entryyield (tons/ha)	142	1.0581	0.5936	0.2500	4.0000
Capital_index	142	0.5657	0.1658	0.0556	1.0000
Labor	142	57.7183	119.8011	1.0000	1100.0000
prop_ownharvest	142	0.7984	0.2882	0.1250	1.0000
prop_temp	142	0.6028	0.2219	0.0000	1.0000
pursued_qualityy	142	3.0634	0.9908	2.0000	5.0000
prop_exports	142	0.3651	0.3642	0.0000	1.0000
outputHa	142	0.0282	0.2513	0.0000	3.0000
outputK	142	1.8166	6.1296	0.0005	52.3636
outputL	142	0.0133	0.0222	0.0000	0.1500
Variable	Obs	Mean	Std. dev.	Min	Max
Below average quality subsample					
ProdinL (million liters)	59	12.4954	47.7598	0.0006	312.0000

Surface (ha)	59	427.2932	1079.9540	1.8000	7000.0000
Entryyield (tons/ha)	59	1.5811	0.6960	0.2000	4.0000
Capital_index	59	0.6168	0.2070	0.1111	1.0000
Labor	59	228.5763	602.5401	1.0000	3000.0000
prop_ownharvest	59	0.6695	0.3042	0.1250	1.0000
prop_temp	59	0.5862	0.2323	0.0000	1.0000
pursued_qualityy	59	0.6780	0.4713	0.0000	1.0000
prop_exports	59	0.3949	0.3202	0.0000	1.0000
outputHa	59	0.0152	0.0140	0.0000	0.0571
outputK	59	14.5323	50.4891	0.0010	330.3529
outputL	59	0.0491	0.0798	0.0000	0.4000

Source: Authors' elaboration.

3.2 Method

The rationale behind efficiency frontiers is that some DMUs, such as firms, state dependencies, or any other organization in or out of the markets, use resources to attain specific outputs and use inputs with different efficiency levels. Some would use fewer resources than others to produce specific outputs. Producing more with less or using fewer inputs to produce a given output defines best practices. A sample's set of best practices defines a "frontier" susceptible to being estimated. The econometric approach and the mathematical programming method are general methodologies for constructing efficiency frontiers. The first is stochastic (distinguishing within the error term, pure randomness -or noise- from inefficiency) and parametric (assuming a specific functional form for the relations it studies - production or cost functions- and estimating its parameters). The second one is most of the time deterministic (assuming that all the residuals of the estimates can be deemed as inefficiency) and non-parametric (not assuming a functional form between the variables and thus not estimating its parameters) (Kumbhakar et al., 2015).

The estimates of stochastic frontiers use the techniques under the umbrella of SFA, which applies econometrics to estimate production and cost frontiers, mainly. The former allows for the estimation of technical efficiency, while the latter permits the estimation of total (technical and allocative) efficiency. For the first set of estimates, it is necessary to access information on outputs and inputs, as well as contextual ("environmental") or non-controlled inputs or qualitative aspects of the productive process under the control of the DMUs. For the second set of estimates, the demand for information includes data on costs, outputs, and relative prices of inputs. According to the type of database the researcher faces, it is possible to estimate cross-sectional or panel models.

The calculation of efficiency departs from the error term of the frontier regression. In the real world, DMUs would have production or costs on top or below other units, and the residues capture divergencies. Efficient units are situated in the best practice frontiers; nevertheless, not all divergencies can be attributed to inefficiency, and some part of the differences in performance are random. Thus, the parametric techniques allow for separating randomness from pure inefficiency. The method permits a series of statistical tests on the goodness of the estimates; however, it does not provide clues for the mathematical form of the relationship between the variables, nor the proper form of separating the two components nor the error term, requiring several decisions from the investigators.

DEA is the most used non-parametric method (and probably the most used frontier method at all). It is a very flexible method; it builds the frontier with only a subset of the sample (the observations lying on the frontier), which allows working with small databases; however, it is sensitive to outliers, which is either a problem or an asset, allowing their detection in large datasets. Another disadvantage is that it does not allow statistical tests of the results (Coelli et al., 1998).

Faria et al. (2021) state that the SFA model arose from the theoretical perspective of a frontier of efficient production, given by a production function. In a production function, outputs are explained by inputs plus environmental variables. These are controls, from the statistical point of view, or "non-discretionary inputs, from the production theory view. They provide context to compare comparable units. The real functional form is unknown; the more common choice is the Cobb-Douglas, which is simple and easy to interpret, and the Trans logarithmic (or "Trans log"), which addresses squared and interaction terms of the variables. The Trans logarithmic function has the advantage of being more flexible than Cobb-Douglas. It does not impose a priori constraints on input substitution feasibility and allows scale economies to vary jointly with the output level. On the other hand, because it includes more coefficients to be estimated, it demands more data (consumes more degrees of freedom) than the Cobb-Douglas, and sometimes the signs of the coefficients are not easy to interpret. We opted for the Cobb-Douglas because of the reduced size of our samples, and we estimated it in the logarithms of the variables. Thus, the estimated coefficients can be interpreted as elasticities.

The composed error term ε_i is the sum of v_i, representing measurement and statistical errors and a one-sided disturbance u_i, that represents inefficiency. Additionally, u_i and v_i are assumed to be independent of each other as well as independent and identically distributed (iid), following the density of ε_i yields:

$$f_{\varepsilon_i}(\varepsilon) = \frac{2}{\sigma} \o \left(\frac{\varepsilon}{\sigma}\right) \left[1 - \Phi\left(\frac{\varepsilon\lambda}{\sigma}\right)\right] , -\infty \leq \varepsilon \leq +\infty \quad (3)$$

Where $\o(.)$ is the standard normal probability density function (pdf), $\Phi(\cdot)$, is the standard normal cumulative density function (CDF), $\sigma^2 = (\sigma_v^2 + \sigma_u^2)$, and $\lambda = \sigma_u / \sigma_v$. Therefore, the observed composite error ε_i for a log-log production function, where y_i and $f(x_i)$ are the observed and estimated outputs for the "I" DMI, is given by:

$$\varepsilon_i = \ln y_i - \ln f(x_i)\,; i = 1, \dots , n \quad (4)$$

As Faria et al. (2021) state, in their original proposal, Aigner et al. (1977) assumed a half-normal distribution for u_i. Other distributions typically used are the exponential (Meeusen and van Den Broeck, 1977), the truncated normal (Stevenson, 1980), or the gamma distributions (Greene, 1980a, 1980b). The SFA model is estimated through maximum likelihood (ML) methods and in two steps: firstly, the estimation of the parameters of the model and secondly, the point estimates of inefficiency through the mean of the conditional distribution, which is $E(u|\hat{\varepsilon})$. Thus, in log-log functional form, productive efficiency (PE) (Battese and Coelli, 1988) is given by

$$PE = E(u|\hat{\varepsilon}) = \exp(-\hat{u}) \quad (5)$$

The conditional expectation is defined by:

$$E(u_i|\varepsilon_i) = \frac{\sigma_v\sigma_u}{\sigma}\left[-\frac{\varepsilon_i\lambda}{\sigma} + \frac{\emptyset(\frac{\varepsilon_i\lambda}{\sigma})}{1-\Phi(\frac{\varepsilon_i\lambda}{\sigma})}\right] \quad (6)$$

This paper uses the standard model for estimating efficiency using a Stochastic Frontier Analysis (SFA) for a production frontier in cross-sectional databases, as described by Kumbhakar et al. (2015). Its general formula is:

$y_i = f(x_i; \beta; z_i) \exp{(v_i - u_i)}$
(7)

Where Y_i is the observed output for each DMU i; x_i is the input vector; selective "environmental" and quality variables would be included in the preceding basic models as control variables, z_i is the environmental variable vector; β is the unknown parameter vector to estimate; v_i is a random error (independently and identically distributed, with zero mean and positive variance), u_i is an inefficiency parameter (whose distribution is assumed to be exponential in this case). Besides, u_i and v_i are independently distributed from each other and the model's covariates. In logarithms,

$$lny_i = lny_{i*} - u_i \quad (8)$$

Where:

$$lny_{i*} = f(x_i; \beta, zi) + v_i$$

The term u_i is the log difference between the maximum lny_{i*} and the actual output lny_i or the percentage by which output can be increased using the same inputs if production is fully efficient. It gives the percentage of output that is lost due to technical inefficiency. The estimated value of u_i is known as the output-oriented (technical) inefficiency, where a value close to 0 implies nearness to total efficiency.

$$-u_i = ln\frac{y_i}{y_{i*}} \quad (9)$$

Given that, $u_i \geq 0$, the ratio (3) is bounded between 0 and 1 (meaning 1 that the DMU is fully efficient), with a value equal to 1 implying that the firm is fully efficient technically.

3.3 Models

Our model to be estimated is a Cobb-Douglas in logarithms,

$$ln\, yi = \propto + \beta\, lnXi + \delta\, Zi + \varepsilon i \quad (10)$$

Where i are the wineries, y_i is their output, X_i is the input vector (land, capital, labor, grape), Z_i is the vector of environmental variables, and ε_i is the composite error term.

According to Faria et al. (2021), cross-sectional SFA models do not allow for consistent estimates of technical efficiency, bringing only an estimate of the conditional mean of the efficiency level. Additionally, the cross-sectional model assumes the error components are not correlated with the regressors, which is problematic, considering that inefficiency derives from unobservable managerial capacities and is not independent of the input levels chosen by DMUs. Panel data would determine how efficiency varies between firms and over time. However, given that our database is a cross-section, we estimate the conditional mean of the efficiency level.

4. Results: Presentation and Discussion

In Table 5, we present the production function estimates of the two models using OLS for Cobb-Douglas in logs specifications. The signs of the coefficients are the expected for the input and raw material variables when the estimated coefficients are significantly different from zero. In the Below Average Pursued Quality subsample, only the log of the surface is significant in explaining the volumes of wine produced. Instead, in the Above Average Pursued Quality subsample, surface, entry yield, and labor are significant in explaining production. Also, in the latter model, the proportion of own harvest is significantly different from zero and negative (if the firm purchases part of its grape, it is more productive), and the same significance and sign holds for the proportion of temporary employees (the more significant the proportion of temporary, the lower the production). The OLS model for the Above Average Pursued Quality subsample explains 67.5 percent of the variance of the log or production, whereas for the Below Average Pursued Quality subsample, the R-square is 78.6 percent.

Thus, we can answer our first investigative question: We find different technologies to produce Above-and Below-Average Pursued Quality. The sum of the significant coefficients of factors capital, labor, and land for both samples is 1 for sample A and slightly greater than 1 for sample B, indicating that there are no economies of scale in the first case. In contrast, there are modest economies of scale in the second case.

Table 5: OLS Production Function Estimates

Dependent: ln_ProdinL	**Above Average Quality Sample**		**Below Average Quality Sample**	
ln_Surface	0.662***	(0.188)	1.166***	(0.150)
ln_Entryyield	0.298*	(0.160)	0.515	(0.329)
ln_new_capital	0.463	(0.290)	-0.502	(0.466)
ln_labor	0.372*	(0.196)	0.118	(0.137)
prop_ownharvest	-1.510***	(0.375)	-0.910	(0.600)
prop_temp	-1.381***	(0.452)	-0.424	(0.491)
Constant	-3.223***	(0.651)	-5.538***	(0.927)
F stat	128.4400		82.8400	
Prob. > F	0.0000		0.0000	
Observations	142		59	
R-squared	0.675		0.786	

Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' elaboration.

Table 6 presents our efficiency SFA models, estimated by ML, and we assume an exponential distribution for the error term. Land and entry-yield results significantly differ from zero, and the coefficients are positive, as expected. The absolute value of the elasticities indicates the need for more land and grapes in the case of the Below Average Pursued Quality Wines subsample, as expected. The log of capital is not significant in explaining the log of wine production in either of the models. The log of labor is positive and significantly different from zero in the Above Average Pursued Quality subsample and not significant in the Below Average Pursued Quality subsample.

Among the environmental variables, the signs are negative. Both variables are significant in both models. While the estimated coefficients are similar in the proportion of own harvest, the negative effect of the proportion of temporary employees on output is more pronounced in the case of the Above Average Pursued Quality subsample.

Table 6: SFA Technical Efficiency Estimates (exponential model)

Dependent: ln_ProdinL	**Above Average Pursued Quality (pursued_quality>=2)**		**Below Average Pursued Quality (pursued_quality<2)**	
ln_Surface	0.703***	(0.209)	0.934***	(0.0687)
ln_Entryyield	0.322*	(0.167)	0.997***	(0.206)
ln_new_capital	0.475	(0.291)	-0.310	(0.372)
ln_labor	0.357*	(0.212)	0.110	(0.0833)
prop_ownharvest	-1.723***	(0.352)	-1.768***	(0.279)
prop_temp	-0.855**	(0.405)	-0.663*	(0.360)
Constant	-2.645***	(0.672)	-2.807***	(0.443)
Sigma_u	0.80577***	(0.1830)	-0.026	(0.446)
sigma_v	0.80532***	(0.15967)	-3.524***	(1.088)
Lambda	1.00056***	(0.27499)	5.749	(0.285)
Gamma	0.50028		0.5	
Log-likelihood	-216.5646		-67.1661	
Wald Chi2	925.47		2381.26	
Prob > chi2	0.0000		0.0000	
Observations	142		59	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' elaboration.

Lambda (λ) indicates the value of the ratio $\frac{\sigma_u}{\sigma_v}$ and the parameter gamma (γ) indicates the share of total variance accounted for by inefficiency (variance of inefficiency over the sum of the variances of inefficiency and randomness) or the ratio $\frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2}$. Their values imply that our models explain 50 percent of inefficiency within the error term of each regression.

Concerning our second and third investigative questions, in Table 7, we present descriptive statistics of efficiency for each subsample (Above- and Below- Average Pursued Quality) and their further subsamples (Above the Average Export Intensity of the subsample, Below the Average Export Intensity of the subsample, and Non-Exporters), and in Table 8, we show correlations between the efficiency scores of the models and partial productivity. The efficiency mean of the wineries producing Above-Average Pursued Quality wines is 0.56, with a standard deviation of 0.16. For the Below-Average Pursued Quality subsample, the numbers are respectively 0.53 and 0.28. These numbers should not be compared since they depend on the relative position of each winery within its subsample and frontier.

We find differences when splitting each subsample into groups based on export intensity: exporters with higher export intensity than the mean of the sample, exporters with lower export intensity than the mean of the sample, and non-exporters.

Within the Above-Average Pursued Quality subsample, wineries with higher export intensity exhibit greater average efficiency and a higher pursued quality index on average (0.59, 3.21). Wineries that export but with lower intensity than the mean of the subsample, show lower efficiency levels and quality index (0.53, 2.70). Non-exporters have the lowest efficiency levels (0.52), with an intermediate pursued quality index of 3.05, compared with other wineries in the subsample.

Concerning the Below-Average Pursued Quality sample, the efficiency and pursued quality index is higher for the low-intensity exporting wineries than for those with higher export intensity (0.60 and 0.70 against 0.48 and 0.67). Non-exporters have lower efficiency but higher pursued quality among the three subsamples in this sample (0.49 and 0.82).

We present in Appendix A two Tables with the wineries ranked by efficiency, identified by internal codes to preserve the anonymity of respondents.

Table 7: Descriptive statistics of efficiency models and subsamples.

Technical efficiency	**Mean**	**Std. Dev.**	**Min**	**Max**
Technical Efficiency (Above-Average Pursued Quality sample, N = 142)	0.5634	0.1654	0.0015	0.8840
Technical Efficiency (Below-Average Pursued Quality sample, N = 59)	0.5284	0.2784	0.0005	0.9199
Sample and subsamples	**Statistic**	**Technical Efficiency**	**Prop exports**	**Pursued quality**
pursued_quality >= 2	Average	0.56337	0.37	3.06
N = 142	Std. Dev.	0.16537	0.36	0.99
Exports above average	Average	0.59724	0.66	3.21
n = 72	Std. Dev.	0.14371	0.27	0.98
Exports below average	Average	0.53156	0.15	2.70
n = 27	Std. Dev.	0.20041	0.09	0.95
Non-exporters	Average	0.52662	0.00	3.05
n = 43	Std. Dev.	0.16742	0.00	1.00
Samples and subsamples	**Statistic**	**Technical Efficiency**	**Prop exports**	**Pursued quality**
pursued_quality<2	Average	0.5284	0.39	0.68
N = 59	Std. Dev.	0.3062	0.43	0.47
Exports above average	Average	0.4763	0.67	0.67
n = 30	Std. Dev.	0.2734	0.19	0.48
Exports below average	Average	0.6022	0.13	0.70
n = 18	Std. Dev.	0.2454	0.12	0.47
Non-exporters	Average	0.4986	0.00	0.82
n = 11	Std. Dev.	0.3184	0.00	0.40

Source: Authors' elaboration.

Table 8 shows the correlation between efficiency scores, partial productivity ratios, and two selected variables: the proportion of exports and pursued quality. The correlation between efficiency and these variables is very low. The correlation between efficiency and input productivity is positive but low, except for labor. The highest correlation is between the productivity of capital and labor in the high-pursued-quality subsample and between the productivity of capital and land in the below pursued quality subsample.

Table 8 Correlations between efficiency, partial productivity, and selected variables

N = 142	Technical Efficiency	Prop exports	Pursued quality	outputHa	outputK	outputL
Technical Efficiency	1.0000					
prop_exports	0.0574	1.0000				
pursued_quality	0.0068	0.1713	1.0000			
outputHa	0.1799	0.0356	0.0782	1.0000		
outputK	0.1767	0.0651	-0.0411	0.0540	1.0000	
outputL	0.4424	0.0004	-0.0179	0.2608	0.4795	1.0000
N = 59	**Technical Efficiency**	**Prop exports**	**Pursued quality**	**outputHa**	**outputK**	**outputL**
Technical Efficiency	1.0000					
prop_exports	-0.0878	1.0000				
pursued_quality	0.0379	-0.0796	1.0000			
outputHa	0.4735	-0.0306	0.0133	1.0000		
outputK	0.0714	0.1331	0.1086	0.5014	1.0000	
outputL	0.2223	-0.2588	-0.0129	0.3176	0.1622	1.0000

Source: Authors' elaboration.

5. Conclusions

Argentina's evolution from a prominent domestic wine producer to a notable international player illustrates the transformative impact of strategic quality improvements. The increase in the relative price of Argentine wines over the past decades not only reflects a rise in perceived quality but also indicates a successful shift towards premium positioning in the global market.

Our analysis reveals important differences in production practices and efficiencies between wineries focused on high-quality versus lower-quality wines. The differentiation in production functions highlights that wineries producing high-quality wines employ specialized techniques and resource combinations that do not benefit from economies of scale. This contrasts with lower-quality producers, who experience modest economies of scale. These findings suggest that high-quality production involves more complex and refined processes that are less scale-sensitive but potentially more resilient in establishing a competitive edge through differentiation.

The study also emphasizes the role of export intensity in shaping production efficiency. Wineries with higher export volumes exhibit better efficiency and higher pursued quality indices compared to those with lower export intensity. This implies that engaging in international markets not only enhances efficiency but also drives improvements in quality. Non-exporting wineries, in contrast, demonstrate lower efficiency and intermediate quality levels, suggesting that the lack of export activity may limit their opportunities for achieving higher quality and operational efficiency.

Additionally, the study examines the relationship between export intensity and production efficiency. Wineries with higher export intensity tend to exhibit higher efficiency and better pursued quality indices compared to those with lower export intensity. The observed correlation suggests that wineries engaged in higher levels of export activity may also demonstrate improved efficiency and quality, but it does not imply a direct causal relationship.

The findings from this study may have broader implications for other emerging economies in the agri-food sector. They underscore the importance of focusing on quality differentiation and innovation as strategies for enhancing global competitiveness. For emerging markets, investing in advanced production techniques, improving quality management practices, and fostering innovation can contribute to better positioning in international markets and more significant export opportunities.

Supporting export-oriented strategies and creating conducive environments for quality enhancement can also benefit emerging economies. By providing resources and support for quality improvements and market access, governments and industry stakeholders can help enhance the global competitiveness of their agri-food sectors.

While the cross-sectional nature of the data limits the ability to track changes over time, future research using panel data could offer more dynamic insights into how efficiency and quality evolve with time and market engagement. Such research could provide additional insights into the dynamics of production efficiency and quality differentiation, contributing to a deeper understanding of their relationships and impacts on competitiveness.

In summary, this study provides valuable insights into the relation between quality differentiation, production efficiency, and export intensity in the Argentine wine industry. These insights are relevant not only for Argentina but also for other emerging markets aiming to leverage quality improvements to strengthen their positions in global agri-food markets.

References

Aigner, D., Lovell, C., and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. Journal of Econometrics,.6(1), 21-37. https://doi.org/10.1016/0304-4076(77)90052-5

Amodio, F. and Martinez-Carrasco, M. A. (2018). Input allocation, workforce management, and productivity spillovers: Evidence from personnel data. The Review of Economic Studies, 85(4), 1937–1970.

Atkin, D., Khandelwal, A. K., and Osman, A. (2017). Exporting and firm performance: Evidence from a randomized experiment. The Quarterly Journal of Economics, 132(2), 551–615.

Barros, C. P., and Santos, J. C. Gomes (2007). Comparing the Productive Efficiency of Cooperatives and Private Enterprises: The Portuguese Wine Industry as a Case Study. Journal of Rural Cooperation, 35(2), 1-14.

Bas, M. and Strauss-Kahn, V. (2014). Does importing more inputs raise exports? Firm-level evidence from France. Review of World Economics, 150(2), 241–275.

Bastos, P., Silva, J., and Verhoogen, E. (2018). Export destinations and input prices. American Economic Review, 108(2), 353–92.

Battese, G., and Coelli, T. (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. Journal of Econometrics, 38(3), 387-399.

Battese, G., and Coelli, T. (1992). Frontier production functions, technical efficiency, and panel data: with application to paddy farmers in India. Journal of Productivity Analysis, 3(1-2), 153-169.

Battese, G., and Coelli, T. (1995). A model for technical inefficiency effects in a stochastic frontier production function for Panel Data. Empirical Economics, 20(2), 325-332.

Belotti, F., Daidone, S., Ilardi, G. and Atella, V. (2013). Stochastic Frontier Analysis Using Stata. Stata Journal, 13(4), 718-758.

Bernard, A. B., and Jensen, J. B. (1999). Exceptional exporter performance: cause, effect, or both? Journal of International Economics, 47(1), 1-25.

Brambilla, I., Depetris Chauvin, N., and Porto, G. (2017). Examining the export wage premium in developing countries. Review of International Economics, 25(3), 447-475.

Cavusgil, S. T., and Knight, G. (2015). The born global firm: An entrepreneurial and capabilities perspective on early and rapid internationalization. Journal of International Business Studies, 46 (1), 3-16.

Charters, S. and Pettigrew, S. (2007). The dimensions of wine quality. Food quality and preference, 18(7), 997–1007.

Chen, Y., Jiang, Y., Wang, C., and Hsu, W. C. (2014). How do resources and diversification strategy explain the performance consequences of internationalization? Management Decision, 52 (5), 897-915.

Clerides, S., S. Lach, and J. Tybout (1998). "Is Learning-by-Exporting Important? Micro-dynamic Evidence from Colombia, Mexico, and Morocco." Quarterly Journal of Economics, 63 (3), 903–47.

Combris, P., Lecocq, S., and Visser, M. (2000). Estimation of a hedonic price equation for Burgundy wine. Applied Economics, 32(8), 961–967.

Conradie, B., Piesse, J., Thirtle, C. and Vink, N. (2018). South African wine grape production, 2005–2015: regional comparisons of scale and technical efficiencies and total factor productivity, Agrekon, DOI: 10.1080/03031853.2018.1537190

Crozet, M., Head, K., & Mayer, T. (2012). Quality sorting and trade: Firm-level evidence for French wine. The Review of Economic Studies, 79(2), 609-644.

Depetris-Chauvin, N. and Villanueva, E. C. (2024). Anatomy of Exporting Wineries of Argentina. International Journal of Wine Business Research, Vol. 36 No. 3, pp. 329-350. https://doi.org/10.1108/IJWBR-08-2023-0049.

Depetris-Chauvin, N., Fernández Olmos, M., Hallak, J. C, and Mosquera, J. S. (2023). Quality, Vertical Integration, and Adaptability. RedNIE Working Paper N°221.

Depetris-Chauvin, N., and Fernández-Olmos, M. (2024). Disentangling the relationships between denomination of origin regulatory councils activities and Spanish wineries' export performance. *Agribusiness*.

Faria, S., Gouveia, S., Guedes, A., and Rebelo, J. (2021). Transient and Persistent Efficiency and Spatial Spillovers: Evidence from the Portuguese Wine Industry. Economics and Business Letters 11 (1), 16 – 23. https://doi.org/10.3390/economies9030116

Ferro, G. and Benito-Amaro, I. (2018). What factors explain the price of top-quality wines? International Journal of Wine Business Research 30(1), 117-134.

Golovko, E., & Valentini, G. (2011). Exploring the complementarity between innovation and export for SMEs' growth. Journal of international business Studies, 42, 362-380.

Greene, W. H. (1980a). Maximum likelihood estimation of econometric frontier functions. Journal of Econometrics, 13(1), 27-56. https://doi.org/10.1016/0304-4076(80)90041-X

Greene, W. H. (1980b). On the estimation of a flexible frontier production model. Journal of Econometrics, 13(1), 105-115. https://doi.org/10.1016/0304-4076(80)90045-7

Hallak, J. C. (2006). Product quality and the direction of trade. Journal of International Economics, 68(1), 238–265.

Hallak, J. C. and Sivadasan, J. (2013). Product and process productivity: Implications for quality choice and conditional exporter premia. Journal of International Economics, 91(1), 53–67.

Halpern, L., Koren, M., and Szeidl, A. (2015). Imported inputs and productivity. American Economic Review, 105(12), 3660–3703.

Helpman, E., Melitz, M., and Rubinstein, Y. (2008). Estimating trade flows: Trading partners and trading volumes. The Quarterly Journal of Economics, 123(2), 441-487.

Head, K., & Ries, J. (1999). Rationalization effects of tariff reductions. Journal of International economics, 47(2), 295-320.

Kallas, Z., and Lehnhardt, F. (2010). Technical efficiency and firm exit in the wine and meat sector: Policy implications. New Medit¸. 9(2), 25-31.

Knight, G., Moen, Ø., and Madsen, T. K. (2020). Antecedents to differentiation strategy in the exporting SME. International Business Review, 29 (6), 101740.

Kugler, M. and Verhoogen, E. (2012). Prices, plant size, and product quality. The Review of Economic Studies, 79(1), 307–339.

Kumbhakar, S. C., Wand, H.-J., and Horncastle, A. P. (2015). A Practitioner's Guide to Stochastic Frontier Analysis Using Stata. Oxford University Press.

Lileeva, A., & Trefler, D. (2010). Improved access to foreign markets raises plant-level productivity for some plants. The Quarterly Journal of Economics, 125(3), 1051-1099.

Marta-Costa, A., Martinho, V., and Santos, M. (2017). Productive efficiency of Portuguese vineyard regions. Regional Science Inquiry, IX (2), 97-107.

Meeusen, W., and van Den Broeck, J. (1977). Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. International Economic Review, 18(2), 435-444. https://doi.org/10.2307/2525757

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. Econometrica, 71(6), 1695-1725.

Moreira, V. H., Troncoso, J. L., and Bravo-Ureta, B. E. (2011). Technical efficiency for a sample of Chilean wine grape producers: A stochastic production frontier analysis. Ciencia e Investigación Agraria, 38(3), 321-329.

Nerlove, M. (1995). Hedonic price functions and the measurement of preferences: The case of Swedish wine consumers. European economic review, 39(9), 1697–1716.

Neves, E., Dias, A., Ferreira, M. and Henriques, C. (2022). Determinants of wine firms' performance: the Iberian case using panel data. International Journal of Accounting and Information Management, Vol. 30 No. 3, pp. 325-338. https://doi.org/10.1108/IJAIM-10-2021-0203

Oczkowski, E. (1994). A hedonic price function for Australian premium table wine. Australian Journal of Agricultural Economics, 38(1), 93–110.

Oczkowski, E., and Doucouliagos, H. (2015). Wine prices and quality ratings: a meta-regression analysis. American Journal of Agricultural Economics, 97(1), 103-121.

Piesse, J., Conradie, B., Thirtle, C., and Vink, N. (2018). Efficiency in wine grape production: comparing long-established and newly developed regions of South Africa. Agricultural Economics 49(2), 203-212.

Parman, B. J., and Featherstone, A. M. (2019). A comparison of parametric and nonparametric estimation methods for cost frontiers and economic measures, Journal of Applied Economics, 22:1, 60-85, DOI: 10.1080/15140326.2018.1526868

Rebelo, J., Gouveia, S., Lourenço-Gomes, L., and Marta-Costa, A. A. (2018). Wine Firm's Size and Economic Performance: Evidence from Traditional Portuguese Wine Regions. Grapes and Wines - Advances in Production, Processing, Analysis and Valorization. https://doi.org/10.5772/intechopen.71320.

Reynolds, A. G. (2010). Managing wine quality: viticulture and wine quality. Elsevier.

Santos, M., Antón Rodríguez, X., and Marta-Costa, A. (2021). Productive efficiency of wine grape producers in the North of Portugal. Wine Economics and Policy 10(2): 3-14. doi:10.36253/wep-8977.

Schnabel, H., and Storchmann, K. (2010). Prices as quality signals: Evidence from the wine market. Journal of Agricultural and Food Industrial Organization, 8(1).

Schott, P. K. (2004). Across-product versus within-product specialization in international trade. The Quarterly Journal of Economics, 119(2), 647–678.

Sellers, R., and Alampi-Sottini, V. (2016). The influence of size on winery performance: Evidence from Italy. Wine Economics and Policy, 5(1), 33-41.

Stevenson, R. E. (1980). Likelihood functions for generalized stochastic frontier estimation. Journal of econometrics, 13(1), 57-66.

Tóth, J., and Gál, P. (2014). Is the New Wine World more efficient? Factors influencing technical efficiency of wine production. Studies in Agricultural Economics, 116, 95-99 https://doi.org/10.7896/j.1411

Urso, A., Timpanaro, G., Caracciolo, F., and Cembalo, L. (2018). Efficiency analysis of Italian wine producers. Wine Economics and Policy, 7(1), 3–12. https://doi.org/10.1016/j.wep.2017.11.003

Van Leeuwen, C. and Darriet, P. (2016). The impact of climate change on viticulture and wine quality. Journal of Wine Economics, 11(1), 150–167.

Vidoli, F., Cardillo, C., Fusco, E., and Canello, J. (2016). Spatial nonstationarity in the stochastic frontier model: An application to the Italian wine industry. Regional Science and Urban Economics, 61, 153–164. https://doi.org/10.1016/j.regsciurbeco.2016.10.003

Villanueva, E., Depetris-Chauvin, N., and Pinilla, V. (2023). “The Wine Industry: Drivers and Patterns of Global Transformation”. Forthcoming in Kipping, M., T. Kurosawa, and D. Westney (eds), The Oxford Handbook of Industry Dynamics. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190933463.001.0001.

Wagner, J. (2007). "Exports and Productivity: A Survey of the Evidence from Firm-Level Data," The World Economy, vol. 30(1), pp. 60–82, January.

Appendix A. Wineries and their relative efficiency within each sample

Tables A1 and A2 present the rankings of each sample by efficiency levels. Both tables have the same logic: Columns 1 to 4 present the ranking order by decreasing the order of efficiency scores without any other consideration. In contrast, columns 5 to 8 reorder the rankings grouping by export proportion and decreasing efficiency scores. In both tables, columns 5 to 8 permit differentiation between wineries with exports above the sample's average, below the sample's average (shadowed in gray), and non-exporters.

Table A1: Sample A, Pursued Quality >= 2

Winery Code	teAe	Prop exports	Pursued quality	Winery Code	teAe	Prop exports	Pursued quality
90	0.8840	0.50	4	134	0.7208	1.00	2
160	0.8390	0.00	5	16	0.7067	1.00	5
171	0.7964	0.50	3	77	0.6922	1.00	3
54	0.7881	0.30	2	153	0.6891	1.00	3
97	0.7751	0.00	4	26	0.6751	1.00	3
126	0.7511	0.70	4	222	0.6635	1.00	3
190	0.7388	0.05	2	182	0.6624	1.00	4
78	0.7262	0.50	5	63	0.6549	1.00	2
135	0.7227	0.30	2	51	0.6500	1.00	5
151	0.7211	0.15	2	55	0.6433	1.00	2
134	0.7208	1.00	2	30	0.6368	1.00	3
50	0.7202	0.00	2	136	0.5842	1.00	5
46	0.7197	0.70	2	100	0.5841	1.00	4
164	0.7187	0.30	3	67	0.5778	1.00	3
132	0.7169	0.15	2	124	0.5527	1.00	5
33	0.7167	0.05	2	152	0.5505	1.00	5
166	0.7093	0.30	3	140	0.5315	1.00	3
99	0.7088	0.50	3	73	0.5105	1.00	2
16	0.7067	1.00	5	74	0.4947	1.00	4
220	0.7051	0.05	2	83	0.4089	1.00	4
61	0.7040	0.50	4	95	0.3507	1.00	4
111	0.7009	0.05	3	64	0.3416	1.00	4
117	0.6956	0.00	3	208	0.2951	1.00	2
216	0.6926	0.15	2	130	0.0015	1.00	2
77	0.6922	1.00	3	126	0.7511	0.70	4
104	0.6911	0.70	3	46	0.7197	0.70	2
19	0.6892	0.30	3	104	0.6911	0.70	3
153	0.6891	1.00	3	39	0.6885	0.70	5
39	0.6885	0.70	5	123	0.6401	0.70	2
187	0.6858	0.00	3	71	0.6167	0.70	2
80	0.6833	0.15	2	125	0.6165	0.70	4
184	0.6819	0.15	4	199	0.5586	0.70	3
230	0.6809	0.50	2	37	0.5046	0.70	3
93	0.6785	0.50	2	138	0.4606	0.70	4
156	0.6752	0.50	2	96	0.4358	0.70	4

26	0.6751	1.00	3	48	0.2772	0.70	4
35	0.6748	0.50	4	90	0.8840	0.50	4
122	0.6745	0.00	3	171	0.7964	0.50	3
17	0.6700	0.00	3	78	0.7262	0.50	5
47	0.6688	0.30	3	99	0.7088	0.50	3
222	0.6635	1.00	3	61	0.7040	0.50	4
18	0.6626	0.00	2	230	0.6809	0.50	2
182	0.6624	1.00	4	93	0.6785	0.50	2
227	0.6610	0.00	4	156	0.6752	0.50	2
165	0.6608	0.50	2	35	0.6748	0.50	4
215	0.6584	0.30	4	165	0.6608	0.50	2
139	0.6552	0.15	4	53	0.6551	0.50	4
53	0.6551	0.50	4	198	0.6412	0.50	3
63	0.6549	1.00	2	101	0.6219	0.50	4
72	0.6514	0.30	4	88	0.6181	0.50	2
51	0.6500	1.00	5	118	0.6167	0.50	2
213	0.6483	0.00	5	79	0.6122	0.50	2
210	0.6471	0.00	2	84	0.5950	0.50	3
202	0.6446	0.00	2	196	0.5707	0.50	3
55	0.6433	1.00	2	191	0.5470	0.50	2
198	0.6412	0.50	3	12	0.5287	0.50	3
123	0.6401	0.70	2	219	0.3842	0.50	3
14	0.6389	0.00	2	56	0.3836	0.50	4
30	0.6368	1.00	3	66	0.2160	0.50	3
1	0.6352	0.05	4	54	0.7881	0.30	2
24	0.6314	0.30	2	135	0.7227	0.30	2
174	0.6299	0.05	3	164	0.7187	0.30	3
157	0.6272	0.05	2	166	0.7093	0.30	3
214	0.6235	0.30	4	19	0.6892	0.30	3
149	0.6230	0.30	4	47	0.6688	0.30	3
101	0.6219	0.50	4	215	0.6584	0.30	4
65	0.6185	0.30	2	72	0.6514	0.30	4
88	0.6181	0.50	2	24	0.6314	0.30	2
118	0.6167	0.50	2	214	0.6235	0.30	4
71	0.6167	0.70	2	149	0.6230	0.30	4
125	0.6165	0.70	4	65	0.6185	0.30	2
4	0.6163	0.00	4	200	0.5791	0.30	4
79	0.6122	0.50	2	205	0.5193	0.30	2
108	0.6095	0.00	2	86	0.5027	0.30	2
143	0.6078	0.05	3	180	0.4870	0.30	3
181	0.5981	0.00	4	218	0.3963	0.30	5
84	0.5950	0.50	3	116	0.2955	0.30	2
183	0.5939	0.00	3	42	0.2272	0.30	2
6	0.5871	0.15	4	151	0.7211	0.15	2
136	0.5842	1.00	5	132	0.7169	0.15	2
100	0.5841	1.00	4	216	0.6926	0.15	2

31	0.5795	0.00	3	80	0.6833	0.15	2
200	0.5791	0.30	4	184	0.6819	0.15	4
67	0.5778	1.00	3	139	0.6552	0.15	4
89	0.5757	0.00	2	6	0.5871	0.15	4
8	0.5751	0.00	2	212	0.5739	0.15	4
212	0.5739	0.15	4	23	0.5310	0.15	2
177	0.5725	0.00	3	36	0.2448	0.15	4
217	0.5714	0.00	2	107	0.1896	0.15	2
196	0.5707	0.50	3	44	0.0022	0.15	2
207	0.5629	0.00	4	190	0.7388	0.05	2
199	0.5586	0.70	3	33	0.7167	0.05	2
9	0.5566	0.00	2	220	0.7051	0.05	2
124	0.5527	1.00	5	111	0.7009	0.05	3
25	0.5518	0.00	3	1	0.6352	0.05	4
152	0.5505	1.00	5	174	0.6299	0.05	3
191	0.5470	0.50	2	157	0.6272	0.05	2
140	0.5315	1.00	3	143	0.6078	0.05	3
23	0.5310	0.15	2	94	0.2828	0.05	2
12	0.5287	0.50	3	160	0.8390	0.00	5
20	0.5209	0.00	4	97	0.7751	0.00	4
205	0.5193	0.30	2	50	0.7202	0.00	2
73	0.5105	1.00	2	117	0.6956	0.00	3
37	0.5046	0.70	3	187	0.6858	0.00	3
185	0.5039	0.00	3	122	0.6745	0.00	3
34	0.5038	0.00	5	17	0.6700	0.00	3
86	0.5027	0.30	2	18	0.6626	0.00	2
189	0.4969	0.00	4	227	0.6610	0.00	4
74	0.4947	1.00	4	213	0.6483	0.00	5
188	0.4939	0.00	2	210	0.6471	0.00	2
21	0.4892	0.00	2	202	0.6446	0.00	2
180	0.4870	0.30	3	14	0.6389	0.00	2
22	0.4673	0.00	2	4	0.6163	0.00	4
192	0.4622	0.00	2	108	0.6095	0.00	2
138	0.4606	0.70	4	181	0.5981	0.00	4
127	0.4367	0.00	3	183	0.5939	0.00	3
96	0.4358	0.70	4	31	0.5795	0.00	3
7	0.4243	0.00	2	89	0.5757	0.00	2
83	0.4089	1.00	4	8	0.5751	0.00	2
218	0.3963	0.30	5	177	0.5725	0.00	3
219	0.3842	0.50	3	217	0.5714	0.00	2
56	0.3836	0.50	4	207	0.5629	0.00	4
195	0.3809	0.00	3	9	0.5566	0.00	2
95	0.3507	1.00	4	25	0.5518	0.00	3
64	0.3416	1.00	4	20	0.5209	0.00	4
3	0.3171	0.00	3	185	0.5039	0.00	3
15	0.2967	0.00	4	34	0.5038	0.00	5

116	0.2955	0.30	2	189	0.4969	0.00	4
208	0.2951	1.00	2	188	0.4939	0.00	2
2	0.2860	0.00	3	21	0.4892	0.00	2
94	0.2828	0.05	2	22	0.4673	0.00	2
48	0.2772	0.70	4	192	0.4622	0.00	2
36	0.2448	0.15	4	127	0.4367	0.00	3
42	0.2272	0.30	2	7	0.4243	0.00	2
66	0.2160	0.50	3	195	0.3809	0.00	3
13	0.2009	0.00	4	3	0.3171	0.00	3
228	0.1935	0.00	5	15	0.2967	0.00	4
107	0.1896	0.15	2	2	0.2860	0.00	3
110	0.1517	0.00	2	13	0.2009	0.00	4
70	0.0926	0.00	4	228	0.1935	0.00	5
44	0.0022	0.15	2	110	0.1517	0.00	2
130	0.0015	1.00	2	70	0.0926	0.00	4

Source: Authors' elaboration

Table A2: Sample B, Pursued Quality < 2

Winery Code	teAe	Prop exports	Pursued quality	Winery Code	teAe	Prop exports	Pursued quality
68	0.9199	0.15	0	45	0.8200	1.00	1
147	0.9190	0.30	1	109	0.8157	1.00	0
144	0.9107	0.00	1	105	0.6862	1.00	0
32	0.9083	0.50	1	38	0.6111	1.00	1
173	0.8575	0.05	1	98	0.5461	1.00	1
203	0.8531	0.00	1	75	0.1197	1.00	0
87	0.8366	0.50	0	103	0.8278	0.70	1
103	0.8278	0.70	1	146	0.6982	0.70	1
145	0.8272	0.50	1	5	0.6418	0.70	1
45	0.8200	1.00	1	62	0.5418	0.70	1
109	0.8157	1.00	0	167	0.5069	0.70	1
169	0.8058	0.15	1	193	0.3121	0.70	0
179	0.8011	0.00	0	142	0.2591	0.70	1
223	0.7756	0.15	0	159	0.1976	0.70	0
197	0.7662	0.15	0	85	0.1842	0.70	1
204	0.7273	0.15	1	226	0.1314	0.70	0
40	0.7232	0.15	0	32	0.9083	0.50	1
129	0.7192	0.00	1	87	0.8366	0.50	0
60	0.7165	0.50	0	145	0.8272	0.50	1
146	0.6982	0.70	1	60	0.7165	0.50	0
105	0.6862	1.00	0	69	0.6585	0.50	1
28	0.6737	0.30	1	121	0.6287	0.50	1
194	0.6597	0.30	1	59	0.4183	0.50	1
69	0.6585	0.50	1	162	0.3868	0.50	1
81	0.6496	0.05	1	229	0.2959	0.50	1

5	0.6418	0.70	1	52	0.2499	0.50	1
170	0.6382	0.30	0	137	0.1744	0.50	1
121	0.6287	0.50	1	133	0.1344	0.50	0
76	0.6183	0.15	1	128	0.1165	0.50	0
211	0.6180	0.30	1	102	0.0382	0.50	1
38	0.6111	1.00	1	147	0.9190	0.30	1
168	0.5733	0.00	1	28	0.6737	0.30	1
209	0.5565	0.00	0	194	0.6597	0.30	1
98	0.5461	1.00	1	170	0.6382	0.30	0
62	0.5418	0.70	1	211	0.6180	0.30	1
167	0.5069	0.70	1	131	0.1216	0.30	1
176	0.5068	0.00	1	68	0.9199	0.15	0
58	0.5034	0.05	0	169	0.8058	0.15	1
49	0.4253	0.15	1	223	0.7756	0.15	0
59	0.4183	0.50	1	197	0.7662	0.15	0
162	0.3868	0.50	1	204	0.7273	0.15	1
186	0.3274	0.00	1	40	0.7232	0.15	0
193	0.3121	0.70	0	76	0.6183	0.15	1
229	0.2959	0.50	1	49	0.4253	0.15	1
142	0.2591	0.70	1	29	0.0005	0.15	0
52	0.2499	0.50	1	173	0.8575	0.05	1
159	0.1976	0.70	0	81	0.6496	0.05	1
85	0.1842	0.70	1	58	0.5034	0.05	0
137	0.1744	0.50	1	144	0.9107	0.00	1
201	0.1625	0.00	1	203	0.8531	0.00	1
133	0.1344	0.50	0	179	0.8011	0.00	0
226	0.1314	0.70	0	129	0.7192	0.00	1
131	0.1216	0.30	1	168	0.5733	0.00	1
75	0.1197	1.00	0	209	0.5565	0.00	0
128	0.1165	0.50	0	176	0.5068	0.00	1
206	0.0550	0.00	1	186	0.3274	0.00	1
102	0.0382	0.50	1	201	0.1625	0.00	1
41	0.0187	0.00	1	206	0.0550	0.00	1
29	0.0005	0.15	0	41	0.0187	0.00	1

Source: Authors' elaboration