International Comparison of Winery Efficiency: A Stochastic Frontier Analysis of Value and Premium Wines

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Abstract

The global wine market is increasingly segmented by quality, yet little is known about how production technologies and efficiency differ across these segments internationally. We address this gap by estimating separate stochastic production frontiers for wineries specializing in 'value' and 'premium' wines. Using a unique cross-sectional database of 1,254 wineries across eight Old and New World countries, we employ Stochastic Frontier Analysis to compare their production technologies and technical efficiency. Our results reveal three key findings. First, the production technologies for value and premium wines are structurally different; value wine production exhibits stronger diminishing returns to land, while premium wine production shows greater complementarity between capital and labor. Second, a significant efficiency gap exists within our sample, with Old World producers being, on average, more efficient than their New World counterparts in both quality segments. Third, factors such as product diversification (number of labels) are positively associated with output, suggesting the presence of economies of scope. These findings challenge a monolithic view of the wine industry and provide nuanced insights for firm strategy and regional competitiveness.

Keywords: Technical Efficiency; Stochastic Frontier Analysis; Wine Quality; Old World; New World.

JEL codes: D24; L66; Q13; C21.

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1. Introduction

The global wine industry has undergone a profound transformation over the last half-century. Once a sector dominated by the heritage and terroir of the Old World (Europe), it has expanded into a dynamic global market across all mild-weather continents (Villanueva et al., 2021; Anderson & Pinilla, 2023). Fundamental shifts on both the supply and demand sides have driven this evolution. Once concentrated in traditional producing nations, consumers are spread worldwide, gradually uniformizing consumption patterns as new markets grow (Anderson, 2020). Concurrently, consumer preferences have shifted towards higher-quality wines, with a recent emphasis on sustainability and "experiences" (Anderson & Nelgen, 2021). Initially, the global competition was framed as a simple rivalry between Old World producers, focused on terroir, and New World producers, who championed grape varieties (Banks & Overtone, 2010). Today, however, the landscape is far more complex, defined by increasing market segmentation and diverse business models (Villanueva & Ferro, 2022). These shifts raise a critical question for producers and policymakers: what drives productive efficiency in this new globalized and quality-segmented market?

While the literature on wine efficiency is extensive, it often overlooks a fundamental source of heterogeneity: wine quality. Comparing wineries without accounting for their target market segment is problematic, as the underlying production processes, from viticultural practices to oenological techniques, are fundamentally different. A 'value' wine producer, focused on volume, and a small batch 'premium' producer operate on distinct technological frontiers. Aggregating them into a single analysis can obscure crucial differences and lead to misleading conclusions about their relative performance.

This paper addresses this critical gap. Using a unique firm-level database of 1,254 wineries from eight major exporting nations, we separate producers specializing exclusively in 'value' wines (priced under $10/bottle) from those focused on 'premium' wines ($10-$40/bottle). This clean separation allows us, for the first time in a cross-country context, to: (1) estimate and compare the distinct production technologies for each quality segment, and (2) assess technical efficiency within each segment, comparing performance across countries and between the Old and New Worlds. We employ Stochastic Frontier Analysis (SFA), an econometric method that rigorously distinguishes technical inefficiency from random statistical noise.

Three central hypotheses guide our analysis. First, we hypothesize that the production technologies for value and premium wines are structurally different (H1). We expect to find different elasticities for key inputs like land, labor, and capital, reflecting the distinct business models inherent to each segment. Second, we posit that Old World producers exhibit higher technical efficiency on average, even within the same quality segment (H2), potentially due to accumulated know-how and terroir-specific expertise. Third, we explore how various operational characteristics influence the production frontier (H3), testing for the effects of product scope (number of labels), labor composition (temporary vs. permanent staff), and production methods.

Our findings confirm these hypotheses, revealing significant differences in production technologies and a persistent efficiency advantage for Old World producers across both market segments. This study's main contribution is twofold: it provides the first international, firm-level evidence on how production frontiers differ by wine quality and offers a more nuanced view of the Old World versus New World efficiency debate. By demonstrating that quality segmentation is a crucial lens for analysis, we provide valuable insights for firm strategy and regional competitiveness in the modern wine economy.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the methodology, data, and empirical models. Section 4 presents and discusses the results. Finally, Section 5 concludes with key implications and directions for future research.

2. Literature Review

The study of productive efficiency in the wine industry is well-established, with a rich body of work exploring performance across various dimensions. A central challenge in this literature is ensuring the comparability of the units under analysis, as wine is far from a homogeneous product. Consequently, researchers have adopted multiple levels of analysis to control for heterogeneity. These approaches can be broadly categorized into studies focusing on geographical and institutional factors and those examining firm-level characteristics and production technologies.

A significant stream of literature investigates how efficiency varies across geographical and institutional lines. At the broadest level, Tóth & Gál (2014) provide a foundational cross-country comparison, concluding that New World producers exhibit higher technical efficiency, which they attribute to superior technology and greater market openness. This macro-level finding, however, masks considerable variation at more granular levels. In Europe, for example, Vidoli et al. (2016) and Faria et al. (2021) show that spatial factors are significant drivers of performance. Using spatial econometric models, they find that local business climates in Italy and peer-to-peer spillovers in Portugal create regional efficiency clusters, affecting long-term productivity. Similarly, Marta Costa et al. (2017) and Piesse et al. (2017) identify notable efficiency differences between wine regions within Portugal and South Africa, often linked to the accumulated experience and superior infrastructure of long-established areas compared to newer ones. At an even more specific institutional level, studies in Spain by Aparicio et al. (2013) and Vidal et al. (2013) analyze efficiency across Designated Origins (DOs). Their findings suggest that technical inefficiency, rather than allocative inefficiency, is the primary barrier to performance, and they highlight certain DOs, like Cava, as national benchmarks for technical best practices.

A second, complementary body of work examines firm-level heterogeneity, focusing on how operational and organizational characteristics drive efficiency. The role of scale is a recurring and powerful theme. Numerous studies across different countries consistently find that larger wineries or vineyards tend to be more efficient. For instance, in Italy, Sellers-Rubio & Alampi-Sottini (2016) determine that the largest wineries perform better economically due to scale advantages in distribution and marketing, while Urso et al. (2018) establish that efficiency is influenced by farm size alongside production type and location. This finding is robust in Portugal, where Santos et al. (2021) find scale to be a key determinant of efficiency, and both Henriques et al. (2009) and Carvalho et al. (2008) report a positive influence of size on the technical efficiency of vineyards in the Alentejo region. The ownership structure also matters, as Barros and Santos (2007) found that cooperatives in Portugal outperformed private firms due to resource-sharing benefits among smaller producers.

Furthermore, production methods and technology have been shown to impact efficiency. The comparison between organic and conventional farming has yielded mixed results; Cisilino et al. (2021) found organic farms in Italy to be more technically efficient, suggesting that input savings can outweigh lower yields, while Arandia Miura et al. (2007) observed that organic wine farms in Spain achieve higher environmental efficiency. However, their conventional counterparts typically have higher yields. Technological adoption is another key factor. Goncharuk & Lazareva (2015) and Goncharuk & Figurek (2017) found that wineries in emerging regions like Ukraine and Bosnia lag international benchmarks due to outdated equipment and less advanced technological practices. An international benchmarking study by Goncharuk and Lazareva (2017) further confirmed these significant efficiency gaps between Ukrainian wineries and leading global producers. Finally, some studies focus on the efficiency of grape production at the vineyard level, linking

performance to specific training systems in Chile (Moreira et al., 2011), unique location and vineyard characteristics in Portugal's Douro region (Santos et al., 2018), and the achievement of notable scale efficiency in South Africa (Conradie et al., 2018).

Various methods and a strong geographical focus on specific European countries characterize this research's empirical landscape. The majority of studies, particularly those with smaller samples or focusing on specific regions, utilize Data Envelopment Analysis (DEA), a non-parametric method well-suited for benchmarking (Barros & Santos, 2007; Aparicio et al., 2013; Vidal et al., 2013; Arandia Miura et al., 2007; Cisilino et al., 2021; Conradie et al., 2018; Santos et al., 2018; Goncharuk & Lazareva, 2015, 2017; Kallas & Lehnhardt, 2011; Santos et al., 2021; Marta Costa et al., 2017; Goncharuk & Figurek, 2017; Piesse et al., 2017). Parametric Stochastic Frontier Analysis (SFA), which allows for statistical inference and is better suited for hypothesis testing in larger samples, has been employed in key cross-country and national studies (Tóth & Gál, 2014; Moreira et al., 2011; Carvalho et al., 2008; Henriques et al., 2009). A smaller set of recent papers has also applied spatial econometric models to account for neighborhood effects (Faria et al., 2021; Vidoli et al., 2016). Geographically, the literature is heavily concentrated on Old World producers, with a wealth of studies on Italy (Vidoli et al., 2016; Kallas & Lehnhardt, 2011; Urso et al., 2018; Sellers-Rubio & Alampi-Sottini, 2016; Cisilino et al., 2021), Portugal (Barros & Santos, 2007; Santos et al., 2021; Marta Costa et al., 2017; Faria et al., 2021; Carvalho et al., 2008; Henriques et al., 2009; Santos et al., 2018), and Spain (Arandia Miura et al., 2007; Aparicio et al., 2013; Vidal et al., 2013). Cross-country studies remain scarce, with notable exceptions being the work of Goncharuk and Lazareva (2017), Tóth and Gál (2014), and Goncharuk & Figurek (2017). Table 1 comprehensively summarizes the studies we analyzed in the field.

Table 1: Summary of the literature review

Author	Level of analysis	Method	Country and/or Region Focus	Period of Analysis
Aparicio et al. (2013).	DO	DEA	Spain	2008-2010
Arandia Miura et al. (2007).	Organic versus conventional	DEA	Spain	2000s
Barros & Santos (2007).	Cooperative and private enterprises	DEA	Portugal	2000s
Carvalho et al. (2008).	Wine farms	SFA	Portugal (Alentejo region)	2000-2005
Cisilino et al. (2021).	Organic versus conventional	DEA	Italy	2010s
Conradie et al. (2018).	Vineyards	DEA	South Africa	2005-2015
Faria et al. (2021).	Wine regions	Spatial econometrics	Portugal	2000s-2010s
Vidal et al. (2013).	DO	DEA	Spain	2008-2011
Goncharuk & Figurek (2017).	Wine farms	DEA	Ukraine, Bosnia	2000s
Goncharuk & Lazareva (2015).	Wine farms	DEA	Ukraine	2000s
Goncharuk & Lazareva (2017).	Wine farms	DEA	International benchmarking	2000s

Henriques et al. (2009).	Wine farms	SFA	Portugal (Alentejo region)	2000s
Kallas & Lehnhardt (2011).	Wine farms	DEA	Italy	2000s
Marta Costa et al. (2017).	Wine regions	DEA	Portugal	2000s-2010s
Moreira et al. (2011).	Vineyards	SFA	Chile	2000s
Piesse et al. (2017).	Wine regions	DEA	South Africa	2000s
Santos et al. (2018).	Vineyards	DEA	Portugal (Douro region)	2010s
Santos et al. (2021).	Wine farms	DEA	Portugal	2000s-2010s
Sellers-Rubio & Alampi-Sottini (2016).	Wine farms	DEA and SFA	Italy	2005-2013
Tóth & Gál (2014).	Countries	SFA	Old World (Europe) vs. New World (Americas, South Africa, Oceania)	1995-2007
Urso et al. (2018).	Wine farms	DEA and Tobit regression model	Italy	2005 and 2010
Vidoli et al. (2016).	Wine regions	Spatial Stochastic Frontier Analysis (SSFA)	Italy	2013

Source: Authors' elaboration

Despite this rich literature, a critical dimension remains underexplored: the explicit modeling of production technology and efficiency across quality segments in an international context. While some national studies, such as Urso et al. (2018), distinguish between "quality vs. common wine," no research to our knowledge has used a large, international, firm-level dataset to estimate separate production frontiers for wineries specializing in different, price-defined quality tiers. Previous cross-country studies like Tóth & Gál (2014) treat wine as a homogenous good, potentially conflating technological differences with quality-driven heterogeneity.

Our study directly addresses this gap. We can isolate and compare their distinct production technologies and efficiency levels by analyzing wineries specializing exclusively in "value" or "premium" wines. This allows us to contribute to the literature in two ways: first, by providing a more nuanced understanding of the Old World versus New World efficiency debate, and second, by establishing quality segmentation as a crucial and previously overlooked source of heterogeneity in global winery performance.

3. Method, Data, and Models

3.1 Method: Stochastic Frontier Analysis

Our research objectives, data characteristics, and sample size guide the choice of methodology. We employ Stochastic Frontier Analysis (SFA), an econometric approach to building efficiency frontiers. This choice is preferable to non-parametric methods like Data Envelopment Analysis (DEA) for two primary reasons. First, our large sample size is well-suited to the statistical properties of SFA. Second, and more importantly, SFA allows for formal hypothesis testing on the parameters of the production function, which is central to our goal of comparing the technologies of value and premium wine production. While DEA is a flexible tool for benchmarking, especially with small samples, it is deterministic and does not allow for such statistical inference (Kumbhakar et al., 2015).

The key advantage of SFA is its ability to distinguish technical inefficiency from random shocks. The analysis begins by estimating a production frontier, where the error term for each decision-making unit (DMU), in our case, a winery, is decomposed. The standard SFA production model is specified as:

$$y_i = f(x_i; \beta; z_i) \exp(v_i - u_i) \quad (1)$$

Where y_i is the observed output for each winery i; x_i is a vector of conventional inputs; z_i is a vector of operational characteristics that shift the frontier; and β is the vector of parameters to be estimated, which can be partitioned such that $\beta=[\beta_x, \delta_z]$, corresponding to the input vector x_i and the operational characteristics vector z_i, respectively. The composed error term $\epsilon_i = v_i - u_i$, consists of two independent components:

- v_i is a two-sided, symmetric random error, assumed to be independently and identically distributed as $N(0, \sigma_v^2)$. This term captures statistical noise from factors beyond the firm's control (e.g., favorable weather, luck) and measurement errors.
- u_i is a one-sided, non-negative error term ($u_i \geq 0$) representing technical inefficiency. It captures the shortfall in output from the maximum possible frontier output.

Following the original formulation by Aigner et al. (1977), we assume a half-normal distribution for the inefficiency term, $u_i \sim N^+(0, \sigma_u^2)$. Other distributional assumptions are possible, such as the exponential (Meeusen & van Den Broeck, 1977), the truncated normal (Stevenson, 1980), or the gamma distribution (Greene, 1980a, 1980b), but the half-normal is standard for cross-sectional models. The density of ε_i yields:

$$f_{\varepsilon_i}(\varepsilon_i) = \frac{2}{\sigma} \phi\left(\frac{\varepsilon_i}{\sigma}\right) \Phi\left(\frac{-\epsilon_i \lambda}{\sigma}\right) \quad (2)$$

Where, $\sigma^2 = \sigma_v^2 + \sigma_u^2, \lambda = {\sigma_u}/{\sigma_v}$, $\phi(.)$ is the standard normal probability density function (PDF), and $\Phi(\cdot)$, is the standard normal cumulative density function (CDF). The parameter λ indicates the relative contribution of inefficiency to the overall variance of the error term.

The SFA model is estimated using Maximum Likelihood. From the estimated parameters, we can derive the firm-specific technical efficiency (TE) score for each winery following Battese & Coelli (1988). The TE score is the ratio of observed output to the potential frontier output:

$$TE_i = \frac{y_i}{f(x_i; z_i; \beta) \exp(v_i)} = \exp(-u_i) \quad (3)$$

Since u_i is unobservable, we estimate it using the conditional expectation of u_i given the composed error term ϵ_i, as proposed by Jondrow et al. (1982):

$$E(u_i|\varepsilon_i) = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi(\frac{\varepsilon_i\lambda}{\sigma})}{\Phi(-\frac{\varepsilon_i\lambda}{\sigma})} - \frac{\varepsilon_i\lambda}{\sigma}\right] \quad (4)$$

The TE score is bounded between 0 and 1, where a value of 1 implies the firm is fully efficient. As a limitation, it is important to note that cross-sectional SFA models provide an estimate of the conditional mean of the efficiency level and assume the error components are uncorrelated with the regressors. This assumption can be problematic if unobserved managerial ability influences input choices and efficiency (Faria et al., 2021). Given our cross-sectional data, we acknowledge this as a necessary safeguard in our interpretation.

3.2 Data and Variable Definitions

Our analysis uses data from a large-scale international survey of wineries. The database was constructed from a survey of nearly 5,300 wineries across 23 countries, conducted between 2019 and 2021, with data pertaining to the 2018/2019 period to avoid distortions from the COVID-19 pandemic. The survey instrument underwent extensive pilot testing and data verification to ensure reliability. The full dataset, survey methodology, and data collection process are described in detail in Depetris-Chauvin (2025). For the specific purposes of this study on production efficiency, we use a subsample covering eight representative wine-producing countries: three from the Old World (France, Spain, Italy) and five from the New World (South Africa, Chile, Argentina, Brazil, Uruguay). It is important to note that our final sample is heavily weighted towards the three Old World countries (France, Spain, Italy), which comprise over 80% of our observations. Furthermore, while representing major South American producers, our New World sample notably omits the United States and Australia. This composition should be considered when interpreting the subsequent Old World versus New World comparisons.

A key feature of our research design is the explicit separation of wineries by their market segment. The survey defines 'Value' wines as those priced under USD 10 per bottle and 'Premium' wines as priced between USD 10 and USD 40. To ensure the integrity of the production frontiers and avoid the confounding problem of unobserved input allocation in multi-product firms, we restricted our sample to wineries that reported producing 100% of their output in either the 'Value' or 'Premium' category. This rigorous selection process results in two distinct and comparable subsamples: 534 wineries specializing in 'Value' wines and 720 specializing in 'Premium' wines.

The variables used in our production frontier are defined in Table 2. The output variable is the total wine production in liters. The primary inputs (x_i) are:

- Surface: Total vineyard area in hectares.
- Grape Input: This variable estimates the winery's own grape production. It is calculated by multiplying a winery's total vineyard area (Surface) by its self-reported average yield. We acknowledge that this method, while accurately estimating estate-grown fruit, does not explicitly account for grapes that may be purchased from third-party growers. Our approach, therefore, assumes that a winery's production volume is a strong proxy for its overall scale of operation, including any purchased fruit. Any unobserved inputs from purchased grapes are expected to be captured by the stochastic component (v_i) of the frontier model's error term.
- Labor: Total number of employees.
- Capital Index: We construct a proxy, as physical capital data is notoriously difficult to collect. The index is derived using Principal Component Analysis from 18 dummy variables indicating a winery's ownership of specific capital goods and technologies (e.g., temperature-controlled fermentation tanks, sorting tables, cross-flow filters, automated bottling lines). See Appendix A for a full list of capital indicators.

In addition to these inputs, we include a vector of operational characteristics variables (z_i) to control for operational characteristics that may shift the production frontier. These include the number of grape varieties vinified, the number of distinct labels produced, the proportion of temporary to permanent employees, and variables controlling for production methods (e.g., proportion of conventional, organic, or biodynamic production). Country dummies are also included to capture unobserved national-level heterogeneity, with France as the base category.

Table 2: Variable definitions and units of measurement

Variable	Definition	Unit

Production	Wine production	Liters
Surface	Vine area	Hectares
Grape input	Grape production	Kilograms
Capital index	Index of capital goods	Derived from 18 dummies by Principal Component Analysis
Employees	Persons employed in the winery	People
Conventional or traditional production	Conventional + Traditional / Total production	Proportion
Grapes vinified	Number of different grapes	Number of grapes vinified
Percentage of domestic sales volume	Volume sold locally as a percentage of total volume	Volume sold locally / volume sold
Zero revenues from other activities	No other economic activity besides wine production	Value 1 if true, zero otherwise
The proportion of temporary to permanent employees	Temporary / Permanent employees	Ratio
Labels produced	Number of different labels	Number of labels
Certified organic production	Organic production / Total production	Proportion
Biodynamic production	Biodynamic / Total production	Proportion
France	The winery belongs in this country	Value 1 if true, zero otherwise
Spain	The winery belongs in this country	Value 1 if true, zero otherwise
Italy	The winery belongs in this country	Value 1 if true, 0 otherwise
South Africa	The winery belongs in this country	Value 1 if true, 0 otherwise
Chile	The winery belongs in this country	Value 1 if true, 0 otherwise
Argentina	The winery belongs in this country	Value 1 if true, 0 otherwise
Brazil	The winery belongs in this country	Value 1 if true, 0 otherwise
Uruguay	The winery belongs in this country	Value 1 if true, 0 otherwise
The average productivity of land	Wine production/hectare	Liters/hectare
The average productivity of labor	Wine production/laborer	liters/employee
The average productivity of capital	Wine production/capital index	liters/unit of capital index
The average productivity of grapes	Wine production/grape	liters/kilograms

Source: Authors' elaboration

Table 3 shows the descriptive statistics of the two subsamples. The average "value" wine producer operates at a much larger scale, producing almost five times the output of the average "premium" winemaker. This is reflected in the inputs: on average, value producers use significantly more surface area and total grape input. In contrast, the average availability of capital and labor is quite similar across the two groups, which

indicates that the input intensity per liter of wine is substantially higher for “premium” wines. This is also true in the simple partial productivity measures; for example, the average productivity of land (liters/hectare) is nearly double for “value” wines.

The operational characteristics variables also reveal structural differences. “Premium” wine producers are more likely to engage in certified organic (36% vs 16%) and biodynamic (7% vs 1%) production. Conversely, “value” wine producers rely more heavily on conventional or traditional methods (90% vs 64%). The proportion of wineries reporting zero revenues from other activities is similar across both groups (around 50%), suggesting a comparable level of specialization. The country composition also differs, with France, for example, representing 18% of the “Value” subsample but 33% of the “Premium” one. The average values for the country dummies should be interpreted as the proportion of each country in the respective subsample.

Table 3: Descriptive statistics of the subsamples

	“Value”				**“Premium”**			
	N = 534				**N = 720**			
Variable	**Mean**	**Std. dev.**	**Min**	**Max**	**Mean**	**Std. dev.**	**Min**	**Max**
Production	1327427	4835072	300	60000000	271112	2850326	30	75000000
Surface	170	589	0.30	5000	36	215	0.50	5436
Grape input	1938291	8449143	1050	109000000	262361	1622763	2400	40800000
Capital index	7.67	1.67	0.86	11.33	7.44	1.74	0.49	11.15
Employees	17	28	1	300	18	30	1	575
The average productivity of land	10098	53378	3.75	1200000	5244	10552	0.92	266667
The average productivity of labor	60578	141750	3	1702636	35289	489822	3	12500000
The average productivity of capital	188265	708595	38	8396516	40944	522173	4	13900000
The average productivity of grapes	0.99	2.22	0.00	40.00	0.79	1.21	0.00	26.67
Conventional or traditional production	0.90	0.30	0	1	0.64	0.48	0	1
Zero revenues from other activities	0.53	0.50	0	1	0.49	0.50	0	1

Certified organic production	0.16	0.36	0	1	0.36	0.48	0	1
Biodynamic production	0.01	0.11	0	1	0.07	0.25	0	1
Grapes vinified	5.40	4.15	1	48	4.71	3.14	1	28
Labels produced	7.25	7.00	0	45	6.60	5.25	0	40
Percentage of domestic sales volume	77.40	31.16	0	100	61.60	30.74	0	100
Proportion of temporary to permanent employees	3.23	5.09	0	70	3.76	5.34	0	101
France	0.18	0.38	0	1	0.33	0.47	0	1
Spain	0.34	0.48	0	1	0.15	0.35	0	1
Italy	0.32	0.47	0	1	0.41	0.49	0	1
South Africa	0.03	0.16	0	1	0.02	0.15	0	1
Chile	0.03	0.17	0	1	0.03	0.17	0	1
Argentina	0.08	0.27	0	1	0.05	0.21	0	1
Brazil	0.01	0.12	0	1	0.00	0.04	0	1
Uruguay	0.01	0.11	0	1	0.01	0.08	0	1

Source: Authors' elaboration

3.3 Model Specification

The precise functional form of a production function is unknown. We therefore estimate two widely used specifications: the restrictive Cobb-Douglas and the more flexible Trans logarithmic (Translog) form. The Translog function, which includes squared and interaction terms of the inputs, does not impose constant elasticities and allows for more complex substitution patterns and scale effects. Given our large sample size and the likelihood of non-linearities in wine production, the Translog is our preferred specification. We formally test this assumption using a likelihood ratio test.

The Cobb-Douglas model is specified as:

$$\ln(y_i) = \beta_0 + \sum_{j=1}^{4} \beta_j \ln(x_{ji}) + \sum_{k=1}^{K} \delta_k z_{ki} + v_i - u_i \qquad (5)$$

The more flexible Translog model is specified as:

$$\ln(y_i) = \beta_0 + \sum_{j=1}^{4} \beta_j \ln(x_{ji}) + \frac{1}{2}\sum_{j=1}^{4}\sum_{m=1}^{4} \beta_{jm} \ln(x_{ji}) \ln(x_{mi}) + \sum_{k=1}^{K} \delta_k z_{ki} + v_i - u_i \qquad (6)$$

The βj coefficients are directly interpreted as production elasticities in the Cobb-Douglas specification. For the Translog frontier, the elasticity of output with respect to input j is not constant and is calculated as:

$$E_j = \frac{\partial \ln (y_i)}{\partial \ln (x_{ji})} = \beta_j + \sum_{m=1}^{4} \beta_{jm} \ln (x_{mi}) \quad (7)$$

4. Results

This section presents the statistical results from the Stochastic Frontier Analysis. We first detail the choice of the functional form for the production frontier, then provide a detailed account of the estimated parameters for the production technology and the operational characteristics variables, and finally report the resulting technical efficiency scores.

4.1 Functional Form Selection and Model Diagnostics

Table 4 presents the estimation results for both the Cobb-Douglas and the more flexible Translog production frontiers for the 'Value' and 'Premium' wine subsamples. We performed a likelihood ratio (LR) test on the significance of the quadratic and interaction terms in the Translog models to determine the most appropriate functional form. The test strongly rejects the null hypothesis that these terms are jointly zero for both the value (LR$\chi^2(10)$ = 24.96, $p<0.01$) and premium (LR$\chi^2(10)$ = 23.37, $p<0.01$) models. This result, supported by the lower Akaike Information Criterion for the Translog specifications, confirms that the Translog provides a statistically superior fit to the data. Consequently, our analysis will focus on the results from the Translog frontiers, which better capture the complex, non-linear relationships in wine production.

All models' estimated λ parameters are large and statistically significant. The λ values for the preferred Translog specifications are 0.939 for value wines and 1.069 for premium wines. These values indicate that the variance of the one-sided inefficiency term (σ_u^2) constitutes a substantial and significant portion of the total error variance (σ^2), confirming that technical inefficiency is a prominent feature of the data and that the SFA model is appropriate.

4.2 Production Frontier Estimates

The estimated coefficients for the Translog production frontiers, shown in Table 4, reveal significant differences in production technology across the two market segments.

For 'Value' wines, technology appears to be driven by returns to scale in land and capital. The squared term for surface is negative and statistically significant at the 5% level ($\ln(\text{surface})^2 = -0.538$), as is the squared term for the capital index ($\ln(\text{capital\_index})^2 = -0.834$). This suggests that for mass-market wine production, there are clear diminishing marginal returns to both land and capital expansion. Furthermore, the interaction between surface and grape input is positive and significant at the 10% level ($\ln(\text{surface}) \times \ln(\text{grape\_input}) = 0.384$), indicating a complementarity where higher grape yields, a hallmark of a volume-focused production strategy, enhance the productivity of land.

For 'Premium' wines, the production technology is markedly different. Here, the squared term for employees is positive and significant ($\ln(\text{employees})^2 = 0.0738$), suggesting increasing returns to labor specialization. The most crucial difference is the interaction between capital and employees, which is positive and highly significant at the 5% level ($\ln(\text{capital}) \times \ln(\text{employees}) = 0.208$). This points to a strong synergy between advanced machinery and a skilled workforce. In contrast, the interaction between surface and employees is negative and significant ($\ln(\text{surface}) \times \ln(\text{employees}) = -0.136$), which may suggest that for premium production, expanding labor is more effective when focused on capital-intensive cellar work rather than being spread across larger land holdings.

Regarding the operational characteristics' variables, the number of 'Labels produced' has a positive and highly significant (p<0.01) coefficient in both the value and premium Translog models. The proportion of temporary to permanent employees has a negative and statistically significant coefficient in both models (p<0.05 for value, p<0.1 for premium). The number of 'Grapes vinified' is positive and significant for value wines but not for premium wines. 'Conventional or traditional production' is positive and significant for premium wines but not for value wines. Other variables, including certified organic/biodynamic production and the percentage of domestic sales, are not statistically significant in either model.

The country-fixed effects (with France as the baseline) show significant heterogeneity. Among Old World producers, Spain exhibits a positive and highly significant coefficient in both models, while Italy is positive and significant for premium wines. The results for New World countries are more varied. Argentina and Uruguay show positive and significant coefficients for "value" wines, while South Africa shows a negative and significant coefficient for the same products. Brazil shows a large, negative, and highly significant coefficient for premium wines (a result that should be interpreted with extreme caution, as it is derived from a very small number of premium Brazilian wineries in our sample).

Table 4: Estimates

Ln production	**Cobb-Douglas Value**	**Trans Log Value**	**Cobb-Douglas Premium**	**Trans Log Premium**
Ln capital index	0.0202	-1.097	-0.0555	-2.036
	(0.143)	(2.649)	(0.0716)	(1.530)
Ln employees	0.0721	0.0184	0.0205	-0.639
	(0.0455)	(0.825)	(0.0301)	(0.576)
Ln surface	0.267***	0.475	0.486***	1.594***
	(0.0942)	(0.680)	(0.0645)	(0.458)
Ln grape input	0.681***	-1.264	0.535***	-1.055
	(0.0856)	(1.204)	(0.0605)	(0.870)
Ln surface squared		-0.538**		-0.0631
		(0.250)		(0.203)
Ln grape input squared		-0.272		-0.223
		(0.187)		(0.152)
Ln employees squared		0.124**		0.0738*
		(0.0575)		(0.0399)
Ln capital index squared.		-0.834**		0.167
		(0.356)		(0.170)
Ln surface*grape input		0.384*		0.170
		(0.213)		(0.168)
Ln surface*capital index		-0.0910		-0.251
		(0.330)		(0.185)
Ln surface*employees		-0.0216		-0.136*
		(0.0878)		(0.0716)
Ln capital index*employees		0.0318		0.208**
		(0.158)		(0.0838)
Ln capital index*grape input		0.0812		0.205
		(0.297)		(0.174)
Ln employees*grape input		0.0182		0.0618

		(0.0825)		(0.0642)
Conventional or traditional production	0.128	0.141	0.220*	0.233*
	(0.184)	(0.183)	(0.123)	(0.122)
Grapes vinified	0.0202*	0.0190*	-0.00670	-0.00438
	(0.0115)	(0.0115)	(0.00861)	(0.00876)
Percentage of domestic sales volume	-0.00184	-0.00187	-0.000646	-0.00117
	(0.00129)	(0.00127)	(0.000812)	(0.000819)
Zero revenues from other activities	0.134*	0.112	-0.0223	-0.0196
	(0.0697)	(0.0696)	(0.0470)	(0.0465)
The proportion of temporary to permanent employees	-0.0124*	-0.0164**	-0.00485	-0.00869*
	(0.00749)	(0.00794)	(0.00442)	(0.00481)
Labels produced	0.0224***	0.0201***	0.0300***	0.0313***
	(0.00633)	(0.00635)	(0.00552)	(0.00559)
Certified organic production	0.0287	0.0499	0.0721	0.0970
	(0.152)	(0.152)	(0.117)	(0.116)
Biodynamic production	-0.158	-0.124	-0.0612	-0.0561
	(0.305)	(0.304)	(0.103)	(0.103)
Spain	0.280***	0.317***	0.236***	0.233***
	(0.106)	(0.108)	(0.0779)	(0.0787)
Italy	0.0751	0.157	0.189***	0.150**
	(0.107)	(0.110)	(0.0567)	(0.0591)
South Africa	-0.419	-0.612**	0.00332	-0.112
	(0.257)	(0.263)	(0.172)	(0.173)
Chile	-0.260	-0.283	0.0153	0.0408
	(0.233)	(0.235)	(0.159)	(0.161)
Argentina	0.383**	0.382**	-0.111	-0.107
	(0.163)	(0.161)	(0.124)	(0.126)
Brazil	0.335	0.350	-8.677***	-8.589***
	(0.425)	(0.422)	(0.569)	(0.562)
Uruguay	0.523	0.670**	-0.183	-0.166
	(0.320)	(0.326)	(0.316)	(0.310)
Constant	2.500***	29.05*	3.690***	21.17*
	(0.804)	(15.11)	(0.553)	(11.27)
Wald(chi2)	3090.17	3267.66	3492.68	3540.13
Prob>chi2	0.0000	0.0000	0.0000	0.0000
Lambda	0.9458***	0.9394***	1.0728***	1.0691***
	(-0.0691)	(-0.0655)	0.0443	0.0449
Observations	534	534	720	720
Log likelihood ratio	-641.9216	-629.4392	-725.0991	-713.4149
LR Chi2(10)	24.96***		23.37***	
Df	22	32	22	32
Akaike Information Criteria (AIC)	1327.843	1322.878	1494.198	1490.83
Bayesian Information Criteria (BIC)	1422.012	1459.85	1594.942	1637.366

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' elaboration

4.3 Interpretation Caveats and the Translog Specification

While the likelihood ratio test confirms the statistical superiority of the Translog specification, its flexibility introduces a well-known econometric challenge: high multicollinearity among its regressors. This highlights a common trade-off between statistical fit and theoretical consistency.

As shown in Table 5, the more restrictive Cobb-Douglas specification yields plausible elasticities, suggesting constant returns to scale for both value and premium wines. In contrast, the statistically superior Translog model produces several large, negative elasticities, an economically implausible result that violates the monotonicity assumption. This is a common artifact when multicollinearity is present and suggests that the individual coefficients of the Translog frontier should not be interpreted as reliable measures of marginal productivity.

Indeed, high multicollinearity can also lead to instability in the estimated coefficients for the interaction terms. However, the primary consequence is inflated standard errors, which makes it more difficult to achieve statistical significance. The fact that key interaction terms, such as the synergy between capital and labor in the premium model, are found to be highly significant despite this, suggests a strong, non-spurious underlying relationship. Therefore, while the precise magnitude of these coefficients should be interpreted cautiously, their signs and significance provide robust evidence for the structural differences in production technology that form the basis of H1.

Given this, our interpretative strategy is to focus on two robust findings from the model:

1. The signs and significance of the interaction terms as evidence of different production processes.
2. The technical efficiency scores derived from the more flexible frontier.

Our subsequent discussion will center on these findings, and Section 5.4 will further assess the credibility of the efficiency scores.

Table 5: Mean Production Elasticities by Functional Form

Input	Value Wines		Premium Wines	
	Cobb-Douglas	Translog	Cobb-Douglas	Translog
Surface	0.27	3.02	0.49	2.59
Grape Input	0.68	**-3.01**	0.54	**-2.64**
Labor	0.07	0.59	0.02	0.28
Capital	0.02	**-2.00**	**-0.06**	0.56
Sum (Returns to Scale)	**1.04**	**-1.40**	**0.99**	**0.79**

Note: Cobb-Douglas elasticities are the direct coefficients from Table 4. Translog elasticities are calculated using formula (7) at the mean of the input variables for each respective subsample. Problematic, economically implausible elasticities are shown in bold.
Source: Authors' elaboration

4.4 Technical Efficiency Scores

Table 6 presents the descriptive statistics of the technical efficiency scores derived from the four estimated models. Focusing on our preferred Translog specification, the mean technical efficiency for the entire sample is 0.654 for 'Value' wine producers and 0.678 for 'Premium' producers, suggesting that premium wine producers are, on average, slightly closer to their production frontier.

A more distinct pattern emerges when we segment the results by Old and New World regions. For 'Value' wines, the mean efficiency score for the 448 Old World wineries (0.663) is higher than that of the 86 New World wineries (0.605). A two-sample t-test assuming unequal variances confirms this gap of nearly six percentage points is statistically significant (t=2.44, p=0.017). This efficiency advantage for Old World producers is even more pronounced for 'Premium' wines. Here, the 642 Old World producers achieve an average efficiency of 0.687, compared to an average of 0.611 for the 78 New World producers. This results in a highly significant gap of over seven percentage points, as confirmed by the same test (t=2.66, p=0.009).

Table 6: Descriptive statistics of the efficiency measures

Variable	Observations	Mean	Std. dev.	Min	Max
Cobb-Douglas Value	534	0.647	0.156	0.001	0.912
Trans Log Value	534	0.654	0.153	0.000	0.912
Cobb-Douglas Premium	720	0.675	0.166	0.002	0.949
Trans Log Premium	720	0.678	0.165	0.002	0.951
Cobb-Douglas Value Old World	448	0.659	0.136	0.061	0.902
Trans Log Value Old World	448	0.663	0.138	0.057	0.902
Cobb-Douglas Premium Old World	642	0.683	0.151	0.048	0.949
Trans Log Premium Old World	642	0.687	0.150	0.054	0.951
Cobb-Douglas Value New World	86	0.589	0.226	0.001	0.912
Trans Log Value New World	86	0.605	0.212	0.000	0.912
Cobb-Douglas Premium New World	78	0.607	0.249	0.002	0.900
Trans Log Premium New World	78	0.611	0.247	0.002	0.899

Source: Authors' elaboration

5. Discussion

In this section, we interpret the empirical results presented in Section 4, connecting them to our guiding hypotheses and the broader literature on wine economics. Our findings provide strong evidence that segmenting the analysis by wine quality reveals crucial differences in production technology and offers a more nuanced perspective on the Old World versus New World efficiency debate.

5.1 H1: Divergent Production Technologies in Value and Premium Segments

Our findings strongly support our first hypothesis, that the production technologies for "value" and "premium" wines are structurally different. The significant coefficients on the squared and interaction terms in the Translog models reveal that the two segments differ in scale and the fundamental relationship between inputs.

For 'Value' wine production, the technology is characterized by strong diminishing returns to land, as evidenced by the significant negative coefficient on the squared surface term. This aligns with a mass-market logic where, after a certain point, simply acquiring more land is an inefficient strategy for increasing output. The technology instead favors a model where large surface areas are combined with high yields, shown by the positive complementarity between surface and grape input. This suggests a production function maximizing volume from a given land base.

In stark contrast, a powerful synergy between capital and labor defines the technology for 'Premium' wines. The significant positive interaction term suggests that investments in advanced equipment are most productive when paired with skilled labor, and vice versa. This reflects the demands of high-quality winemaking, where sophisticated technology requires expert human oversight to produce nuanced, terroir-driven wines. This finding extends the literature on scale economies (e.g., Sellers-Rubio & Alampi-Sottini, 2016; Santos et al., 2021) by suggesting that the nature of scale is different; for premium wines, it is about the efficient combination of capital and skill, not just land and volume.

5.2 H2: Re-examining the Old World vs. New World Efficiency Gap

Our results offer a nuanced perspective on the long-standing Old World versus New World efficiency debate. Our analysis, which segments wineries by quality, finds that Old World producers in our sample are, on average, more technically efficient in both the value and premium segments. This finding contrasts with influential cross-country studies like Tóth & Gál (2014), which found an aggregate efficiency advantage for the New World when treating wine as a homogeneous product.

Furthermore, the robustness of this finding is strengthened when we consider a key limitation of our Grape Input variable. If New World wineries, as a business model, rely more heavily on purchased grapes than their more estate-focused Old World counterparts, our proxy would systematically underestimate their true total inputs. This measurement error would bias their efficiency scores upwards, making them appear more efficient than they actually are. The fact that we still find Old World producers to be significantly more efficient, even in the presence of this potential bias favoring the New World group, suggests that our results are robust and potentially conservative.

At the same time, the generalizability of our findings is subject to two additional factors. First is our explicit quality segmentation, which avoids conflating different production technologies. Second, and critically, is our sample composition. The "New World" in our study is represented by major South American producers and South Africa, but notably omits key technological leaders like the United States and Australia.

Considering these important considerations, the persistent efficiency gap within our dataset remains a central finding. For the countries studied, it suggests that the advantages of the Old World, be it accumulated viticultural knowledge, a deep understanding of terroir, or established institutional frameworks, confer a tangible productivity advantage that transcends market segments. Our findings, therefore, caution against a monolithic view of "New World" performance. The narrative of uniform productive superiority may be an oversimplification, highly dependent on which countries are included in the analysis and whether quality differences are controlled.

The results from our sample suggest that while these New World wineries may compete effectively on other dimensions (e.g., marketing, branding), they appear to lag, on average, in the technical process of converting inputs into output. Furthermore, the strong, positive country-fixed effect for Spain, even after controlling for inputs, is noteworthy. This suggests that unobserved national factors, perhaps related to specific institutional support or widespread viticultural techniques, contribute to a higher production efficiency relative to our baseline, highlighting that significant heterogeneity persists even within the Old World.

5.3 H3: The Role of Operational Characteristics

Our third hypothesis explored how other firm characteristics shift the production frontier. The consistently positive and significant effect of the number of 'Labels produced' across both segments provides evidence for economies of scope. This suggests that product diversification allows wineries to leverage their fixed assets, such as cellar equipment, brand reputation, and distribution networks, more effectively, leading to higher output. While we interpret this as evidence for economies of scope, we also acknowledge that the number of labels could correlate with other unobserved firm characteristics, such as overall scale, age, or marketing sophistication, which may contribute to the production frontier.

The negative coefficient for the proportion of temporary to permanent employees supports the notion that a stable, experienced workforce is conducive to higher productivity. This may reflect lower agency costs or the accumulation of firm-specific human capital, which is particularly valuable in the complex winemaking process.

Finally, the non-significant result for certified organic and biodynamic production is noteworthy. It does not imply these methods are unimportant, but rather that, for the specialized producers in our sample, adopting these practices does not systematically shift the entire production frontier up or down. This null result may reflect offsetting economic forces; while organic practices can lead to lower physical yields, they may also enable access to niche markets or command a price premium. This could create a selection effect where only the most productive or well-managed firms can successfully adopt these methods, neutralizing the average impact on technical efficiency across our broad international sample. This finding contrasts with single-country studies (e.g., Cisilino et al., 2021). It reinforces the possibility that in a large, diverse sample, the effects are either highly heterogeneous or are balanced by these unobserved firm-level capabilities, resulting in no discernible average impact on the frontier's position.

5.4 Consistency and Credibility of Results

As a final check on the robustness of our findings, we consider the consistency conditions proposed by Bauer et al. (1998). Table 7 shows two key results. First, the efficiency scores derived from our flexible Translog model are almost perfectly correlated (0.97 for Value, 0.99 for Premium) with those from the restrictive Cobb-Douglas specification, confirming the robustness of the efficiency rankings. Second, the correlations between these scores and simple partial productivity ratios are consistently positive, indicating that wineries deemed more efficient by our SFA models also tend to have higher output per unit of land, labor, and capital. This alignment with standard performance measures lends strong credibility to our efficiency estimates and their conclusions.

Table 7: Correlations between efficiency scores and partial productivity ratios for “Value” and “Premium” wines.

N = 534	Cobb-Douglas Value Efficiency	Trans Log Value Efficiency	The average productivity of land	The average productivity of capital	The average productivity of labor	The average productivity of grapes
Cobb-Douglas Value Efficiency	1.0000					
Trans Log Value Efficiency	0.9729	1.0000				
The average productivity of land	0.1638	0.1604	1.0000			
The average productivity of capital	0.1020	0.0948	0.2280	1.0000		

The average productivity of labor	0.1743	0.1926	0.0927	0.7786	1.0000	
The average productivity of grapes	0.3150	0.3090	0.8883	0.1761	0.0947	1.0000

N = 720	**Cobb-Douglas Premium Efficiency**	**Trans Log Premium Efficiency**	**The average productivity of land**	**The average productivity of capital**	**The average productivity of labor**	**The average productivity of grapes**
Cobb-Douglas Premium Efficiency	1.0000					
Trans Log Premium Efficiency	0.9866	1.0000				
The average productivity of land	0.2679	0.2646	1.0000			
The average productivity of capital	0.0605	0.0350	0.0729	1.0000		
The average productivity of labor	0.0659	0.0386	0.0717	0.9672	1.0000	
The average productivity of grapes	0.3458	0.3410	0.9221	0.0741	0.0802	1.0000

Source: Authors' elaboration

6. Conclusions

This paper investigates the drivers of winery efficiency in a globalized market, arguing that the distinction between 'value' and 'premium' production is a more fundamental source of heterogeneity than the traditional Old versus New World divide. We provide a more nuanced understanding of the international wine industry's competitive landscape by estimating separate stochastic production frontiers for wineries specializing in each segment across eight countries.

Our empirical analysis yields three main findings. First, we provide robust evidence that the production technologies for value and premium wines are structurally different. Value wine production is characterized by a scale-based model with strong diminishing returns to land, whereas premium wine production relies on a powerful synergy between capital and skilled labor. This confirms that wineries in different quality segments make different products and operate on fundamentally distinct production frontiers.

Second, our results challenge the prevailing narrative of New World productive dominance. Within our specific sample, we find a persistent efficiency gap, with Old World producers being, on average, more technically efficient than their New World counterparts in both the value and premium segments. This suggests that the Old World's deep-rooted viticultural knowledge and terroir-specific expertise confer a durable productivity advantage that holds even when comparing like-for-like producers.

Third, we identify economies of scope, evidenced by the positive effect of producing more labels, as a significant factor for wineries in both segments. Conversely, a higher reliance on temporary labor is associated with lower productivity, highlighting the importance of a stable, experienced workforce.

These findings have important implications. For winery managers, our results underscore that competing across quality segments requires fundamentally different strategies. For instance, a New World premium producer cannot simply scale down a value-oriented production model; success requires a different "production recipe" that prioritizes the efficient combination of capital and skill. For policymakers, our findings suggest that industry support policies should be tailored to market segments. Fostering

competitiveness in the premium tier may require investments in technology and workforce training, while support for the value tier might focus on logistics and land consolidation.

This study is subject to certain limitations. Our analysis is based on cross-sectional data, which precludes the examination of efficiency dynamics over time. Furthermore, our capital variable remains a proxy for the actual capital stock, and our sample composition requires careful consideration. The dataset is heavily weighted towards the three Old World countries, which comprise over 80% of our observations. Moreover, our sample of New World producers notably omits two of the most technologically advanced producers: the United States and Australia. These limitations open promising avenues for future research. Using panel data could allow researchers to disentangle persistent from transient inefficiency. Future work should also aim to incorporate a more balanced global sample, including the aforementioned New World leaders, to test the robustness of our findings. This could also extend the framework to a tripartite comparison between Old, New, and "Emerging" market producers, as conceptualized by Villanueva and Ferro (2022). Finally, extending the analysis to the 'luxury' and 'icon' tiers would be a valuable next step to determine if the technological and efficiency patterns we identify hold at the very top of the market.

In conclusion, this paper demonstrates that segmenting the wine industry by quality is not just a marketing exercise but an economic imperative for understanding production and efficiency. Moving beyond monolithic comparisons, we provide a clearer picture of the factors driving success in the complex and competitive global wine market.

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Appendix. Capital Index construction using Principal Component Analysis (PCA)

We constructed a composite capital index using Principal Component Analysis (PCA) to create a robust proxy for capital stock. This method allowed us to reduce the dimensionality of 18 binary variables, each indicating the presence of a specific capital good (listed in Table A1), into a single, continuous measure.

The PCA results are presented in Table A2. Following the standard Kaiser-Guttman criterion, we identify five components with eigenvalues greater than 1, which together account for 53.4% of the total variance. The scree plot in Figure A1 clearly visualizes this, showing a distinct "elbow" where the explanatory power of subsequent component levels off.

The first principal component, which is by far the most significant (capturing 20% of the variance), was selected to serve as the capital index. As the component scores are centered around zero, we transformed the index by subtracting the minimum value from each score, ensuring all values are non-negative for their inclusion in the log-linear production function.

Table A1. Physical capital variables

Variable names	Variable labels
Grape sorting table	Grape sorting table (=1, if Yes)
Grape crusher	Grape crusher (=1, if Yes)
Presser	Presser (=1, if Yes)
Tanks	Tanks (=1, if Yes)
Pumps	Pumps (=1, if Yes)
Filters	Filters (=1, if Yes)
Bottling equipment	Bottling equipment (=1, if Yes)
Automated winery control	Automated winery control (=1, if Yes)
Under vine weeders	Under vine weeders (=1, if Yes)
Pre pruners	Pre pruners (=1, if Yes)
Trimmers	Trimmers (=1, if Yes)
Sprayers	Sprayers (=1, if Yes)
Shredder	Shredder (=1, if Yes)
Picking machine	Picking machine (=1, if Yes)
Tractors	Tractors (=1, if Yes)
Irrigation equipment	Irrigation equipment (=1, if Yes)
Automated vineyard control	Automated vineyard control (=1, if Yes)
Crops cover	Crops cover (=1, if Yes)

Source: Authors' elaboration.

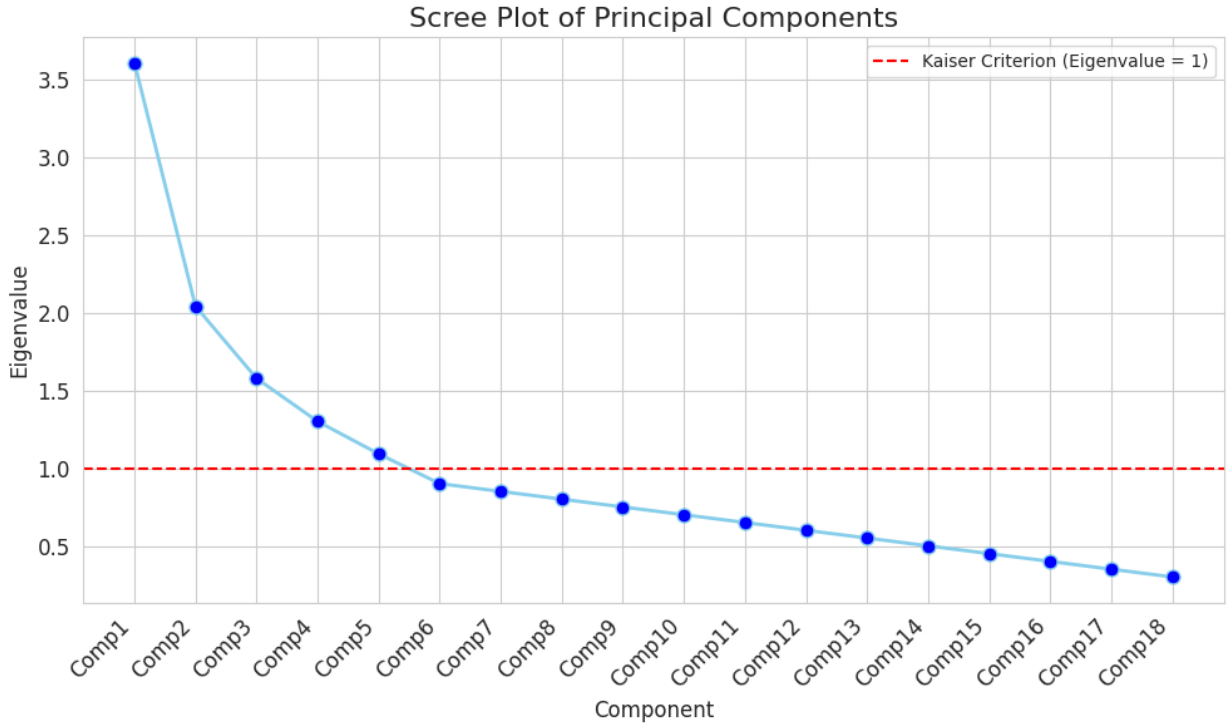
Table A2. Eigenvectors from the first five components of PCA

Principal components/correlation			Observations	3,437
			Components	18
			Trace	18
Rotation: (unrotated = principal)			Rho	1
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.6039	1.5643	0.2002	0.2002

Comp2	2.0397	0.4632	0.1133	0.3135
Comp3	1.5764	0.2766	0.0876	0.4011
Comp4	1.2998	0.2083	0.0722	0.4733
Comp5	1.0915	0.1640	0.0606	0.5340

Source: Authors' elaboration.

Figure A1. Scree Plot of Eigenvalues for Capital Index Components



Source: Authors' elaboration.