Measuring efficiency in the Chilean wine industry: A robust DEA approach

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Abstract

The Chilean wine industry has been quite innovative in terms of winemaking and trading. Yet, to survive in this competitive industry, wine managers should be aware of the relevance of monitoring their performance. In this paper, we assess how the five wineries listed on the Santiago Stock Exchange of Chile are efficient while using their critical resources for making profits. Particularly, we apply data envelopment analysis (DEA) to benchmark and rank these wineries' technical efficiency based on four inputs and one output. We use data gathered from consolidated financial statements that are prepared using estimates, judgments, and assumptions. To account for some level of ex-post adjustments in data, we evaluate these wineries' relative efficiency using a robust DEA model, which deals with ambiguous, imprecise, and uncertain input-output parameters. We analyze several levels of variability suitable for this data source, and we evaluate how changing the conservatism level affects technical efficiency and the rankings of the wineries. We also conduct a comparison between the five Chilean wineries and nine others from the New World. As the main conclusion, we found that Chilean wineries keep their efficiency level when including international firms in the analysis.

Keywords: Wine Industry, Data Envelopment Analysis, Robust Optimization, Monte-Carlo Simulation, Case study.

1. Introduction

The Chilean wine industry has been quite innovative in terms of winemaking and trading. This industry, composed of more than 100 wine producers, plays an important role in Chile's economy. In 2018, it represented almost 0.5% of the gross domestic product and generated almost 100,000 direct jobs. Since the 1990s, Chile's wine sector has been mostly export-oriented, focusing on larger and much more competitive markets than the Chilean one. In fact, in 2018, Chile was the world's fourth-largest wine exporter, being China the first destination for bottled wine exports (15% volume), followed by the USA (15%), Brazil (15%), and United Kingdom (10%).

This industry has also played a significant role in positioning Chile as a relevant brand worldwide. For instance, in 2018, 1.9 billion people in the world consumed a bottle that said *Wine of Chile*. Also, the *Love Wine, Love Chile* consumer campaign, launched in 2016, has increased the awareness of Chilean wines. According to the country's leading wine trade association, Wines of Chile, which includes 72 partners, the current Chilean international strategy includes: raising exports average prices, improving wine production sustainability, and strengthening the presence in traditional markets.

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However, the global wine industry has increased its competition level, showing a strong fragmentation with plenty of medium-to-small suppliers. According to the Wine-Searcher database, there are 62,390 wine producers worldwide. Therefore, to survive in this challenging environment, Chilean wine companies, especially export-focused ones, need to continuously adapt their supply chain processes to meet their customer demands. This need also implies to improve their productivity for remaining profitable, which can be achieved by applying innovative technologies, more efficient production technologies, or combining both. Any production change, however, must be adequately justified. The evaluation must be supported at least by a benchmarking of the best production practices. Therefore, ranking the wineries allows them to understand their strengths and weaknesses compared to both the Chilean and international contexts, which may have a sizable impact when determining the areas subject to improvement.

In this paper, we use Operations Research (OR) tools to assess how some relevant Chilean wine companies use their critical resources for wine production. Particularly, we use data envelopment analysis (DEA) to benchmark and rank the technical efficiency of five Chilean wineries based on four inputs and one output. We use data gathered from consolidated financial statements prepared using estimates, judgments, and assumptions, thus prone to change. The working data belongs to the following five areas that involve a higher degree of judgments or complexity: revenue, working capital, property plant and equipment, and intangible assets. To account for some level of ex-post adjustments in data, we evaluate the relative efficiency of these wineries using a robust DEA model, which deals with ambiguous, imprecise, and uncertain input-output parameters. We analyze several levels of variability suitable for this data source, and for each of them, we evaluate how changing the conservatism level affects both the technical efficiency and the rankings of the wineries.

The contribution of this paper is twofold. First, we benchmark and discuss five of the most relevant wineries' technical efficiency in the Chilean wine industry using a robust optimization approach that deals with ambiguous, imprecise, and uncertain input-output parameters. To the best of our knowledge, this is the first study in the relevant literature. Moreover, we devise a novel classification scheme for ranking DMUs based on robust solutions. This approach could be used to develop new insights when using a robust DEA approach.

The rest of this paper is structured as follows. In Section 2, we discuss the related literature. Section 3 describes the robust DEA framework. In Section 4, we describe the case study, and we analyze the results. Finally, in Section 5, we provide a discussion, some concluding remarks, and directions for future research.

2. Literature review

Operations research (OR) models have been widely used to improve supply chain efficiency and support decision making in several productive sectors. Particularly, in the natural resource industry, OR models have been successfully used in agriculture (Plà et al., 2014; Carvajal et al., 2019; Rohmer et al., 2019), fishery (Björndal et al., 2004; Abedi and Zhu, 2017; Liu et al., 2020), forestry (Rönnqvist et al., 2015; Vafaeenezhad et al., 2019; Basso et al., 2020a), and mining (Newman et al., 2010; Silva et al., 2017; Rezakhah et al., 2020), among others. For a comprehensive review of relevant contributions in these four areas, we refer the reader to Bjørndal et al. (2012), while for a review of OR contributions to the agriculture supply chain management, we refer the reader to Weintraub and Romero (2006) and Sharma et al. (2020). On this topic, agri-food products, i.e., agricultural food products obtained from crops (Ahumada and Villalobos, 2009), are a relevant subset of the agricultural product portfolio, being the wine a representative example.

The wine supply chain comprises four stages: grape production, manufacturing, packaging, and distribution (Basso et al., 2020b). The grape production stage involves agricultural tasks such as grape growth mainly. The manufacturing stage comprises all the activities required to process the grape and transforming it into wine. In the packaging stage, the wine is bottled and labeled. Finally, the distribution stage includes all transport activities needed to reach the end consumer. These stages are described more in detail in Petti et al. (2006). Works focusing on the wine supply chain behavior/performance can be found in Rugani et al. (2013); Mac Cawley (2014); Ting et al. (2014); Varsei and Polyakovskiy (2017).

Throughout the wine supply chain, several issues must be addressed to improve or maintain production efficiency. Examples include, but are not limited to, scheduling of harvest operations, tank management, wine manufacturing, bottling scheduling, packaging postponement, wine distribution, vertical/horizontal collaboration, and network design. A wide range of OR models and methodologies have been applied to tackle these problems (Moccia, 2013; Varas, 2016). Relevant applications for wine grape harvesting can be found in Ferrer et al. (2008); Bohle et al. (2010); Arnaout and Maatouk (2010); Varas et al. (2020). For wine manufacturing, two novel applications are developed in Cakici et al. (2006); Palmowski and Sidorowicz (2018). Several applications, on the other hand, have been developed for wine packaging. Some examples include Cholette (2009); Basso and Varas (2017); Varas et al. (2018, 2019); Basso et al. (2020b); Finally, for the distribution stage, Cholette (2007) proposes a linear programming model to match distributors and sellers.

Literature shows that efficiency measurement has been a topic of wide interest, especially considering that organizations have struggled to improve productivity (Cook and Seiford, 2009). In this work, we focus on the Data Envelopment Analysis (DEA) framework, a non-parametric method for computing the technical efficiency based on linear programming. The technical efficiency concept traces back to the work of Farrell (1957) and can be defined as the production unit's ability to obtain the maximum output from a given (and limited) set of inputs. This approach's original idea was to identify those units exhibiting best practices within a set of comparable DMUs, thus forming an efficient frontier. Moreover, DEA enables measuring the efficiency of non-frontier units and identifying benchmarks for the inefficient units (Cook and Seiford, 2009). DEA has been applied in several real-world situations, including banking, health care, agriculture, transportation, education, and government (Contreras et al., 2019; Liu et al., 2019). Surveys of DEA applications are developed in Liu et al. (2013) and Emrouznejad and Yang (2018). Under this framework, several OR models have been devised for computing efficiency measures. Examples include: the constant returns to scale (CCR) model (Charnes et al., 1978), the variable returns to scale model(Banker et al., 1984), the additive model (Charnes et al., 1985), the weighted additive model Lovell and Pastor (1995), the slacks-based measures model (Tone, 2001), and the range-bounded additive model (Cooper et al., 2011).

For the wine industry, several efforts in benchmarking and performance measurement have been developed using DEA. A comprehensive literature review is developed in Sellers-Rubio et al. (2016). We describe some relevant works next. Vázquez-Rowe et al. (2012) follows a combined implementation of Life Cycle Assessment (LCA) and a slacks-based measures model to analyze the operational and environmental performance of 40 Galician vineyards (Spain). Aparicio et al. (2013) devises a new output-oriented weighted additive model. The authors illustrate the use of the proposed approach by analyzing a sample of 24 Spanish Designation of Origin (DO) from the perspective of revenue, technical and allocative inefficiency. Jiménez et al. (2013) analyzes the efficiency of a subset of 34 DO, which covers 59.3% of the Spanish Protected Designation of Origin wine surface, using a range-bounded additive model. The authors also address changes in productivity computing a biennial Malmquist index. Sellers and Alampi-Sottini (2016) analyzes the influence of winery size on efficiency estimations considering a sample of 723 Italian wineries. To do so, the authors employ a methodology based on both traditional profitability measures and input-oriented variable returns to scale model for estimating efficiency. Urso et al. (2018) perform an efficiency analysis of wine and grapevine producers in Italy using a variable return to scale model. The authors also investigated which factors affect the differences in efficiency levels using econometric analysis.

An underlying assumption in original DEA models is that all the data are measured with full accuracy. However, in practice, data may be subject to perturbations or imprecisions, which means that some parameters lie within bounded intervals. Two relevant approaches for dealing with imprecise data can be found in Cooper et al. (1999) and Despotis and Smirlis (2002). Cooper et al. (1999) proposes the first unified approach to cope with imprecise data in DEA. The authors develop the Imprecise Data Envelopment Analysis (IDEA) method, dealing directly with a mixture of imprecisely and exactly known data. For IDEA, the authors convert the non-linear model into a linear equivalent by replacing the product of variables by artificial ones and applying a scale transformation on data. Despotis and Smirlis (2002) develops an alternative approach for handling inaccurate data in DEA. The authors transform the non-linear model of Charnes et al. (1978) into an equivalent linear model, completely different than

IDEA. Under their framework, the CCR multiplier model with exact input-output data is a particular instance of the proposed imprecise DEA model.

Most of the interval DEA approaches assess DMU's performance by considering the lower and upper bound of their efficiency. Nevertheless, when dealing with imprecise data, the rankings' maximum conformity may occur neither in the pessimist nor in the optimistic case. To tackle this drawback, Shokouhi et al. (2010) proposes an alternative approach to interval DEA, which is based on the robust approach of Bertsimas and Sim (2004).

Robust optimization is an alternative modeling approach for finding solutions that, without assuming a particular distribution for uncertain parameters, are less sensitive to uncertain data (Varas et al., 2014). The first efforts on this stream were developed by Soyster (1973). The author proposes a linear optimization model, finding solutions that always remain feasible for a column-wise uncertainty case when data change. A new modeling approach, less conservative than Soyster's, is developed independently by Ben-Tal and Nemirovski (1998, 1999, 2000), El Ghaoui and Lebret (1997), and El Ghaoui et al. (1998). These authors assume that uncertain data is constrained to be within a set with a particular geometric structure. Nevertheless, a disadvantage of their approach is that, depending on the set used, the resulting models are non-linear problems, so they are harder to solve than Soyster's model. Bertsimas and Sim (2004) proposes a new approach for robust optimization that keeps Soyster's modeling advantages and shows at least the same level of flexibility that Ben-Tal and Nemirovski and El-Ghaoui and Lebret approach. For an overview of robust optimization developments since 2007, see Gabrel et al. (2014). A practical guide can be found in Gorissen et al. (2015), whereas recent theoretical advances can be found in Bertsimas et al. (2018).

Several works in DEA literature use robust optimization to cope with data uncertainty. For instance, Sadjadi and Omrani (2008) proposes a robust DEA model for assessing the performance of electricity distribution companies. Sadjadi et al. (2011) proposes a robust super-efficiency DEA model for ranking provincial gas companies in Iran. Omrani (2013) proposes a robust optimization approach to find common weights in DEA with uncertain data. The model is also tested using data from provincial gas companies in Iran. Mardani and Salarpour (2015) proposes a robust DEA method assuming both outputs and inputs uncertainty. The authors analyze efficiencies in potato production using data from 23 provinces in Iran. Aghayi et al. (2016) present a robust DEA model with a common set of weights (CSWs), and demonstrate its applicability by assessing the problem of performance measurement in the banking industry. Finally, Aghayi and Maleki (2016) proposes a robust optimization framework for computing DMUs efficiency considering undesirable outputs and applies it to the Iranian bank industry.

3. The robust DEA framework

For the sake of exposition, we begin this section by reviewing the seminal work of Charnes et al. (1978) that assumes that data are measured with full accuracy. Afterward, we review Shokouhi et al. (2010) approach, which is used for handling inaccurate data in DEA and fits with the prone-to-change nature of the data used for computing the efficiency scores. We end this section by discussing the model used in the case study.

3.1. The seminal model of Charnes et al. (1978)

Assume that n Decision Making Units (DMUs) convert m inputs into s outputs, and let $i \in \{1,\dots,m\}$, $r \in \{1,\dots,s\}$, $j \in \{1,\dots,n\}$, and $p \in \{1,\dots,n\}$. Suppose x_{ij} is the quantity of input i used by DMU_j, and y_{rj} is the quantity of output r produced by DMU_j. Consider problem (1). This is the so-called CCR multiplier model proposed by Charnes et al. (1978), which assumes constant return to scale. In this problem, v_i and u_r, that is, the input and output weights, are the decision variables. In contrast, ε is a parameter representing a non-Archimedean infinitesimal used to guarantee the boundedness of problem (1) dual. The relative efficiency of DMU_p, denoted by θ_p, is given by the optimal value of this problem.

$$
\begin{aligned}
\text{maximize } \theta_p = \quad & \sum_{r=1}^{s} u_r y_{rp} \\
\text{subject to} \quad & \sum_{i=1}^{m} v_i x_{ip} = 1, \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad \forall j \\
& u_r, v_i \ge \varepsilon, \qquad\qquad\qquad \forall r,\ i
\end{aligned} \tag{1}
$$

Literature shows several attempts to compute an interval or exact value for parameter ε. For example, see Mehrabian et al. (2000); Amin and Toloo (2004); Alirezaee (2005). In this paper, we considered the approach of Mehrabian et al. (2000), which looks for an assurance interval of ε. Consider problem (2). According to the authors, the largest ε that guarantees boundedness is $\varepsilon^* = min\{\varepsilon_1, \ldots, \varepsilon_n\}$, where ε_p denotes the optimal value of problem (2) when analyzing DMU$_p$.

$$
\begin{aligned}
\text{maximize } \varepsilon_p = \quad & \bar{\varepsilon} \\
\text{subject to} \quad & \sum_{i=1}^{m} v_i x_{ip} = 1, \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad \forall j \\
& u_r, v_i \ge \bar{\varepsilon}, \qquad\qquad\qquad \forall r,\ i
\end{aligned} \tag{2}
$$

3.2. The robust reformulation of Shokouhi et al. (2010)

For each DMU$_j$, let us consider that $\mathscr{J}_j^x$ (indexed by i) and $\mathscr{J}_j^y$ (indexed by r) represent the index sets of inputs and outputs, respectively, that are imprecise or subject to uncertainty. The elements of these sets, x_{ij} and y_{rj}, are modeled as random variables that are independent, bounded and symmetric. It is assumed that these random variables are defined over the supports $[x_{ij}^L, x_{ij}^U]$ and $[y_{rj}^L, y_{rj}^U]$, respectively. Let $z_{ij}^x = (x_{ij} - x_{ij}^L)/(x_{ij}^U - x_{ij}^L)$ and $z_{rj}^y = (y_{rj} - y_{rj}^L)/(y_{rj}^U - y_{rj}^L)$ be the scaled deviation of these variables from their lower bounds. Therefore, $0 \le z_{ij}^x \le 1$ and $0 \le z_{rj}^y \le 1$. Consider further the non-negative parameters γ_j^x and γ_j^y taking value in the bounded intervals $[0, |\mathscr{J}_j^x|]$ and $[0, |\mathscr{J}_j^y|]$, respectively. These are the so-called *budgets of uncertainty* used to control the conservatism level of the robust solution by bounding the total scaled variation of the uncertain parameters.

In a robust optimization framework, the notions about both robust counterparts and uncertainty sets are relevant. Bounded and convex deterministic sets are used typically to describe data uncertainty. Bertsimas and Sim (2004) assumes that the uncertain parameters are constrained to be within polyhedral uncertainty sets. Shokouhi et al. (2010), particularly, uses the polyhedral uncertainty sets stated in (3).

$$
\begin{aligned}
U^x &= \{X \in \mathbb{R}^{m \times n} : x_{ij} = x_{ij}^L + z_{ij}^x(x_{ij}^U - x_{ij}^L),\ \forall i, j; \quad \sum_{i \in \mathscr{J}_j^x} z_{ij}^x \le \gamma_j^x,\ \forall j; \quad z_{ij}^x \le 1,\ \forall i, j\} \\
U^y &= \{Y \in \mathbb{R}^{s \times n} : y_{rj} = y_{rj}^L + z_{rj}^y(y_{rj}^U - y_{rj}^L),\ \forall r, j; \quad \sum_{r \in \mathscr{J}_j^y} z_{rj}^y \le \gamma_j^y,\ \forall j; \quad z_{rj}^y \le 1,\ \forall r, j\}
\end{aligned} \tag{3}
$$

The uncertain problem addressed by Shokouhi et al. (2010), therefore, is given by problem (4).

$$
\begin{array}{lll}
\text{maximize } \tilde{\theta}_p = & \sum_{r=1}^{s} u_r y_{rp} & \\
\text{subject to} & \sum_{i=1}^{m} v_i x_{ip} = 1, & \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0, & \forall j \\
& u_r, v_i \geq \varepsilon, & \forall r,\ i \\
& x_{ij} \in U_{ij}^{x}, & \forall i,\ j \\
& y_{rj} \in U_{rj}^{y}, & \forall r,\ j
\end{array} \tag{4}
$$

The deterministic problem related to an uncertain problem is called the Robust Counterpart. Different robust counterparts, which may differ on their tractability level, are obtained using different uncertainty sets. The robust counterpart is constructed by using protection functions. Shokouhi et al. (2010) proposes using the protection functions (5).

$$
\begin{array}{lll}
\beta_j^x(x, \gamma_j^x) = & \text{maximize} & \sum_{i \in \mathscr{J}_j^x} v_i (x_{ij}^U - x_{ij}^L) z_{ij}^x \\
& \text{subject to} & \sum_{i \in \mathscr{J}_j^x} z_{ij}^x \leq \gamma_j^x \\
& & 0 \leq z_{ij}^x \leq 1, \qquad \forall i \in \mathscr{J}_j^x. \\
\beta_j^y(y, \gamma_j^y) = & \text{maximize} & \sum_{r \in \mathscr{J}_j^y} u_r (y_{rj}^U - y_{rj}^L) z_{rj}^y \\
& \text{subject to} & \sum_{r \in \mathscr{J}_j^y} z_{rj}^y \leq \gamma_j^y \\
& & 0 \leq z_{rj}^y \leq 1, \qquad \forall r \in \mathscr{J}_j^y.
\end{array} \tag{5}
$$

Therefore, the robust counterpart of (4) is given by problem (6).

$$
\begin{array}{lll}
\text{maximize } \bar{\theta}_p = & \sum_{r=1}^{s} u_r y_{rp}^U - \beta_p^y(y, \gamma_p^y) & \\
\text{subject to} & \sum_{i=1}^{m} v_i x_{ip}^L + \beta_p^x(x, \gamma_p^x) = 1 & \\
& \sum_{r=1}^{s} u_r y_{rj}^L - \sum_{i=1}^{m} v_i x_{ij}^U + \beta_j^y(y, \gamma_j^y) + \beta_j^x(x, \gamma_j^x) \leq 0, & \forall j \neq p \\
& \theta_p \leq 1, & \forall p \\
& u_r, v_i \geq \varepsilon, & \forall r,\ i
\end{array} \tag{6}
$$

By Theorem 1 of Bertsimas and Sim (2004), the application of strong duality on (5) implies that problem (6) is equivalent to problem (7).

$$
\begin{array}{lll}
\text{maximize } \bar{\theta}_p = & \sum_{r=1}^{s} u_r y_{rp}^U - z_p^y \gamma_p^y - \sum_{r=1}^{s} p_{rp} & \\
\text{subject to} & \sum_{i=1}^{m} v_i x_{ip}^L + z_p^x \gamma_p^x + \sum_{i=1}^{m} q_{ip} = 1 & \\
& \sum_{r=1}^{s} u_r y_{rj}^L - \sum_{i=1}^{m} v_i x_{ij}^U + z_j^y \gamma_j^y + z_j^x \gamma_j^x + \sum_{r=1}^{s} p_{rj} + \sum_{i=1}^{m} q_{ij} \leq 0, & \forall j \neq p \\
& z_j^y + p_{rj} \geq u_r (y_{rj}^U - y_{rj}^L), & \forall r,\ j \\
& z_j^x + q_{ij} \geq v_i (x_{ij}^U - x_{ij}^L), & \forall i,\ j \\
& \theta_p \leq 1, & \forall p \\
& u_r, v_i \geq \varepsilon, & \forall r,\ i \\
& z_j^x, z_j^y, q_{ij}, p_{rj} \geq 0, & \forall i,\ j,\ r
\end{array}
\tag{7}
$$

A remarkable feature of Shokouhi et al. (2010) model, i.e., problem (7), is that the protection functions provide enough flexibility to shift from optimistic to a pessimistic viewpoint. Particularly, if $\gamma_j^x = \gamma_j^y = 0$, then $\beta_j^x(x,0) = \beta_j^y(y,0) = 0$, and problem (7) reduces to the optimistic case. Similarly, if $\gamma_j^x = |\mathscr{J}_j^x|$ and $\gamma_j^y = |\mathscr{J}_j^y|$, then $\beta_j^x(x, |\mathscr{J}_j^x|) = \sum_{i=1}^m v_i(x_{ij}^U - x_{ij}^L)$ and $\beta_j^y(y, |\mathscr{J}_j^y|) = \sum_{r=1}^s u_r(y_{rj}^U - y_{rj}^L)$, respectively, and problem (7) reduces to the pessimistic case.

Finally, following Mehrabian et al. (2000) approach, the largest ε that guarantees boundedness of problem (7) is $\varepsilon^* = min\{\varepsilon_1, \ldots, \varepsilon_n\}$, where ε_p denotes the optimal value of the auxiliary problem obtained by replacing $\bar{\theta}_p$ by $\varepsilon_p = \bar{\varepsilon}$ and ε by $\bar{\varepsilon}$, in the objective function and constraints, respectively, of problem (7).

3.3. A constrained robust DEA model

Shokouhi et al. (2010) proposes including the following constraints (8) in order to reduce the complexity of problem (7). Particularly, the authors use a single uncertainty budget for all DMUs (Γ), which reduces the combinatorial burden of instance generation and facilitate the analysis of results.

$$
\begin{array}{ll}
z_j^y = z_j, & \forall j \\
z_j^x = z_j, & \forall j \\
\gamma_j^y + \gamma_j^x = \Gamma_j, & \forall j \\
\gamma_p^x \leq m, & \\
\gamma_p^y \leq s, & \\
\Gamma_j = \Gamma & \forall j
\end{array}
\tag{8}
$$

Several approaches have been used to set the uncertainty budgets in order to represent different levels of conservatism. Some approaches are reviewed in Bertsimas and Thiele (2006); Bienstock and Özbay (2008); Varas et al. (2014). In this paper, we follow the approach of Bienstock and Özbay (2008) which considers the use of linear functions. Specifically, we set Γ as shown in (9), where $\phi \in [0,1]$, and $|\mathscr{J}_j^x| + |\mathscr{J}_j^y|$ is the total number of parameters under uncertainty for the j-th DMU.

$$
\Gamma = \phi \cdot \max_j \{ |\mathscr{J}_j^x| + |\mathscr{J}_j^y| \} \tag{9}
$$

Overall, problem (10), which results from adding constraints (8) and (9) to model (7), is the model used in all the computational experiments.

$$
\begin{array}{lll}
\text{maximize } \hat{\theta}_p^* = & \sum_{r=1}^{s} u_r y_{rp}^U - z_p^y \gamma_p^y - \sum_{r=1}^{s} p_{rp} & \\
\text{subject to} & \sum_{i=1}^{m} v_i x_{ip}^L + z_p^x \gamma_p^x + \sum_{i=1}^{m} q_{ip} = 1 & \\
& \sum_{r=1}^{s} u_r y_{rj}^L - \sum_{i=1}^{m} v_i x_{ij}^U + z_j^y \gamma_j^y + z_j^x \gamma_j^x + \sum_{r=1}^{s} p_{rj} + \sum_{i=1}^{m} q_{ij} \leq 0, & \forall j \neq p \\
& \Gamma = \phi \cdot \max_j \{ |\mathscr{J}_j^x| + |\mathscr{J}_j^y| \} & \\
& z_j^y + p_{rj} \geq u_r (y_{rj}^U - y_{rj}^L), & \forall r,\ j \\
& z_j^x + q_{ij} \geq v_i (x_{ij}^U - x_{ij}^L), & \forall i,\ j \\
& \theta_p \leq 1, & \forall p \\
& z_j^y = z_j, & \forall j \\
& z_j^x = z_j, & \forall j \\
& \gamma_j^y + \gamma_j^x = \Gamma_j, & \forall j \\
& \gamma_p^x \leq m, & \\
& \gamma_p^y \leq s, & \\
& \Gamma_j = \Gamma & \forall j \\
& u_r, v_i \geq \varepsilon, & \forall r,\ i \\
& z_j^x, z_j^y, q_{ij}, p_{rj} \geq 0, & \forall i,\ j,\ r
\end{array}
\tag{10}
$$

Finally, the largest ε that guarantees boundedness of problem (10) is $\varepsilon^* = min\{\varepsilon_1, \ldots, \varepsilon_n\}$, where ε_p denotes the optimal value of the auxiliary problem obtained by replacing $\bar{\theta}_p$ by $\varepsilon_p = \bar{\varepsilon}$ in the objective function, and ε by $\bar{\varepsilon}$ in the constraints of problem (10).

4. Computational Experiments

This section is structured as follows. In Subsection 4.1, we describe the five Chilean wine companies considered, the data sources, and we motivate the use of a robust DEA approach. Then, in Subsection 4.2, we describe the design of the computational experiments. Afterward, in Subsection 4.3, we show and discuss the results concerning the Chilean wine industry, whereas, in Subsection 4.4, we expand our analysis by incorporating some international wineries.

4.1. The case study

The Chilean wine industry is a very dynamic sector in terms of production innovation, business practices, and trading. This industry is composed of almost 100 wine producers with a strong focus on exports, especially to larger and much more competitive markets than the Chilean one. Table 1 shows the main characteristics of the Chilean wine sector in 2018.

Table 1: Chilean wine industry data.

Vineyard surface area (Has)	212,000
Wine production (millions HL)	12.9
Wine exports (million HL)	9.3
Wine consumption (millions HL)	2.3
Wine consumption (litres per capita)	14
Wine producers	100

The most relevant Chilean wineries joint efforts under the Wines of Chile initiative, the leading wine trade association in the country. This paper focuses on the Wines of Chile members listed on the Santiago Stock Exchange of

Chile. Despite the large number of wineries in this country, most small and medium-sized companies are not listed on this Exchange. Particularly, the wineries listed are Concha y Toro, Emiliana, Los Vascos, San Pedro, and Santa Rita. As Figure 1 depicts, these five companies are among the largest in the country and account for a significant share of the Chilean wine exports: 61.8% and 63.2% in volume and revenue, respectively. Figure 2, on the other hand, depicts these wineries' location. Four of these wineries are located in the Metropolitan Region, whereas Los Vascos is located in the O'Higgins Region, all in Chile's central zone.

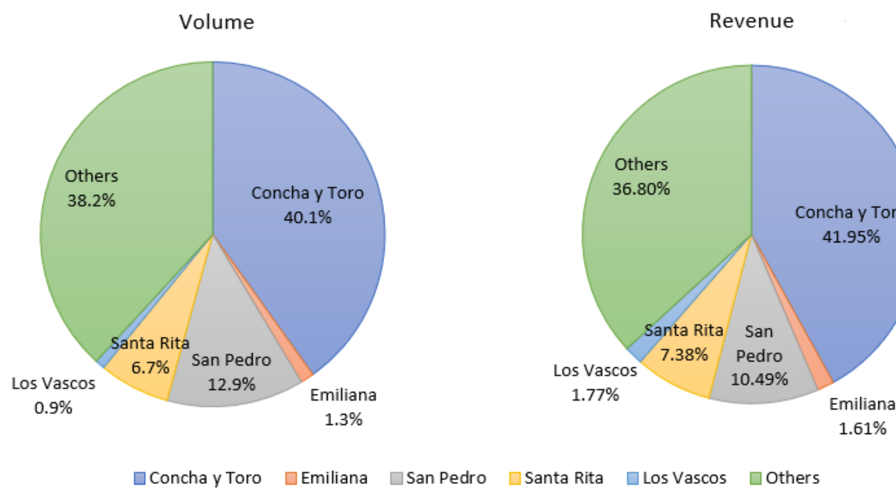

Figure 1: Share of export bottled wine.

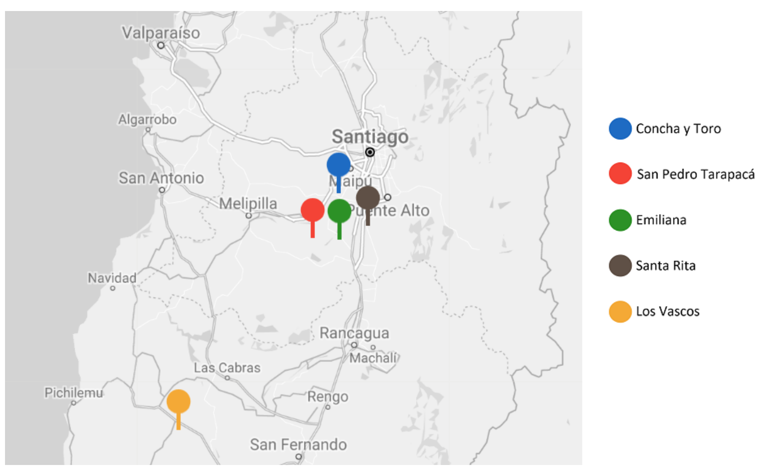

Figure 2: Geographical location of the five Chilean wineries.

To apply the framework presented in Section 3, we gathered data from wineries' financial statements for the years 2017 and 2018, which are commonly available on the companies websites. We consider four inputs and one output. The inputs are inventories, property plants and equipment, intangible assets, and land area. The output is the revenue of each winery. A description of the parameters is provided in Table 2, whereas Table 3 shows the data gathered. All values are expressed in USD considering and an exchange rate of 694.77 Chilean pesos per dollar.

We think that the chosen inputs and outputs are quite useful for computing and compare wineries' efficiency. Particularly, inventories are current assets generated through trading activity and provide information regarding working capital management. Both property, plants, and equipment and intangible assets provide information regarding the physical and non-physical assets used to generate profits and revenues. Land area reflects how wineries secure access to grapes, and it provides information about grape growing and sourcing, an essential component of a wineries business model. Finally, revenue provides information about the production, marketing, and sales and can be used as a proxy of the winery size. On this, from Table 3, we can see that the wineries we are analyzing have different sizes. There is a difference of two orders of magnitude in the revenue of the smallest one, Los Vascos, compared to the largest one, Concha y Toro, which is also Chile's largest winery.

Table 2: Inputs and output description.

Inputs	Inventories	:	Consolidated Statements of Financial Position (or Consolidated Balance Sheets). Current Assets.	Working capital. Includes raw materials, work in process and finished goods.
	Property plant and equipment	:	Consolidated Statements of Financial Position (or Consolidated Balance Sheets). Non-Current Assets.	Operating assets and liabilities. Includes land, freehold buildings, leasehold buildings, vines and vineyard infrastructure, machinery and equipment.
	Intangible Assets	:	Consolidated Statements of Financial Position (or Consolidated Balance Sheets). Non-current Assets.	Operating Assets and liabilities. Includes brands, customer contracts, customer lists, contract co-packaging arrangements, software, and customer-based relationships.
	Land Area	:	Within the document.	Planted hectares.
Output	Total revenue	:	Consolidated Statements of Income (or Consolidated Statement of Earning).	Earnings. Revenue is generated from production, marketing, and sales of the portfolio of branded wine.

Table 3: Inputs and outputs values.

DMU		Inputs				Output
Winery	Country	Inventories (MUS$)	Property, Plant and Equipment (MUS$)	Intangible Assets (MUS$)	Land Area (Ha)	Total Revenue (MUS$)
Concha y Toro	Chile	399,254.12	563,155.79	686,83.69	11,624.00	883,931.24
Emiliana	Chile	19,161.54	36,356.79	1,481.24	769.00	30,929.63
San Pedro	Chile	95,244.52	182,635.44	31,303.49	3,884.00	297,247.62
Santa Rita	Chile	88,185.09	167,730.57	14,383.03	3,369.00	245,672.00
Los Vascos	Chile	15,929.00	52,545.00	76.00	722.00	29,476.00

Nevertheless, the consolidated financial statements are prepared using estimates, judgments, and assumptions. Thus, the reported values are prone to change. In fact, these documents explicitly state which areas involve a higher degree of judgments or complexity, or where assumptions and estimates are significant to the financial statements. These areas include working capital, property plant and equipment, intangible assets, impairment of non-financial assets, income tax, and derivative financial instruments, among others. This paper's working data belongs to the first five areas, which are commonly pointed out in the reviewed documents. To account for some level of ex-post adjustments in data, therefore, we evaluate these wineries' relative efficiency using a robust DEA model, which deals with ambiguous, imprecise, and uncertain input-output parameters, fitting with the nature of the dataset.

4.2. *Computational experiments design*

The computational experiments are based on model (10). For each input i and the single output r, the uncertain parameters for the j-th winery are denoted by x_{ij} and y_{rj}, respectively. We assume that these parameters are i.i.d. random variables, with nominal values denoted by $\bar{x}_{ij}$ and $\bar{y}_{rj}$. Moreover, we considered that the maximum variation is given by a fraction γ_j of the nominal values. Table 3 shows the nominal data, whereas the bounded intervals for the uncertain parameters are given by (11). For experimental purposes, we suppose that $\gamma_j = \gamma, \forall j$, and we considered three maximum variations (or instance variability levels): 1% (low), 5% (medium), and 10% (high), that is, $\gamma \in \{0.01, 0.05, 0.1\}$. We also considered 101 levels of conservatism, specifically: $\phi \in \{0, \ldots, 1\text{: by steps of } 0.01\}$. This allows us to analyze the optimistic case ($\phi = 0$) and several pessimistic cases ($0 < \phi \leq 1$).

$$
\begin{aligned}
[x_{ij}^L, x_{ij}^U] &= [\bar{x}_{ij}(1-\gamma_j), \bar{x}_{ij}(1+\gamma_j)], \quad \forall i, j \\
[y_{rj}^L, y_{rj}^U] &= [\bar{y}_{rj}(1-\gamma_j), \bar{y}_{rj}(1+\gamma_j)], \quad \forall j
\end{aligned}
\tag{11}
$$

In Appendix A, Algorithm 1 shows the steps followed in our computational experiments for gathering insights. Model (10), which is a non-linear optimization problem, was coded in AMPL (Fourer et al., 1990), and was solved

Table 4: Efficiencies and Ranking for three variability levels.

			Conservatism level ϕ									
			0.00 (Optimistic)		0.25		0.50		0.75		1.00 (Pessimistic)	
Variability γ	Winery	Class	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking
1%	Concha y Toro	E^-	96.50%	4°	92.14%	4°	89.66%	4°	88.45%	4°	88.25%	4°
	Emiliana	E^-	89.79%	5°	85.87%	5°	83.65%	5°	82.90%	5°	82.88%	5°
	San Pedro	E^{++}	100.00%	1°	100.00%	1°	100.00%	1°	100.00%	1°	100.00%	1°
	Santa Rita	E^{++}	100.00%	1°	100.00%	1°	100.00%	1°	100.00%	1°	100.00%	1°
	Los Vascos	E^{++}	100.00%	1°	100.00%	1°	100.00%	1°	100.00%	1°	100.00%	1°
Variability γ	Winery	Class	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking
5%	Concha y Toro	E^+	100.00%	1°	91.06%	4°	80.87%	4°	75.43%	4°	74.63%	4°
	Emiliana	E^+	100.00%	1°	84.46%	5°	74.41%	5°	70.72%	5°	70.61%	5°
	San Pedro	E^+	100.00%	1°	100.00%	1°	97.75%	3°	90.62%	3°	90.23%	3°
	Santa Rita	E^+	100.00%	1°	100.00%	1°	100.00%	1°	100.00%	1°	99.48%	2°
	Los Vascos	E^{++}	100.00%	1°	100.00%	1°	100.00%	1°	100.00%	1°	100.00%	1°
Variability γ	Winery	Class	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking
10%	Concha y Toro	E^+	100.00%	1°	90.67%	4°	73.23%	4°	64.74%	4°	62.36%	4°
	Emiliana	E^+	100.00%	1°	83.00%	5°	65.84%	5°	58.90%	5°	57.75%	5°
	San Pedro	E^+	100.00%	1°	100.00%	1°	89.20%	3°	76.60%	3°	73.86%	3°
	Santa Rita	E^+	100.00%	1°	100.00%	1°	95.63%	2°	85.64%	2°	81.35%	2°
	Los Vascos	E^{++}	100.00%	1°	100.00%	1°	100.00%	1°	100.00%	1°	100.00%	1°

using the Baron non-linear solver. All runs were performed on a notebook with an Intel(R) Core(TM) i7-5700HQ CPU@ 2.70 GHz processor and 12 GB RAM. We solve problem (10) obtaining the weights and the wineries efficiency for each variability level and conservatism level. Afterward, we rank the DMUs based on their efficiency scores. We also specify the probability occurrence of the rank positions by computing the so-called conformity level by using Monte-Carlo simulation. To do so, we randomly generate $k = 10,000$ data instances whose inputs and outputs are distributed uniformly between their bounds. We then recalculate the efficiency scores using the robust weights, using expression (12), and we rank the DMUs accordingly. Finally, the conformity level is given by the proportion of ranking positions that match in the robust ranking.

$$\tilde{\theta}_j = u^*_{rj}\tilde{y}_{rj} / \sum_{i=1}^{m} v^*_{ij}\tilde{x}_{ij} \tag{12}$$

4.3. *Computational results*

We discuss first the robust solutions for the extreme cases, i.e., the optimistic ($\phi = 0$) and pessimistic ($\phi = 1$) cases. Table 4 shows the results. Santa Rita and Los Vascos show a relative efficiency of at least 80% in any case, and they prove to be the most efficient Chilean wineries. San Pedro follows closely, displaying efficiencies higher than 70% in all cases. In contrast, both Concha y Toro and Emiliana present low efficiencies for the pessimistic case under high variability (10%).

Considering the classification framework of Despotis and Smirlis (2002), Los Vascos is classified as E^{++} in all cases. That is, for each variability level, this winery is efficient under both the best and the worst conditions. Both San Pedro and Santa Rita are classified as E^{++} under the lowest variability level and E^+ in the other cases. In other words, this means that these wineries are efficient only under the best conditions. Finally, both Concha y Toro and Emiliana are never classified as E^{++}, which means these wineries are inefficient even under the best scenario.

Note, however, that the classification framework of Despotis and Smirlis (2002) is based on the extreme cases ($\phi = 0$ and $\phi = 1$); thus, it hides how the robust solutions change. To dig further into this issue, we focus now on the behavior of robust solutions for intermediate cases. Figure 3 shows the robust efficiencies for the three variability levels considered. To gain some insight into how robust solutions change, we introduce the following definitions:

Definition 4.1. *We define the efficiency threshold of a DMU as the lowest conservatism level that generates an efficiency of 100%. Then, we say that a DMU belongs to the class E^+_α, if it is classified as E^+ –in the sense of Despotis and Smirlis (2002)– and its efficiency threshold is equal to α.*

Table 5: Robust class of the Chilean wineries.

Variability	Winery	Robust Class	Status
1%	Concha y Toro	E^{-}	Inefficient
	Emiliana	E^{-}	Inefficient
	San Pedro	E^{++}	Efficient
	Santa Rita	E^{++}	Efficient
	Los Vascos	E^{++}	Efficient
5%	Concha y Toro	$E^{+}_{0.14}$	Robust inefficient
	Emiliana	$E^{+}_{0.06}$	Robust inefficient
	San Pedro	$E^{+}_{0.43}$	Robust inefficient
	Santa Rita	$E^{+}_{0.82}$	Robust efficient
	Los Vascos	E^{++}	Efficient
10%	Concha y Toro	$E^{+}_{0.18}$	Robust inefficient
	Emiliana	$E^{+}_{0.13}$	Robust inefficient
	San Pedro	$E^{+}_{0.31}$	Robust inefficient
	Santa Rita	$E^{+}_{0.43}$	Robust inefficient
	Los Vascos	E^{++}	Efficient

Definition 4.2. *We say that a DMU in the class E^{+} –in the sense of Despotis and Smirlis (2002)– is robust efficient if it belongs to the class E^{+}_{α} with $\alpha \geq 0.5$. In the other case, we say that the DMU is robust inefficient.*

Intuitively, a winery with an efficiency threshold close to one is likely to be more efficient than another DMU with an efficiency threshold close to zero. Table 5 shows the robust class of the Chilean wineries based on the previous definitions. As mentioned before, Los Vascos is efficient in any case. For each variability level, this winery has an efficiency threshold equal to one. On the other hand, no other winery is efficient in all cases. The closest follower is Santa Rita, which is at least robust efficient for all variability levels except the highest one. Notably, the robust class allows us to discriminate wineries that, according to Despotis and Smirlis (2002) definition, belong to the same class E^{+}. Particularly, it can be seen that Emiliana is the least efficient winery –in a robust sense– in all cases, followed by Concha y Toro.

When dealing with imprecise data, the rankings' maximum conformity may occur neither in the pessimist nor in the optimistic case (Shokouhi et al., 2010). Therefore, we develop a Monte-Carlo simulation to analyze the intermediate cases where the wineries ranking positions occur with high probability. For the three levels of variability considered, Figure 4 depicts the proportion of ranking positions that match to the robust ranking related to a specific conservatism level. For a variability level of 1%, the average conformity ranges between 40.0% to 89.1% and attains its maximum for ϕ equals to 0.04. For this case, the most likely ranking (i.e., when $\phi = 0.04$) is Los Vascos (1°), San Pedro (1°), Santa Rita (1°), Concha y Toro (4°) and Emiliana (5°). For a variability level of 5%, on the other hand, conformity ranges between 20.0% to 93.9% and attains its maximum for a conservatism level equals to 0.9. In this case, the most likely ranking is Los Vascos (1°), Santa Rita (2°), San Pedro (3°), Concha y Toro (4°), and Emiliana (5°). Finally, for the highest level of variability (10%), the conformity ranges between 20.0% to 91.3% and attains its maximum for a conservatism level of 0.78. In this case, the most likely ranking is the same as the previous case: Los Vascos leads, followed by Santa Rita, San Pedro, Concha y Toro, and Emiliana.

4.4. International comparative analysis

To put the results of Subsection 4.3 into context, we now add several international wineries to the analysis. This section aims to analyze how the Chilean wineries fare when compared to similar wineries from other countries, and whether the role model DMUs, i.e., those in the efficient frontier when considering only Chilean DMUs, continue being efficient. To limit the effect of differences in business scope, we restrict our analysis to wineries from the

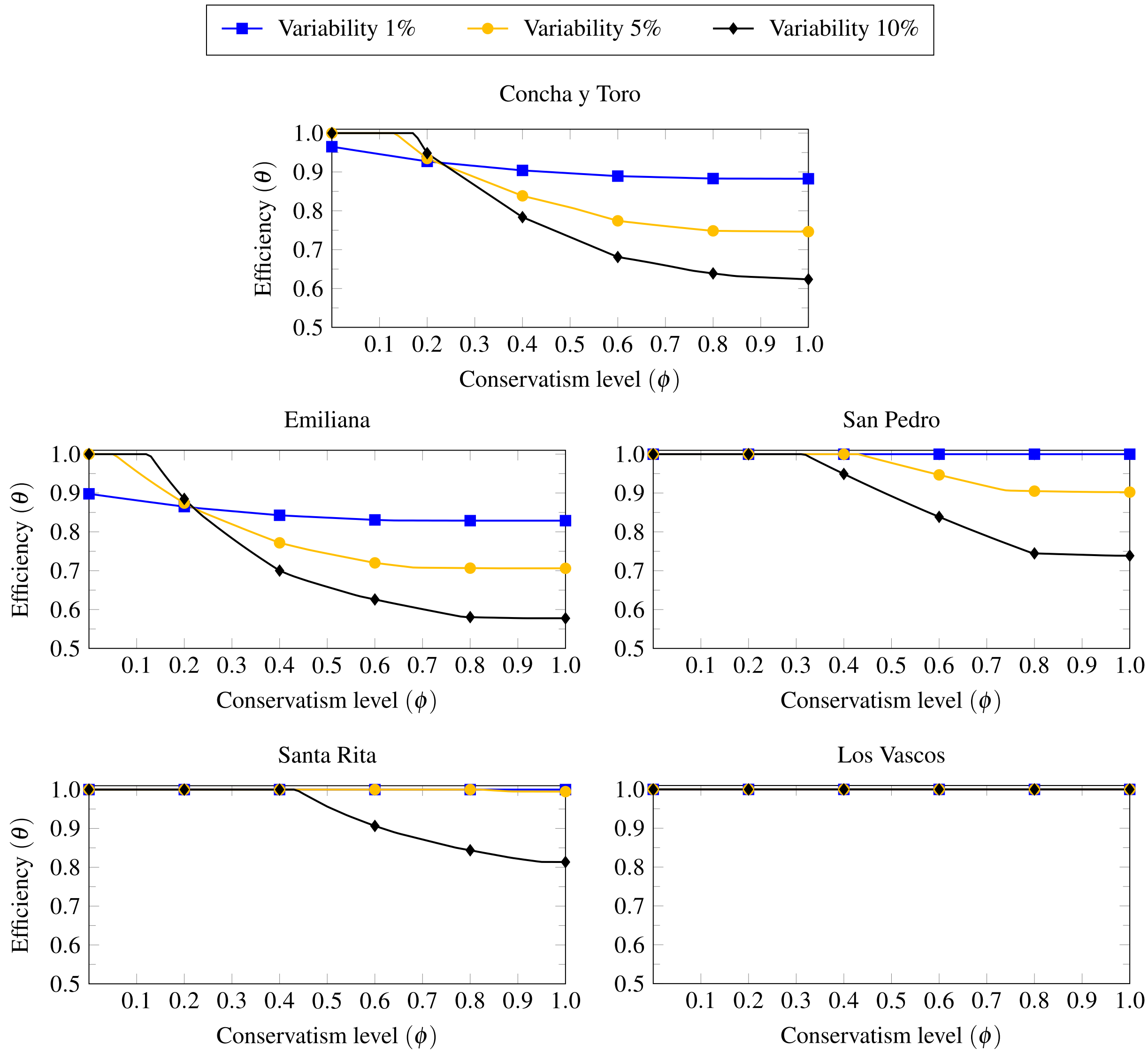

Figure 3: Robust efficiencies for three variability levels.

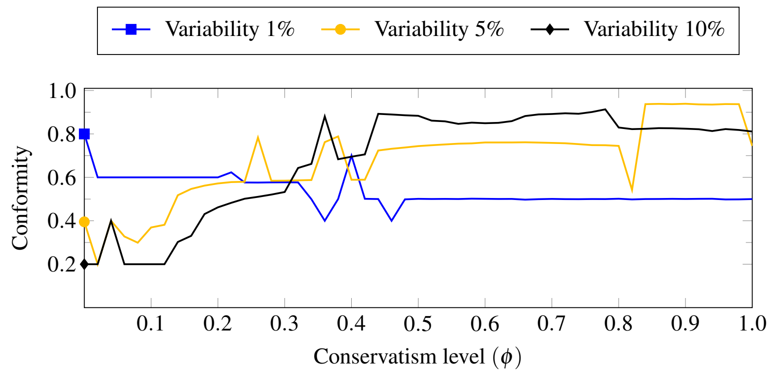

Figure 4: Conformity analysis.

New World, since, as Donthu et al. (2005) points out, DMUs with differences in their scope will have a different set of role models or efficient DMUs to follow.

To develop this extended case study, we considered wineries listed in the Stock Exchange of Australia, Canada, New Zealand, and the United States. We add those wineries with financial statements available in their web sites for the years 2018 or 2019. This procedure leaves us with 14 wineries: five Chilean wineries (described in Subsection 4.3) and nine international wineries. These last wineries are Treasury, Andrew Peller, Diamond State, Delegat, Foley, Palliser State, Marlborough, Crimson, and Willammet. Table 6 presents the input and output data for each one of them. In Appendix B, we provide the financial statement URL, pages consulted for gathering data, and the exchange rates used. Similar to the Chilean scenario, the international wineries considered differ in their sizes, with the biggest one (Treasury) having a total revenue that represents more than six hundred times the revenue from the smallest one (Palliser State).

Table 7 shows the wineries technical efficiency for three variability level ($\gamma = 0.01, 0.05, 0.10$) and five different conservatism levels ($\phi = 0, 0.25, 0.5, 0.75, 1$). For the lowest variability level (1%), six out of the 14 wineries (San Pedro, Santa Rita, Los Vascos, Treasury, Andrew Peller, Diamond State) remain efficient (E^{++}) regardless of the conservatism level. This set reduces to three wineries (Los Vascos, Andrew Peller, Diamond State) and two wineries (Los Vascos, Diamond State) when considering variability levels 5% and 10%, respectively. Conversely, three wineries are inefficient (E^{-}) in any case (Foley, Crimson, Willammet).

For the national wineries, Los Vascos continue being efficient in all cases, and thus, it leads the ranking among all of the 14 wineries, together with Diamond State. Santa Rita and San Pedro belong to, at least, the class E^{+} for all variability levels, and they end up in the top half of the ranking, which resembles the local ranking. Nevertheless, Santa Rita is no longer robust efficient for the 5% variability level. In the case of Concha y Toro and Emiliana, they are in the bottom half of the ranking, just as in the local ranking. Importantly, the inclusion of international wineries produces a decrease in the technical efficiency of Emiliana in the optimistic case for the 5% variability level, which makes them belong to the class E^{-} (inefficient) instead of the class $E^{+}_{0.06}$ (robust inefficient) as in the national analysis.

Table 6: Nominal inputs and outputs of the 14 wineries.

DMU		Inputs				Output
Winery	Country	Inventories (MUS$)	Property, Plant and Equipment (MUS$)	Intangible Assets (MUS$)	Land Area (Ha)	Total Revenue (MUS$)
Concha y Toro	Chile	399,254.12	563,155.79	686,83.69	11,624.00	883,931.24
Emiliana	Chile	19,161.54	36,356.79	1,481.24	769.00	30,929.63
San Pedro	Chile	95,244.52	182,635.44	31,303.49	3,884.00	297,247.62
Santa Rita	Chile	88,185.09	167,730.57	14,383.03	3,369.00	245,672.00
Los Vascos	Chile	15,929.00	52,545.00	76.00	722.00	29,476.00
Treasury	Australia	1,468,598.69	981,474.98	816,644.45	13,025.00	2,023,015.93
Andrew Peller	Canada	120,108.48	149,445.61	12,667.96	2,526.00	285,647.16
Diamond State	Canada	14,561.34	14,947.33	2,360.57	15.38	21,040.78
Delegat	New Zealand	106,030.36	352,346.86	3,324.83	3,460.00	186,710.10
Foley	New Zealand	29,607.74	68,004.43	21,617.41	498.00	32,202.44
Palliser State	New Zealand	2,224.46	7,458.04	44.04	753.00	3,266.43
Marlborough	New Zealand	1,948.42	10,013.13	19.53	153.00	3,613.43
Crimson	United States	77,267.00	126,230.00	11,859.00	337.51	67,766.00
Willammet	United States	16,247.11	25,784.45	4,862.91	285.30	23,079.74

5. Discussion and concluding remarks

The Chilean wine industry has been quite innovative in terms of winemaking and trading. Yet, to survive in this competitive industry, wine managers should be aware of the relevance of monitoring their performance. In this paper, we assessed how the five wineries listed on the Santiago Stock Exchange of Chile are efficient while using their critical resources for making profits. We used data gathered from consolidated financial statements to benchmark and rank these wineries. We considered four inputs and one output, which belong to the following five areas: revenue, working capital, property plant and equipment, and intangible assets. The consolidated financial

Table 7: Efficiencies and Ranking for three variability levels.

			Conservatism level ϕ									
			0.00 (Optimistic)		0.25		0.50		0.75		1.00 (Pessimistic)	
Variability γ	Winery	Class	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking
1%	Concha y Toro	E^-	89.93%	9°	86.06%	9°	83.85%	9°	83.02%	9°	83.02%	9°
	Emiliana	E^-	75.16%	11°	72.08%	11°	70.11%	11°	69.44%	11°	69.38%	11°
	San Pedro	E^{++}	100%	1°	100%	1°	100%	1°	100%	1°	100%	1°
	Santa Rita	E^{++}	100%	1°	100%	1°	100%	1°	100%	1°	100%	1°
	Los Vascos	E^{++}	100%	1°	100%	1°	100%	1°	100%	1°	100%	1°
	Treasury	E^{++}	100%	1°	100%	1°	100%	1°	100%	1°	100%	1°
	Andrew Peller	E^{++}	100%	1°	100%	1°	100%	1°	100%	1°	100%	1°
	Diamond State	E^{++}	100%	1°	100%	1°	100%	1°	100%	1°	100%	1°
	Delegat	$E^+_{0.23}$	100%	1°	99.81%	7°	97.10%	7°	96.66%	7°	96.64%	7°
	Foley	E^-	51.80%	14°	49.84%	14°	48.60%	14°	47.93%	14°	47.81%	14°
	Palliser State	E^-	78.8%	10°	75.17%	10°	72.86%	10°	72.74%	10°	72.74%	10°
	Marlborough	$E^+_{0.12}$	100%	1°	97.65%	8°	94.75%	8°	94.69%	8°	94.69%	8°
	Crimson	E^-	56.97%	13°	54.84%	13°	53.57%	13°	52.74%	13°	52.59%	13°
	Willammet	E^-	66.69%	12°	64.13%	12°	62.33%	12°	61.56%	12°	61.56%	12°
Variability γ	Winery	Class	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking
5%	Concha y Toro	$E^+_{0.05}$	100%	1°	84.83%	9°	75.62%	9°	71.46%	9°	70.72%	9°
	Emiliana	E^-	88.22%	11°	71.74%	11°	64.51%	11°	60.26%	11°	59.11%	11°
	San Pedro	$E^+_{0.38}$	100%	1°	100%	1°	95.46%	4°	91.63%	4°	91.60%	4°
	Santa Rita	$E^+_{0.29}$	100%	1°	100%	1°	90.63%	5°	88.55%	5°	88.50%	5°
	Los Vascos	E^{++}	100%	1°	100%	1°	100%	1°	100%	1°	100%	1°
	Treasury	$E^+_{0.28}$	100%	1°	100%	1°	90.17%	6°	87.08%	6°	86.24%	6°
	Andrew Peller	E^{++}	100%	1°	100%	1°	100%	1°	100%	1°	100%	1°
	Diamond State	E^{++}	100%	1°	100%	1°	100%	1°	100%	1°	100%	1°
	Delegat	$E^+_{0.20}$	100%	1°	96.72%	7°	84.62%	7°	82.32%	7°	82.07%	7°
	Foley	E^-	60.73%	14°	50.07%	14°	44.38%	14°	41.63%	14°	40.68%	14°
	Palliser State	E^-	92.49%	10°	73.8%	10°	64.58%	10°	62.11%	10°	61.98%	10°
	Marlborough	$E^+_{0.18}$	100%	1°	94.33%	8°	80.97%	8°	80.67%	8°	80.66%	8°
	Crimson	E^-	66.81%	13°	55.66%	13°	49.82%	13°	46.27%	13°	44.75%	13°
	Willammet	E^-	78.26%	12°	64.37%	12°	56.24%	12°	52.72%	12°	52.44%	12°
Variability γ	Winery	Class	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking	$\hat{\theta}^*$	Ranking
10%	Concha y Toro	$E^+_{0.12}$	100%	1°	83.67%	9°	67.66%	8°	60.47%	9°	57.85%	9°
	Emiliana	$E^+_{0.03}$	100%	1°	71.84%	11°	58.78%	10°	51.50%	10°	48.34%	11°
	San Pedro	$E^+_{0.29}$	100%	1°	100%	1°	82.50%	4°	76.16%	4°	74.97%	5°
	Santa Rita	$E^+_{0.25}$	100%	1°	100%	1°	76.53%	6°	72.55%	6°	72.52%	6°
	Los Vascos	E^{++}	100%	1°	100%	1°	100%	1°	100%	1°	100%	1°
	Treasury	$E^+_{0.27}$	100%	1°	100%	1°	80.22%	5°	75.74%	5°	75.35%	4°
	Andrew Peller	$E^+_{0.67}$	100%	1°	100%	1°	100%	1°	95.92%	3°	94.53%	3°
	Diamond State	E^{++}	100%	1°	100%	1°	100%	1°	100%	1°	100%	1°
	Delegat	$E^+_{0.20}$	100%	1°	94.1%	7°	74.9%	7°	67.93%	7°	67.5%	7°
	Foley	E^-	74.43%	14°	50.43%	14°	40.12%	14°	35.81%	14°	33.35%	14°
	Palliser State	$E^+_{0.05}$	100%	1°	73.28%	10°	58.38%	11°	51.26%	11°	50.68%	10°
	Marlborough	$E^+_{0.19}$	100%	1°	90.40%	8°	66.55%	9°	65.98%	8°	65.98%	8°
	Crimson	E^-	81.85%	13°	56.89%	13°	46.19%	13°	40.2%	13°	36.67%	13°
	Willammet	E^-	95.74%	12°	64.59%	12°	50.50%	12°	44.40%	12°	42.90%	12°

statements are prepared using estimates, judgments, and assumptions. Thus, the reported values are prone to change. To account for some level of accounting adjustments of the input and output parameters, we evaluated these wineries' relative efficiency using a robust DEA model.

When analyzing only the Chilean case, our computational results showed that Los Vascos is efficient in any case and leads the ranking. Particularly, for each variability level, this winery has an efficiency threshold of one. The closest follower is Santa Rita, efficient for the lowest variability level, robust efficient for the medium variability level, and robust inefficient for the highest variability level. On the other hand, San Pedro is the third-ranked winery, being efficient for the lowest variability level, and robust inefficient for both medium and high variability levels. Concha y Toro and Emiliana are the lowest-ranked. Both wineries are inefficient for the lowest variability level and are robust inefficient for the remaining variability levels. We also conducted a comparison between the five Chilean wineries and nine others from the New World. As the main conclusion, we found that Chilean wineries keep their efficiency level when including international firms in the analysis. This fact supports the increasing relevance of Chilean wineries, which has allowed them to compete successfully in the international context.

By analyzing correlation coefficients, we find that small wineries, in terms of revenue and land area, tend to have lower efficiency. This result is opposed to the findings of Jiménez et al. (2013) that detected Designation of Origin with large surfaces are the most inefficient ones. On the other hand, Urso et al. (2018) finds an increasing trend in the efficiency index in large grapevine producers, particularly those that process and not only sell grapes. Similarly, Sellers and Alampi-Sottini (2016) argues that there is a positive correlation between firm size (measured by total employees and total assets) and profitability, since large firms have at their disposal greater technical and commercial opportunities, allowing them to benefit from real and financial economies of scale. These last two findings are in line with our results.

This research has some limitations. First, we only use quantifiable economic performance indicators, leaving apart other subjective measures, such as the wine's quality. Second, and given the lack of information, only five Chilean wineries were considered. Thus, the generalization of the findings of the paper should be made with caution.

As future research, we plan to develop surveys and semi-structured interviews for collecting data from a larger number of Chilean wineries, broadening the scope. We think this kind of analysis would help the whole Chilean wine industry to make better decisions when managing their scarce resources. Finally, we expect to incorporate emission variables in the wine industry for future research, which have been found to produce a sizable impact (Jradi et al., 2018).

Data availability statement

The data that support the findings of this study are available from the corresponding author, Mauricio Varas, upon email request.

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Appendix A. Algorithm used for the computational experiments

Algorithm 1 in this appendix shows the steps followed for computing the robust efficiencies, the rankings and the conformity levels.

Algorithm 1 Computational experiments steps.

Input: wineries (n), nominal inputs ($\bar{x}$), nominal outputs ($\bar{y}$), variability levels (γ), conservatism levels (ϕ) and number of replications (k).
for each γ **do**
  for each ϕ **do**
    for each p **do**
      Solve model (10).
      Let $\hat{\theta}_p^*$ be the robust efficiency and $\{\{\hat{v}_{ip}^*\}_i, \hat{u}_{rp}^*\}$ be the robust weights.
    end for
    Return robust efficiencies $\{\{\hat{\theta}_{j\gamma\phi}^*\}_j\} \leftarrow \{\{\hat{\theta}_j^*\}_j\}$.
    Rank the wineries based on their efficiency scores $\{\{\hat{\theta}_j^*\}_j\}$. Let $\pi_{\gamma\phi}$ be the robust ranking.
    Generate k sets of random values $\{\{\tilde{x}_{ij}\}_{i,j}, \{\tilde{y}_{rj}\}_j\}$ uniformly distributed within the bounds (11).
    Let $\nu_{\gamma\phi}$ be the conformity level. $\nu_{\gamma\phi} \leftarrow 0$.
    for $l \in \{1, \ldots, k\}$ **do**
      Compute the efficiency scores using expression (12) and rank the DMUs accordingly. Let $\pi_{l\gamma\phi}$ be the simulated ranking and let ν be a given position.
      for $\nu \in \{1, \ldots, n\}$ **do**
        if $\pi_{\gamma\phi}^{(\nu)} = \pi_{l\gamma\phi}^{(\nu)}$ **then**
          Let $\nu_{\gamma\phi} \leftarrow \nu_{\gamma\phi} + 1/(k \cdot n)$.
        end if
      end for
    end for
    Return conformity level $\nu_{\gamma\phi}$.
  end for
end for

Appendix B. Financial statements URL and page numbers

Tables 8 and 9 show information about the gathered data.

Table 8: Documents URL and pages consulted.

DMU					Inputs				Output
Winery	Financial statement URL	Ended period	Currency	Land	Inventories	Prty, Plnt and Eq.	Intangible Assets	Land Area	Total Revenue
Concha y Toro	conchaytoro.com	Dec. 31th 2018	M$CLP	Hectares	p. 8	p. 8	p. 8	p. 83	p. 10
Emiliana	emiliana.cl	Dec. 31th 2018	M$CLP	Hectares	p. 29	p. 29	p. 29	p. 12	p. 30
San Pedro	vsptinvestor.com	Dec. 31th 2018	M$CLP	Hectares	p. 6	p. 6	p. 6	p. 58	p. 8
Santa Rita	santarita.com	Dec. 31th 2018	M$CLP	Hectares	p. 6	p. 6	p. 6	p. 59	p. 8
Los Vascos	vinalosvascos.cl	Dec. 31th 2018	M$USD	Hectares	p. 37	p. 37	p. 37	p. 45	p. 39
Treasury	tweglobal.com	Jun. 30th 2019	MM$AUD	Hectares	p. 65	p. 65	p. 65	p. 81	p. 64
Andrew Peller	andrewpeller.com	Mar. 31th 2019	M$CAD		p. 26	p. 26	p. 26	p.	p. 27
Delegat	delegat.com	Jun. 30th 2019	M$NZD	Hectares	p. 31	p. 31	p. 31	p. 19	p. 26
Crimson	crimsonwinegroup.investorroom.com	Dec. 31th 2018	M$USD	Acres	p. 54	p. 54	p. 54	p. 14	p. 55
Foley	foleywines.co.nz	Jun. 30th 2019	M$NZD	Hectares	p. 24	p. 24	p. 24	p. 53	p. 21
Willamette Valley	wvv.com	Dec. 31th 2018	$USD	Acres	p. 53	p. 53	p. 53	p. 25	p. 54
Diamond Estate	lakeviewwineco.com	Mar. 31th 2019	$CAD	Acres	p. 5	p. 5	p. 5	p. 23	p. 6
Palliser Estate	www.palliser.co.nz	Jun. 30th 2019	$NZD		p. 23	p. 23	p. 23	p.	p. 21
Malborough	nzmwe.com	Jun. 30th 2019	$NZD	Hectares	p. 15	p. 15	p. 15	p. 30	p. 13

Table 9: Exchange.

Country	Currency	Currency Code (ISO 4217)	Period Ended	Value (USD/x)
Chile	Chilean Pesos	CLP	Dec. 31th 2018	0.001439325244
Canada	Canadian Dollar	CAD	Mar. 31th 2019	0.7481669909
New Zealand	New Zealand Dollar	NZD	Jun. 30th 2019	0.6716818915
Australia	Australian Dollar	AUD	Jun. 30th 2019	0.7017051435

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