Ridge Penalization-based weighting approach for Eco-Efficiency assessment: The case in the food industry in the United States

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Abstract. Eco-efficiency assessment is of great importance for monitoring and managing environmental and economic aspects of sustainable development. The eco-efficiency indicators are required to assess and measure the impact of multiple environmental aspects per unit of economic value-added. The aggregation of multiple environmental impacts in the presence of high correlation is a critical challenge to sustainability practitioners. This study presents a weighting approach using ridge penalization-based regression to overcoming the consequence of the high correlation among the environmental aspects and hence providing accurate weighting values. The performance of the proposed approach is assessed using economic and environmental footprints of 20 food industries in the United States. The new weighting approach is expected to provide decision-makers with a quantitative management tool for monitoring and controlling core operational functions associated with the sustainable development and management.

1. Introduction

The eco-efficiency assessment is widely recognized as a powerful management tool for managing environmental sustainability aspects and enhancing the opportunities of the well-being of future generations [1]-[6]. The alignment with the sustainable development goals of the United Nations has recently become the focus of governmental and business organizations at both national and international levels [7]. The eco-efficiency assessment with high dimensional space of environmental impacts imposes a critical challenge to sustainability practitioners in specifying the weight of each environmental indicator to the eco-efficiency value [8],[9].

Several weighting techniques have been proposed and examined in literature, for instance, not limited to, linear programming [10],[11], Principal Component Analysis (PCA), Data Envelopment Analysis (DEA), and Factor Analysis (FA) [12]-[14], Regression Analysis [15]. The equal weighting (EW) is the most common among the existing methods [16]-[18]. Despite the distinctive advantage of mathematical and operational properties, this method has been extensively criticized for the lack of considering the double-counting when multiple indicators measure the same behavior [19].

The extension of statistical methods to the sustainability assessment context has received increasing attention over the recent years; see, for instance [20],[21]. The PCA, DEA, and FA are widely recognized for their ability to accommodate high dimensional space of sustainability indicators. Moreover, these methods are independent of subjective opinions [4]. The PCA is mainly based on the development of the Principal Components (PCs) as a linear combination of the corresponding sustainability indicators, then use their associated weight to complete the aggregation step in order to obtain a single value representing the overall environmental impact of these indicators [22].
The collinearity among two or more of the sustainability indicators describes the extent of linear correlation between the variables [23] thus, critical to the outcome of several of the existing weighting methods. The PCA is extensively used in literatures due to its capability in effectively handling the collinearity among the sustainability indicators [3],[24],[25]. Despite the merits, PCA lacks in interpreting the results of the dimension reduction analysis.

The PCs are linear combinations of all original indicators. A large number of independent variables can result in numerous significant coefficients in the first few PCs. The matter makes these PCs difficult to explicate [23],[26],[27]. Moreover, despite that the PCA is preferred for not relying on subjective and arbitrary opinions, it can be criticized for ignoring the relationship between the independent and dependent variables, especially as a weighting method. The inclusion of this relationship would provide a second criterion, in addition to the variation of the data matrix, to precisely quantify the individual weight of each of the sustainability indicators.

The PCA assigns a high amount of variance to the PC with the largest scale, the matter that results in undesirable skewness in the outcome. The normalization is a very well-known step to overcoming this issue. A difficulty that may result due to the normalization of the data matrix is that the number of PCs increases leading to difficulties in interpreting the results.

In accordance with the above, this paper presents a systematic methodology for eco-efficiency assessment using the ridge penalized regression to overcome the multicollinearity among the sustainability indicators. The ridge penalized regression is widely recognized in statistic for its effectiveness in overcoming the effect of multicollinearity on the accuracy and stability of the regression model. This study uses a dataset that represents the environmental impact of 20 food industries in the United States.

2. Methods

2.1. Input-Output (I-O) Model

The single region industry-by-industry I-O model is used here based on the Eora database that is connected with the UN’s System of National Accounts and COMTRADE databases [21],[28]. In this study, the domestic supply and use tables (SUTs) of the U.S. economy were combined with several sustainability indicators. Then, the I-O model is used to quantify the economic (value-added), and environmental impacts of 15 food consumption industries in US; see Table 1.

| No. | Industrial Category              | Symbol   |
|-----|---------------------------------|----------|
| 1   | Beet sugar manufacturing        | S1-BSM   |
| 2   | Breakfast cereal manufacturing  | S2-BCM   |
| 3   | Cheese manufacturing            | S3-CM    |
| 4   | Coffee and tea manufacturing    | S4-CTM   |
| 5   | Dog and cat food manufacturing  | S5-DCFIM |
| 6   | Fats and oils                   | S6-FAO   |
| 7   | Flour milling and malt          | S7-FMM   |
| 8   | Frozen food manufacturing       | S8-FFM   |
| 9   | Poultry processing              | S9-PP    |
| 10  | Seafood product                 | S10-SP   |
| 11  | Snack food manufacturing        | S11-SFM  |
Table 1. Food industrial sectors (Cont.)

| No. | Industrial Category                | Symbol  |
|-----|-----------------------------------|---------|
| 12  | Soft drink and ice manufacturing  | S12-SDIM|
| 13  | Sugar mills and refining          | S13-SMR |
| 14  | Tortilla manufacturing            | S14-TM  |
| 15  | Wet corn milling                  | S15-WCM |

2.2. Ridge Penalization-based Regression

The multiple regression analysis has been widely recognized in the literature as an effective tool to overcome the collinearity; see, for instance, [29]-[32]. The collinearity refers to the extent to which the indicators are linearly correlated to each other [33]. The multiple regression estimates the weights or relative-importance based on the extent to which each of the sustainability indicators significantly contributes to explaining the variability around the response variable. The penalization-based regression, in particular, has received notable attention as a weighting method; see [34],[35].

This paper uses a ridge penalization-based regression as a weighting method to overcome the multicollinearity phenomenon among the sustainability indicators. The error term \( \varepsilon \), in the generalized linear relationship between response variable \( y \) and predictor variable \( x \) as shown in eq (1), is assumed to have a normal random distribution.

\[
y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i \quad ; i = 1,2,\ldots \quad (1)
\]

where \( \beta_j \) is the coefficient estimate associated with the \( j \)-th indicator, and \( p \) is the number of indicators. The ridge-penalized regression is commonly formulated as a minimization problem of the squared errors when the problem is solved using the Ordinary Least Squared (OLS), Weighted Least Squared (WLS), or Maximum Likelihood Estimation (MLE) methods. The OLS and WLS are easier in practice than the MLE were the decision of selection depends on the practitioner. The ridge-based OLS formulation is as follows:

\[
\hat{\beta}_{\text{Ridge}} = \arg \max_{\hat{\beta} \in \mathbb{R}^p} \left\{ \sum_{i=1}^{n} \left( y_i - \hat{\beta}_0 - \sum_{j=1}^{p} x_{ij} \hat{\beta}_j \right)^2 + \lambda \sum_{j=1}^{p} \hat{\beta}_j^2 \right\} \quad (2)
\]

where \( \hat{\beta} \) is a vector that contains the estimated values of the regression coefficients, \( n \) is the number of observations, and \( \lambda \) is the tuning or shrinkage parameter, and its value is usually specified by K-fold cross-validation. Several computer packages available in the CRAN library and packages such as SPSS and Solver-Excel, can be used to solve the ridge-based OLS formulation, shown in (2). However, Figure 1 shows the outlines of the proposed methodology.

3. Case study

3.1. Data generation and distribution
This study uses five sustainability indicators related to the food and beverage industry in U.S. These are: (1) CO$_2$ (Kt), (2) CO (Kt), (3) HFC-143a (Kt), (4) PM$_{10}$ (Kt), (5) N$_2$O (Kt), and (6) SO$_2$ (Kt). The sustainability impacts of these indicators were estimated by using the Eora database-based economic input-output framework developed by [27] using the latest and high-resolution I-O tables of the U.S. economy; see also [36]. The household consumption (HC) under each food industrial category were calculated and used as the response variable. Figure 2 illustrates the distribution of the highest three impacts under each of the sustainability indicators.

3.2. Measuring Collinearity

This section is dedicated to measuring the level of collinearity among the sustainability indicators. The correlation of determination ($R^2$) is the most widely used method to measure the collinearity. Normalization step is neglected here due to the usage of same units for the selected indicators. In this study, $R^2$ explains the percentage of variation in one of the sustainability indicators that is predictable from the other indicators. The magnitude of the $R^2$ measure is limited between “0” and “1”. The value “0” refers to a “very-poor” linear relationship, while the value “1” to a “very-strong” linear relationship.

![Figure 2. Distribution of the highest three-environmental sustainability impacts](image)

The pairwise correlations among all the potential pairs of the sustainability indicators can be seen in Table 2.

|       | CO$_2$ | CO   | HFC  | PM$_{10}$ | N$_2$O | SO$_2$ |
|-------|-------|------|------|-----------|--------|--------|
| CO$_2$| **1.000** | 0.979 | 0.874 | 0.937     | 0.888  | 0.942  |
| CO   | 0.979 | **1.000** | 0.830 | 0.975     | 0.957  | 0.866  |
| HFC  | 0.874 | 0.830 | **1.000** | 0.829     | 0.754  | 0.922  |
| PM$_{10}$ | 0.937 | 0.975 | 0.829 | **1.000** | 0.986  | 0.820  |
| N$_2$O | 0.888 | 0.957 | 0.754 | 0.986     | **1.000** | 0.726  |
| SO$_2$ | 0.942 | 0.866 | 0.922 | 0.820     | 0.726  | **1.000** |

The correlation matrix shows a moderate to strong positive correlations ranging from 0.726 to 0.986. This finding would justify the need for ridge-penalization based regression.
3.3. Weighting sustainability indicators

To initiate the ridge-penalized regression, we used the Trace-Plotting method, proposed by [25], to determine the optimal value of \( \lambda \). This method has been widely used under different research contexts; see, for instance, [22],[26]. Initially, the ridge regression coefficients are plotted over a wide range of \( \lambda \). Secondly, we define the range of \( \lambda \) that exhibits better stability of the fitted regression coefficients. Finally, we select a single value of \( \lambda \) providing a better criterion of selection. However, The Mean Square Error (MSE), is used as a criterion for the selection of the optimal \( \lambda \). Figure 3 shows the distribution of the ridge regression coefficients over a wide range of the tuning parameter \( \lambda \). From Figure 3, one can easily notice the stability in the changes of the regression coefficients, namely the CO\(_2\), SO\(_2\), HFC-143a, and NO\(_2\), around the optimal \( \lambda \). The best stability can be achieved when the \( \lambda \) value equals 0.014 to 1.4. The MSE at several values of \( \lambda \) has been estimated and the optimal value of \( \lambda \) is found to be 0.090 (MSE = 0.00092).

![Figure 3. Changes of regression coefficients versus the tuning parameter](image)

Table 3. ANOVA Calculation

| Source of Variation | d.f. | SS    | MS    | F       | p-value   |
|---------------------|------|-------|-------|---------|-----------|
| Regression          | 6    | 13.86 | 2.310 | 153.3   | 1.53E-08  |
| Residual            | 9    | 0.135 | 0.015 |         |           |
| Total               | 15   | 14    |       |         |           |

Table 4. Ridge Regression outcome

|          | CO\(_2\) | CO   | HFC  | PM\(_{10}\) | N\(_2\)O | SO\(_2\) |
|----------|----------|------|------|-------------|----------|----------|
| \( \beta \) | 0.46     | 0.11 | 0.152| -0.081      | -0.181   | 0.519    |
| \( R^2 \) | 0.995    |      |      |             |          |          |
| Adjusted \( R^2 \) | 0.983 | | | | | |
| Standard Error | 0.122 | | | | | |
| MSE | 0.000092 | | | | | |

In this study, we replace the individual weight of the sustainability indicator by their associated relative weight (RW). The RW represents the importance of a specific indicator with regard to the other indicators. The RW is found as the absolute value of the individual weight divided by the sum of
the absolute values of the individual weight of all the sustainability indicators. Table 5 reports the calculations of the weighting step.

| Table 5. Weight Calculation |
|----------------------------|
| CO₂ | CO | HFC | PM$_{10}$ | N$_2$O | NO$_2$ |
|-------------------|-----|-----|----------|-------|-------|
| Absolute weight   | 0.46| 0.11| 0.152    | 0.081 | 0.181 | 0.519 |
| Initial Rank      | 2    | 5   | 4        | 6     | 3     | 1     |
| Relative Weight   | 0.31 | 0.07| 0.10     | 0.05  | 0.12  | 0.35  |

### 3.4. Eco-Efficiency score calculation

The eco-efficiency is often calculated as the ratio between the economic value-added and the aggregation of the weighted impacts of the environmental indicators. Using the RW values reported in Table 4, we calculated the eco-efficiency scores for all the industrial categories and reported these scores in Figure 4.

![Figure 4. Eco-efficiency score distribution of the food and beverage industry](image)

From Figure 4, S2-BCM has the highest eco-efficiency score, while the S1-BSM is the lowest. Several of the food and beverage industries have scored high scores, such as S14-TM, S11-SFM, and S5-DCFM. The eco-efficiency ratio or score, calculated can be referred to as the “higher the better” performance measure. This matter makes the comparison between the eco-efficiency performances of the industrial sectors difficult. However, in this paper, we use the average score of the eco-efficiency as a threshold between the “Below-Average,” “On-Average” and “Above-Average” performance and specify the category of each industry based on its location with respect to the threshold value (5.26); see Table 6.
Table 6. Eco-Efficiency categories

| Category | Above-Average | On-Average | Below-Average |
|----------|---------------|------------|---------------|
| Industry | S2-BCM        |            | S1-BSM        |
|          | S4-CTM        |            | S3-CM         |
|          | S5-DCF M      |            | S6-FAO        |
|          | S10-SP        | ---        | S7-FMM        |
|          | S11-SFM       |            | S8-FFM        |
|          | S12-SDIM      |            | S9-PP         |
|          | S14-TM        |            | S13-SMR       |
|          |               |            | S15-WCM       |

The results in Table 5 show that 53.34% of the food industries are classified as “Above-Average” performance, while the rest are “Below-Average” performance. The results also show that none of the industrial categories is classified as “On-Average” performance.

4. Conclusion and Remarks
This research work introduced a penalization-based approach for estimating weights of sustainability indicators. Here, the importance of the penalization in reducing the impact of multicollinearity among the sustainability indicators during the aggregation step is emphasized. The results have shown that more than 50% of the food industries in the US are performing well in terms of eco-efficiency performance. The (BCM) has the best eco-efficiency performance, while the (BSM) has the worst performance comparing with the other indicators. However, in terms of the individual eco-efficiency performance, all the food and beverage industries have scored a value that is greater than 1.

For future research, variable selection methods, such as stepwise regression, can be used to identify the most significant indicators to be included in the weighting process [38]-[40]. The authors also suggest the extension of the adaptive LASSO-based thresholding to enhance the estimation of variance-covariance matrix of the PCA method. The new approach will be used later for developing of a composite indicator of eco-efficiency assessment, further details of the adaptive LASSO can be found in [41],[42]. For future research, the authors also suggest the use of hybrid life cycle sustainability assessment methods [40]-[55]; ecological footprint analysis [56]-[58]; and economic input-output analysis [59], combined with other decision making models such as fuzzy multi criteria decision making [60], forecasting [61], agent based modelling [62],[63], and system dynamic modelling [64]-[68] considering Triple Bottom Line (TBL) approach. Finally, the multivariate regression is another suggested approach [69]-[70] to complete the aggregation step and develop a single composite indicator for the sustainability assessment, ruling out the difficulty in finding an appropriate response variable.

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