UNIVERSITÀ DEGLI STUDI DI MESSINA

DIPARTIMENTO DI ECONOMIA

CORSO DI DOTTORATO IN ECONOMICS, MANAGEMENT AND STATISTICS

XXXVI Ciclo

SSD: SECS-P/02

From EU Recovery and Resilience Plans to Italian Special Economic Zones: First Systematic Analyses

Tesi di Dottorato di:
PAOLO MUSTICA

Supervisore:
Chiar.mo Prof.
EMANUELE MILLEMACI

ANNO ACCADEMICO 2022/2023

Table of Contents

List of Figures

List of Tables

Chapter 3. The impact of Special Economic Zones on Southern Italy..66

Introduction

Textual analysis, European Recovery and Resilience Plans and Italian Special Economic Zones. These are the three keywords that we can use to summarize each chapter of this thesis. Although the contents of these three chapters may seem very different from each other, they are actually linked by a particular leitmotif, that of trying to produce innovation, both in the sense of proposing new methods of analysis and in the sense of exploring policy interventions that have been implemented in the last few years.

In particular, the first chapter proposes a new classifier for the word classification task, the Prior Adaptive Bayes classifier. Although in recent years computer science has made surprising improvements in the field of Natural Language Processing, in Economics and Finance most works continue to use very simple textual analysis methods, and in particular the dictionary-based approach. This method usually entails that authors define *ex ante* a vocabulary of words to which they associate a specific class, and then they count in the analyzed documents the number of words associated with each class. Since textual analysis works are usually linked to different fields, each of which is characterized by a specific jargon, authors often build a vocabulary adapted to the field studied. Thus, we have dictionaries for the field of finance, for that of management, and so on. Those who defend the dictionary-based approach usually state that first such a method is enough for the tasks usually implemented in Economics and Finance, especially that of revealing the prevailing sentiment in documents. Second, those in favor of this approach argue that, unlike other fields such as computer science, Economics needs clear and transparent methods in their functioning. This is because as the complexity of a method increases, the less clear it is how that method achieved certain results, increasing concerns about the interpretability of the final results. Consequently, in the first chapter we proposed something new that can be used in Economics projects that use textual analysis, without neglecting the main concerns of economists. On the one hand, the proposed Prior Adaptive Bayes classifier has the advantage that it can be used for the word classification task on any topic (it can also be adapted to perform sentiment analysis regardless of the jargon used). On the other hand, although it is more complex than the dictionary-based approach, the proposed classifier continues to be easy to understand and transparent in its functioning.

The second chapter is actually related to the previous one, because it proposes an application of the Prior Adaptive Bayes classifier in an economic project aimed at performing a first systematic analysis of the European Recovery and Resilience Plans. These plans are documents that describe the set of reforms and investments to be implemented in each EU member state by the end of 2026 to mitigate the economic and social impact of the Covid-19 pandemic. Since our inputs are documents containing words, we used the Prior Adaptive Bayes classifier to analyze them. The idea is to investigate the Recovery and Resilience Plans in relation to the Sustainable Development Goals, a set of goals proposed by the United Nations in 2015 to be achieved by 2030. This is because these goals should be achieved by any country in the world, regardless of its level of development. Consequently, it makes sense to investigate their presence in the European plans and this is what we did in the second chapter.

Finally, the last chapter deals with a more traditional econometric analysis aimed at performing a preliminary evaluation of the Italian Special Economic Zone program. Indeed, it is a new policy tool in Italy which, although it was introduced in 2017, has only recently become fully operational. Italian Special Economic Zones have an ambitious goal, that of significantly reducing the historic development gap between Northern Italy, whose economy has progressively integrated with the developed European economies since the end of the 19th century, and the economy of Southern Italy, which lagged behind. After an extensive review of the recent literature on Special Economic Zones, we carried out a first quantitative analysis on the effectiveness of this policy on Southern Italy as a whole and on each Italian region treated by this policy.

CHAPTER 1

A Bayes classifier for word classification

Abstract

This chapter proposes the Prior Adaptive Bayes classifier (PAB classifier), a new classifier to assign words appearing in a text to their respective topics. It is an adaption of the Bayes classifier where the prior probabilities of topics are replaced with the corresponding posterior probabilities associated with the surrounding words. We carried out experiments on a dataset usually used to test text algorithms, showing that adapting the priors to the corresponding posteriors given that the preceding words occurred allows us to obtain a significant improvement over the original classifier. Moreover, while for the original classifier the accuracy dropped drastically by adding another class, the PAB classifier continued to maintain good performance. Finally, we observed a further improvement in terms of accuracy considering not only the preceding words but also the following words.

Keywords: Machine learning; Bayes classifier; Prior Adaptive Bayes classifier; textual analysis; text mining

1. Introduction

Natural Language Processing is a subfield of linguistics and computer science that deals with computer applications whose input is natural language (Cohen and Demner-Fushman, 2014). Studies where natural language is the main input have been conducted in several fields, such as history and literature (Bateman and Jeffrey, 2011; Steier, 2019), medicine and psychology (Chapman *et al.*, 2011; Scaccia, 2021), and economics and finance. Focusing on the latter field, in the last years Picault and Renault (2017) developed a field-specific dictionary to measure the stance of the European Central Bank (ECB) monetary policy and the state of the Eurozone economy through the content of ECB press conferences. Starting from this lexicon, they computed a monetary policy indicator and an economic outlook indicator by analyzing the words appeared in each introductory statement of ECB press conferences. Their results show that the proposed dictionary explains future ECB monetary decisions and market volatility. Renault (2017) implemented a novel approach to derive investor sentiment from messages posted on social media. To do this, he constructed a lexicon of words used by stock market investors on social media and tested it on a test set of tagged messages. The accuracy achieved by this lexicon outperformed two well-known dictionaries usually adopted to measure sentiment in newspaper articles. Then, he used his lexicon to examine the relationship between the sentiment of stock market investors and intraday stock returns using a dataset of messages published by online investors on the microblogging platform StockTwits, finding that change in investor sentiment predicts positively the S&P 500 index ETF returns. Thorsrud (2020) constructed a daily business cycle index based on quarterly GDP growth and textual information contained in a daily business newspaper. For the analysis of newspaper data, he combined supervised and unsupervised methods, respectively a dictionary-based technique and a topic model belonging to the Latent Dirichlet Allocation class. He demonstrated that his index classifies the phases of the business cycle with almost perfect accuracy, outperforming coincident indexes based on more traditional economic variables. Alfano and Guarino (2022) analyzed the impact of text structure and given keywords in the announcements of house sales over the internet, finding that using many nouns and adjectives in writing a house sale announcement helps to sell the property at a higher price. More recently, Aprigliano *et al.* (2023) proposed a text-based sentiment index and an economic policy uncertainty index for forecasting Italian economic activity using a dictionary-based approach. They built a dictionary by downloading textual data from four popular national newspapers and assigned to each dictionary item a positive or negative polarity. Then, they used their dictionary to construct the two indices, which were therefore used in econometric analysis. The text-based models were usually able to produce more accurate forecasts of several macroeconomic indicators, such as the variation of the GDP, in comparison to the baseline model not accounting for the text indices.

Although simple textual analysis methodologies, such as the dictionary-based approach, have been used by most of the Economic literature, they present some limitations. The first is that this approach usually needs a field-specific dictionary. Although in the literature there are some validated dictionaries to measure sentiment in the traditional media types, such as the Harvard-IV dictionary (Tetlock, 2007) and the LM dictionary (Loughran and McDonald, 2011), they might not be suitable in those cases where a specific jargon is predominant, such as the comments on financial issues reported in social networks. In these situations, the selection of the words to include in the dictionary may be a very subjective choice. Second, while the dictionary-based approach is usually used for a specific task, that of revealing a sentiment (usually positive or negative) in a text, its use is difficult in non-sentiment analyses. Third, the dictionary-based approach implies that the researcher uses only a few words or groups of words to assign a sentiment, discarding the majority of the words in a text and giving up their potentially interesting content (Hastie *et al.*, 2015).

A step forward in the analysis of unstructured data as textual data is the use of machine learning methods, which usually perform better than dictionary-based approaches (Kalamara *et al.* 2022). Several machine learning algorithms are available depending on the nature of the tasks to be implemented. Athey and Imbens (2019) surveyed machine learning methods that are very popular in the context of regression analysis in economics such as the LASSO and ridge regression (Hoerl and Kennard, 1970; Tibshirani, 1996), regression trees and random forests (Breiman *et al.*, 1984; Breiman, 2001), and neural networks and related deep learning methods (Hornik *et al.*, 1989; White, 1992). On the other hand, for the classification of textual data is often used the Bayes classifier (Sahami *et al.*, 1998; Wang, 2010). The Bayes classifier not only has the great advantage that it works well with textual data, but it is also easy to understand and transparent as compared to other complex methods, such as those based on neural networks (Ash and Hansen, 2022).

This chapter proposes a new textual classifier, an adaption of the Bayes classifier for the word classification task. Its main characteristic is that the prior probabilities of topics are not constant but adapt to the corresponding posterior probabilities associated with the adjacent words. Simulations show that this classifier achieves an improvement of more than 20% over the original classifier. In particular, the chapter is structured as follows: first, the problem of the classification of individual words will be introduced with an example, in which the original Bayes classifier will be applied, describing its main limitations. Then, the proposed classifier and its properties will be described. In the fourth section the original classifier and the proposed algorithm will be compared using a well-known dataset usually used for testing the performance of text classification algorithms. The fifth section introduces other classification strategies. The last section concludes.

2. The Bayes classifier

In a text, words are not randomly distributed but clustered in topics: a group of words generates a topic, another group generates another topic, etc. (Hildum, 1963). In the task of associating words to topics, looking at the adjacent words can help minimize mistakes. To better illustrate this point, consider the following sentence:

"*For me, the best animals are cats and dogs, while the best dishes are cheeseburgers and hot dogs*"

The sentence contains two topics: the first part is about animals, and the second one is about food. After excluding stop words (Alshanik *et al.*, 2020), the sentence becomes:

"*animals cats dogs dishes cheeseburgers hot dogs*"

The word "dogs" occurs twice but it does not belong to the same topic in both cases. To correctly associate each word "dogs" with its respective topic, the adjacent words can be used to improve prediction. One may consider it reasonable to assign the first "dogs" to the topic of animals, being it close to the words "animals" and "cats", and the second "dogs" to the topic of food, being it close to the words "dishes", "cheeseburgers" and "hot".

A well-known algorithm used for document classification is the Bayes classifier (Mitchell, 2019). For the classification of individual words, the Bayes classifier can be written as a maximum *a posteriori* estimation:

$$\arg\max_{j} pr\left(c_j | x_i = w_k\right) = \frac{pr\left(x_i = w_k \middle| c_j\right) pr\left(c_j\right)}{\sum_j pr\left(x_i = w_k \middle| c_j\right) pr\left(c_j\right)}$$

where x_i is the i-th word in the text, w_k is the k-th word in the vocabulary and c_j is the j-th class. Using the framework of Bayes' theorem, $pr\left(c_j | x_i = w_k\right)$ is the posterior probability of the class j given the word i in the text, $pr\left(x_i = w_k \middle| c_j\right)$ is the likelihood of c_j given a fixed x_i and $pr\left(c_j\right)$ is the prior probability of class j. According to the Bayes classifier, x_i will be classified in the class with the maximum posterior probability. For each i-th word in the text, the denominator – known as the normalizing constant – is the same for all classes. Since it is a constant, the denominator can be omitted and the maximization problem can be rewritten in the following way:

$$\arg\max_{j} pr\left(x_i = w_k \middle| c_j\right) pr\left(c_j\right)$$

The likelihood and the prior probability are usually estimated with the frequentist approach, starting from a training set, or with the subjectivist approach, making assumptions about them. In particular:

- $pr\left(x_i = w_k \middle| c_j\right)$ is given by the relative frequency of word k in the vocabulary labeled with class j. To avoid the zero-frequency problem for the probability of the intersection (see below), an observation is usually added for each $w_k | c_j$ before the corresponding relative frequency is calculated (Hae-Cheon *et al.*, 2020).
- $pr\left(c_j\right)$ is given by the relative frequency of all words in the vocabulary labeled with class j or assuming a uniform distribution for the distribution of classes (Peng *et al.*, 2004). The uniform distribution will be considered during the discussion, but the results are similar for the empirical distribution.

Taking the previous example, the Bayes classifier provides the following results (Table 1):

Table 1. Results of word classification with the Bayes classifier

pr(animals|A)pr(A)	0.11	pr(animals|F)pr(F)	0.05
pr(cats|A)pr(A)	0.11	pr(cats|F)pr(F)	0.05
pr(dogs|A)pr(A)	0.11	pr(dogs|F)pr(F)	0.10
pr(dishes|A)pr(A)	0.06	pr(dishes|F)pr(F)	0.10
pr(cheeseburgers|A)pr(A)	0.06	pr(cheeseburgers|F)pr(F)	0.10
pr(hot|A)pr(A)	0.06	pr(hot|F)pr(F)	0.10
pr(dogs|A)pr(A)	0.11	pr(dogs|F)pr(F)	0.10

The values reported in the Table are the products between the likelihood of a class given a fixed word and the prior probability. On the left are reported the values associated with the animal topic (A), on the right those associated with the food topic (F). The classifier classifies each word in the class with the maximum product. Words correctly classified and misclassified are highlighted in light green and light red, respectively.

Words that are correctly classified are highlighted in light green, while those that are misclassified are highlighted in light red. The Bayes classifier classifies words regardless of their position in the text. Only when a word is univocally associated with a topic, the classifier classifies correctly. In our example, the word "dogs" related to the topic of food is wrongly associated with the topic of animals.

3. The Prior Adaptive Bayes classifier

To address this problem, we proposed the Prior Adaptive Bayes classifier (PAB classifier), which exploits the rule that words in a text are clustered in topics (topic clustering assumption). As a consequence, the prior probabilities of topics are not constant for each word but vary according to the topic of the previous word or group of words. Going back to the example above, if the word "dogs" is preceded by words belonging to the topic of animals, the PAB classifier associates a higher prior probability to this topic.

To capture the topic clustering, the PAB classifier adapts the prior probabilities of topics to the corresponding posterior probabilities associated with the previous words. From a mathematical point of view, the priors are replaced by the corresponding posteriors associated with the previous p words:

$$\arg\max_j pr(x_i = w_k|c_j)pr(c_j|x_{i-1} \cap \ldots \cap x_{i-p})$$

The posterior probabilities can be computed by assuming that words are independent (bag-of-words assumption; Ercan and Cicekli, 2012). Consequently, the probability of the intersection of p preceding words is given by the product of their probabilities:

$$pr(c_j|x_{i-1} \cap \ldots \cap x_{i-p}) = \frac{pr(x_{i-1} \cap \ldots \cap x_{i-p}|c_j)pr(c_j)}{\sum_j pr(x_{i-1} \cap \ldots \cap x_{i-p}|c_j)pr(c_j)} = \frac{pr(x_{i-1}|c_j) \ldots pr(x_{i-p}|c_j)pr(c_j)}{\sum_j pr(x_{i-1}|c_j) \ldots pr(x_{i-p}|c_j)pr(c_j)}$$

Going back to the previous example, the PAB classifier provides only correct results with $p = 1$ (Table 2), while it does not happen with $p = 2$ (Table 3). In the latter case, while the words "dogs" are still correctly classified, the word "dishes" is not anymore.

Table 2. Results of word classification with the PAB classifier ($p = 1$)

pr(cats|A)pr(A|animals)	0.15	pr(cats|F)pr(F|animals)	0.03
pr(dogs|A)pr(A|cats)	0.15	pr(dogs|F)pr(F|cats)	0.06
pr(dishes|A)pr(A|dogs)	0.06	pr(dishes|F)pr(F|dogs)	0.10
pr(cheeseburgers|A)pr(A|dishes)	0.04	pr(cheeseburgers|F)pr(F|dishes)	0.13
pr(hot|A)pr(A|cheeseburgers)	0.04	pr(hot|F)pr(F|cheeseburgers)	0.13
pr(dogs|A)pr(A|hot)	0.08	pr(dogs|F)pr(F|hot)	0.13

The values reported in the Table are the products between the likelihood of a class given a fixed word and the posterior probability associated with the previous word. The left-hand side reports the values associated with the animal topic (A), while the right-hand side reports the values associated with the food topic (F). The PAB classifier classifies each word in the class with the maximum product. Words correctly classified and misclassified are highlighted in light green and light red, respectively.

Table 3. Results of word classification with the PAB classifier ($p = 2$)

pr(dogs|A)pr(A|cats∩animals)	0.19	pr(dogs|A)pr(A|cats∩animals)	0.03
pr(dishes|A)pr(A|dogs∩cats)	0.08	pr(dishes|A)pr(A|dogs∩cats)	0.06
pr(cheeseburgers|A)pr(A|dishes∩dogs)	0.04	pr(cheeseburgers|A)pr(A|dishes∩dogs)	0.12
pr(hot|A)pr(A|cheeseburgers∩dishes)	0.03	pr(hot|A)pr(A|cheeseburgers∩dishes)	0.15
pr(dogs|A)pr(A|hot∩cheeseburgers)	0.05	pr(dogs|A)pr(A|hot∩cheeseburgers)	0.15

The values reported in the Table are the products between the likelihood of a class given a fixed word and the posterior probability associated with the two previous words. The left-hand side reports the values associated with the animal topic (A), while the right-hand side reports the values associated with the food topic (F). The PAB classifier classifies each word in the class with the maximum product. Words correctly classified and misclassified are highlighted in light green and light red, respectively.

This outcome is due to the existence of a trade-off: since words in a text are clustered in topics, the greater the number of previous words chosen associated with a topic, the higher the probability that the next word is classified in the same topic. This implies a lower sensitivity of the classifier to the new topic during the change of topic, as occurred for the word “dishes”, which is the first word appeared in the topic of food. The optimal number of previous words to account for depends on the texts but, in general, it is likely to be a parsimonious one. The simulation reported in the subsection below provides evidence for the case of our example.

4. Testing the PAB classifier: data and main results

The Bayes classifier with adaptive a priori probabilities as described in the section above was tested on a well-known dataset usually used for testing the performance of text classification algorithms. The dataset is Reuters-21578, a collection of 21578 documents that appeared on the Reuters newswire in 1987 (Debole and Sebastiani, 2005; Pinheiro *et al.*, 2012; Zhang *et al.*, 2019). The documents were assembled and indexed with categories by personnel from Reuters Ltd. and Carnegie Group Inc. in 1987. Starting from the 90s, David D. Lewis and other researchers have formatted the documents, produced the associated data, and cleaned the collection.

Excluding units without content and units not labeled as training or test units, the number of documents is 18,323. 8,298 documents are labeled with a unique topic: this analysis considers textual data, or clusters of words, labeled with one topic. During the discussion, two experiments will be carried out. First, we will use the PAB classifier for the binary classification task, considering documents labeled with one of the two most frequent topics. Then, we will perform a similar experiment, but considering three classes.

4.1. Binary classification

We will consider documents labeled with one of the two most frequent topics, *acq* (corporate acquisitions) and *earn* (earnings), for a total of 5769 documents – i.e., clusters of words (Table 4):

Table 4. Number of training and test data labeled as *acq* and *earn*

Topic/Set	Training	Test	Total
acq	1435	620	2055
earn	2673	1041	3714
Total	4108	1661	5769

Each cell contains the number of textual data labeled with one topic (*acq* or *earn*) in each set (training or test).

We trained the classifier with 4108 documents, i.e., we used the words contained in these documents to estimate the likelihoods. Then, we tested the classifier on 1661 documents, i.e., we used it to predict the classes of words contained in the test documents. Before training the classifier, we removed stop words and numbers. Moreover, we stemmed words to reduce the dimensionality of data (Singh and Gupta, 2016) and, therefore, the problem of sparsity (Hastie *et al.*, 2015).

Suppose test documents belong to a unique document. Consequently, there are 1661 clusters of words, for a total of 70120 words (a mean of 42 words per cluster). One way to evaluate the performance of a classifier is the accuracy, measured as the percentage of words correctly classified (Bramer, 2020). Other evaluation metrics commonly used to measure the performance of a classifier are precision, recall and F1-score (Han *et al.*, 2011). For a generic class A, precision and recall are calculated as follows:

$$Precision_A = \frac{TP_A}{TP_A + FP_A}$$

$$Recall_A = \frac{TP_A}{TP_A + FN_A}$$

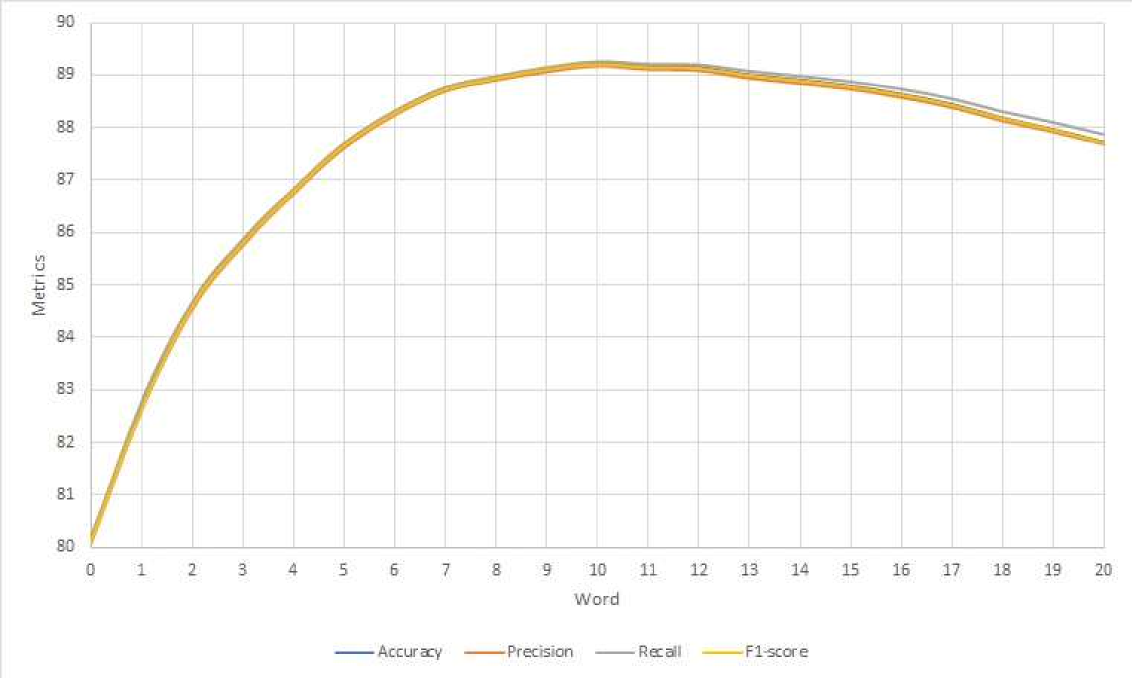
where TP_A, FP_A and FN_A are the number of true positives, false positives and false negatives for class A, respectively. Precision and recall are used to compute the F1-score:

$$F1\ score_A = \frac{2 \cdot Precision_A \cdot Recall_A}{Precision_A + Recall_A}$$

The overall precision, recall and F1-score can be obtained by averaging these metrics across all classes.

Figure 1 shows the overall precision, recall and F1-score as well as the accuracy for both the original classifier not considering preceding words ($p = 0$) and the PAB classifier considering a positive number of preceding words ($1 \leq p \leq 20$):

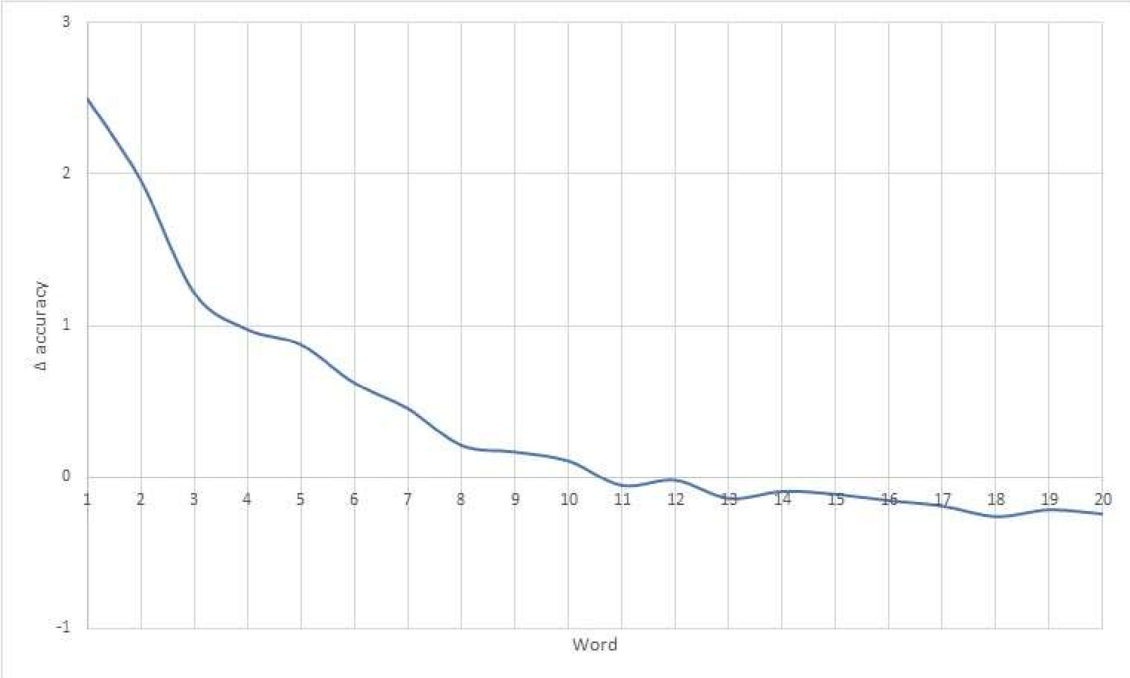
Figure 1. Metrics by number of preceding words (binary classification)



All metrics follow the same trend. With reference to the accuracy, the original classifier provides an accuracy of 80.17%. As the number of lags increases, the accuracy of the PAB classifier increases but at decreasing rates. Moreover, the accuracy begins to decrease slowly starting from a certain number of preceding words. In particular, the maximum accuracy is achieved for 10 previous words, after which it decreases. For 5 preceding words, the accuracy is 87.69% (+7.52% with respect to the case of zero previous words). The accuracy reaches 89.24% for 10 previous words (+9.07%), while it is 88.81% and 87.73% in the case of 15 and 20 preceding words (+8.64% and +7.56%), respectively.

Therefore, a noticeable improvement of the accuracy occurs with only 5 previous words. After this number, the accuracy increases slowly (until 10 preceding words) or even starts to decrease (from 11 previous words). To better explain this point, consider Figure 2, where is reported the variation of accuracy for each number of preceding words. As the number of previous words increases, this variation decreases, meaning that the improvement of accuracy with respect to the previous number of preceding words gets smaller.

Figure 2. Variation of accuracy by number of preceding words (binary classification)



In particular, the variation of accuracy is less than 1% starting from 4 previous words. From 7 to 10 preceding words this variation is less than 0.5%. After 10 previous words, it becomes negative, meaning that the accuracy gets worse than the previous number of preceding words. In any case, the worsening is less than 0.5% in absolute value.

4.2. Non-binary classification

Now we will perform the same experiment considering three classes. In particular, 25% and 45% of textual data are labeled with topics *acq* and *earn*, respectively. The remaining 30% is distributed across 63 categories. Due to the high fragmentation, we grouped these clusters of words into one broad class, named *other* (Table 5).

Table 5. Number of training and test data labeled as *acq*, *earn* and *other*

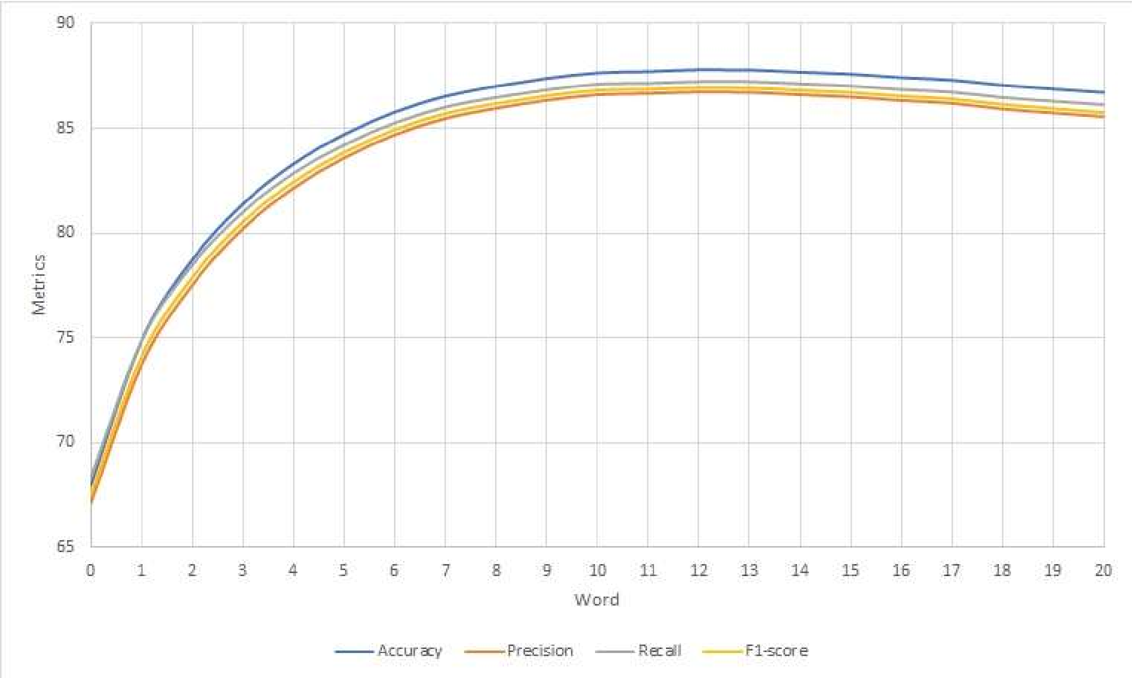
Topic/Set	Training	Test	Total
acq	1435	620	2055
earn	2673	1041	3714
other	1841	688	2529

Total	5949	2349	8298

Each cell contains the number of textual data labeled with one topic (*acq*, *earn* or *other*) in each set (training or test).

Again, textual data related to the test set are supposed to belong to a unique document. The number of clusters of words is 2349, for a total of 128948 words (a mean of 55 words per cluster). Figure 3 reports the classification metrics for the original classifier and the PAB classifier:

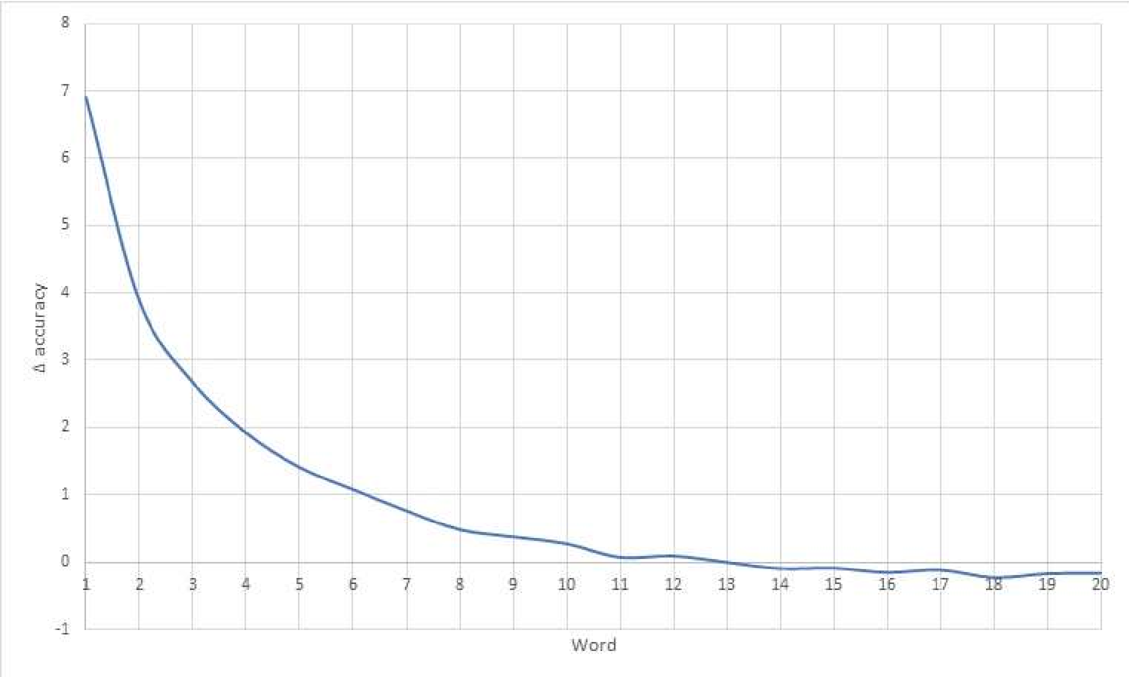
Figure 3. Metrics by number of preceding words (3 classes)



The trend of all metrics continues to be the same. Focusing on the accuracy, it increases again at decreasing rates as the number of preceding words increases and then starts to decrease at some point. In particular, the maximum accuracy is achieved for 12 preceding words (87.81%). However, we can note two important differences with respect to the binary classification experiment. On the one hand, the accuracy of the original classifier (0 previous words) decreased drastically from 80.17% of the binary classification experiment to 67.96% of the classification experiment with three classes. This outcome is due to the increase in classes. Indeed, the greater the number of classes, the greater the likelihood that a word will be used in more contexts. Since the Bayes classifier classifies words regardless of their position in the text, it tends to misclassify those words that are not clearly associated with a topic. On the other hand, although the accuracy of the PAB classifier is systematically lower by adding a third class, it is very similar to the one obtained with the binary classification, especially after a certain number of previous words. For 5 preceding words the accuracy is 84.72% (–2.97% with respect to the binary classification experiment). The accuracy reaches 87.66% for 10 previous words (–1.58%). In the case of 15 and 20 lags the accuracy is 87.61% and 86.73% (–1.20% and –1%), respectively.

Accuracy rapidly reaches its maximum after a few preceding words similarly to the case of two classes (Figure 4):

Figure 4. Variation of accuracy by number of preceding words (3 classes)



After the initial boost of 6.90% over the original classifier, the variation of accuracy decreases exponentially, becoming negative at some point. From 8 to 12 preceding words this improvement is less than 0.5%, while from 13 previous words it becomes systematically negative (less than 0.5% in absolute value).

5. Other strategies

The strategy described so far is basically a backward strategy, meaning that each word is classified taking into account the preceding word or group of words. But what happens if we consider the following words? And what if we select both previous and next words? In this section we will discuss these alternative classification methods in detail, carrying out the same experiments done in the fourth section.

5.1. Forward strategy

If we replace the prior probabilities with the corresponding posterior probabilities given that the following q words occurred, the classification of individual words becomes:

$$\arg\max_j pr(x_i = w_k|c_j)pr(c_j|x_{i+1} \cap \ldots \cap x_{i+q})$$

Figures 5 and 6 show the classification metrics for the original classifier ($q = 0$) and the PAB classifier until 20 next words ($1 \leq q \leq 20$) for both the binary classification and the classification with three classes, respectively:

Figure 5. Metrics by number of following words (binary classification)

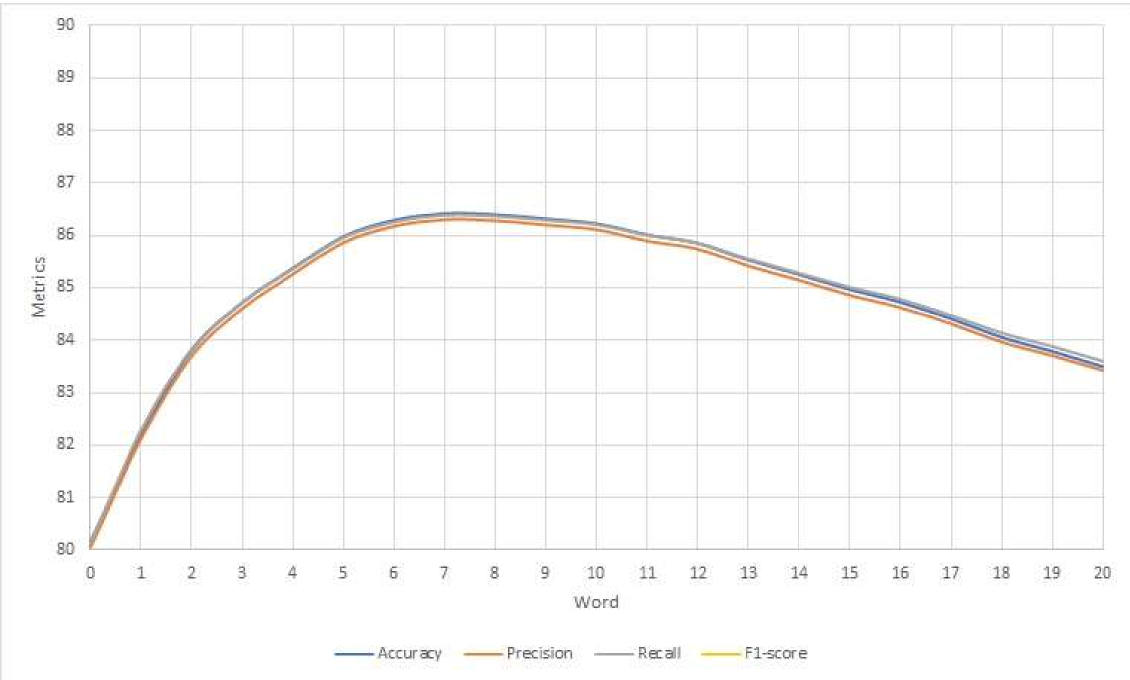
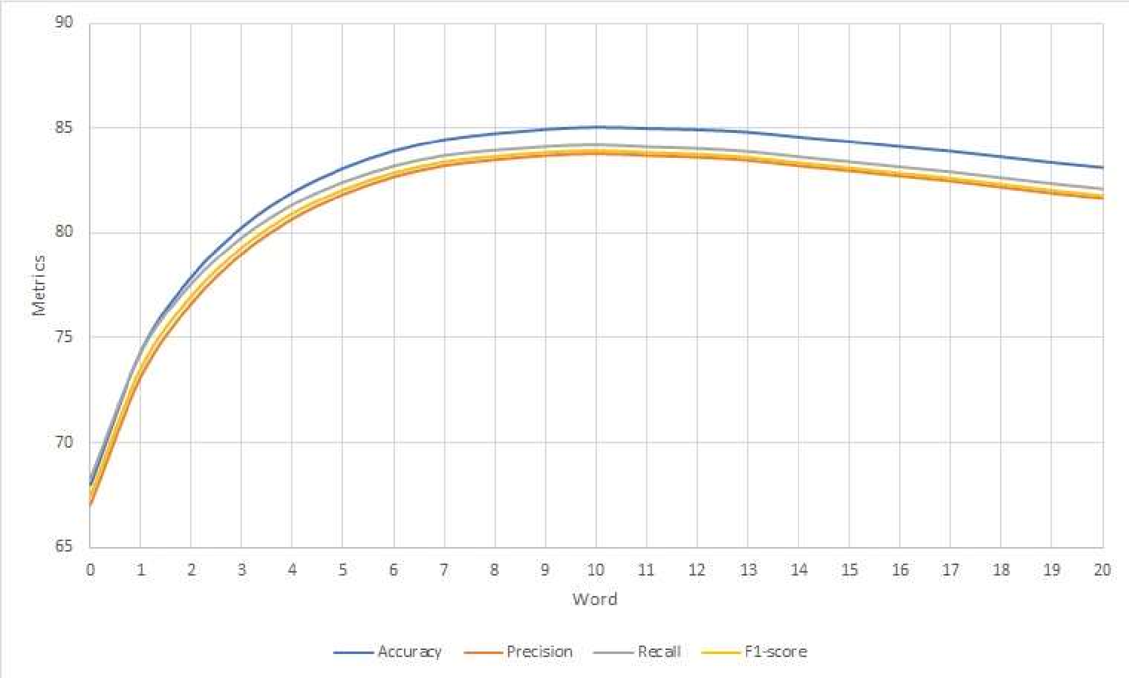


Figure 6. Metrics by number of following words (3 classes)



Although the behavior of the forward strategy is the same as the backward one (all metrics increase at decreasing rates and start to decrease at some point), the performance of the forward strategy is systematically lower than the backward one. In particular, the greater the number of surrounding words, the greater the discrepancy between the two strategies. Moreover, the inflection point is reached earlier. For example, while the forward strategy achieves the maximum accuracy with 7 next words for the binary classification (86.40%) and 10 next words for the non-binary classification (85.06%), the backward strategy reaches the maximum accuracy with 10 previous words (89.24%, binary classification) and 12 previous words (87.81%, classification with three classes).

5.2. Mixed strategy

Now we will analyze the mixed strategy, where we will consider both the preceding and the following words for improving the classification of individual words. In this case, we can write the maximization problem as follows:

$$\arg\max_j pr\left(x_i = w_k \middle| c_j\right) pr\left(c_j \middle| x_{i-1} \cap \ldots \cap x_{i-p} \cap x_{i+1} \cap \ldots \cap x_{i+q}\right)$$

where p and q are the numbers of preceding and following words, respectively. In this subsection, we will perform the previous experiments choosing the same number for both the parameter p and the parameter q (symmetrical approach).

Also in this case all the metrics follow the same trend for both the binary classification (Figure 7) and the classification with three classes (Figure 8). Focusing on accuracy, this strategy reaches a maximum accuracy greater than or equal to the maximum accuracy of the backward method. Indeed, while for the binary classification the maximum accuracy reached with the mixed strategy is basically the same as the maximum accuracy of the backward strategy (89.55% and 89.24%, respectively), for the classification with three classes the maximum accuracy of the mixed strategy is greater than the maximum accuracy of the backward strategy (89.27% vs. 87.81%). Again, the PAB classifier has an accuracy that increases with p and q at decreasing rates. Moreover, starting from a certain level of p and q, the accuracy begins to decrease slowly.

Figure 7. Metrics by number of adjacent words (binary classification)

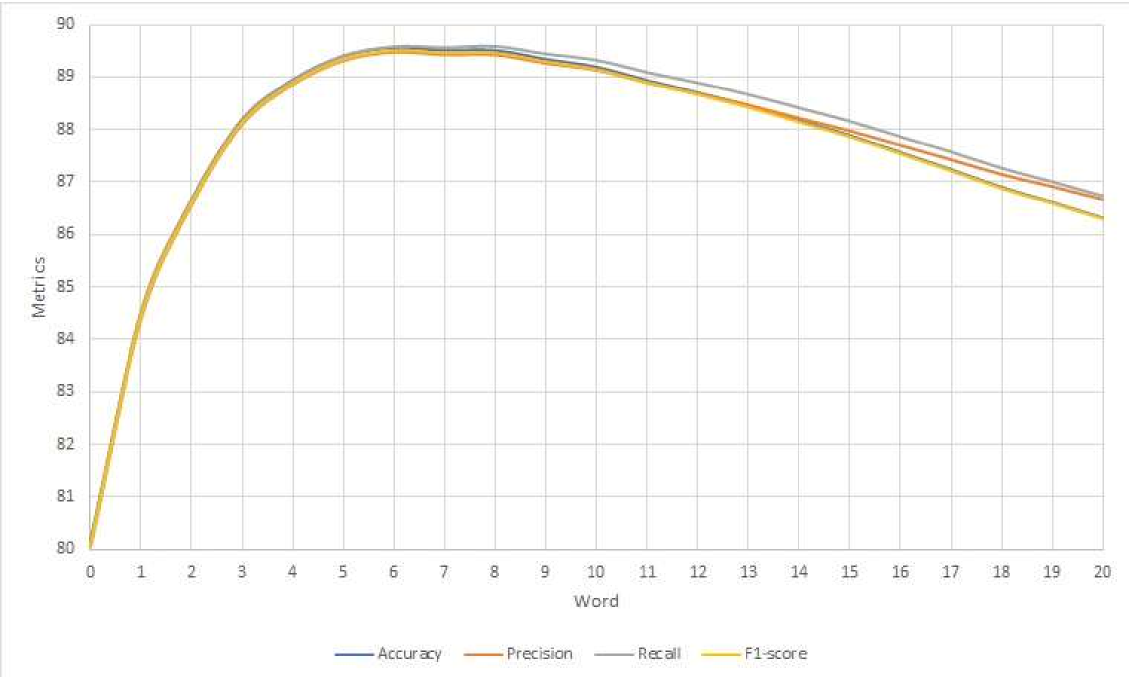
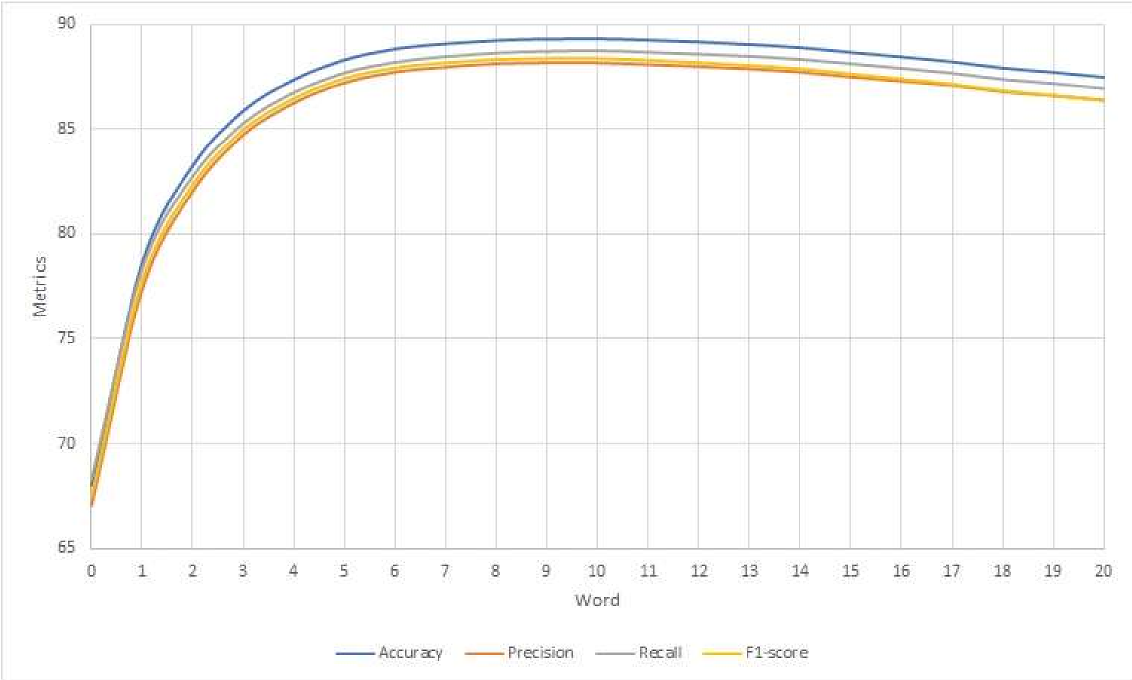


Figure 8. Metrics by number of adjacent words (3 classes)



5.3. Stepwise strategy

For the mixed strategy we adopted a symmetrical approach, i.e., we considered the same number for the preceding and the following words. However, we could have used different numbers to test whether the performance of the PAB classifier would increase significantly or not. This is what we will do with the stepwise strategy proposed in this subsection.

Since the backward strategy is definitely better than the forward strategy (see section 5.1), first we chose the number of preceding words for which the maximum accuracy was achieved. Then, we tested the PAB classifier for an increasing number of following words given the fixed number of preceding words previously chosen. In particular, we have seen that the maximum accuracy for the binary classification and the classification with three classes was with 10 and 12 previous words, respectively: we chose these numbers as fixed for the number of preceding words and increased the number of following words up to 20 (Figures 9 and 10):

Figure 9. Metrics with $p = 10$ and $0 \leq q \leq 20$ (binary classification)

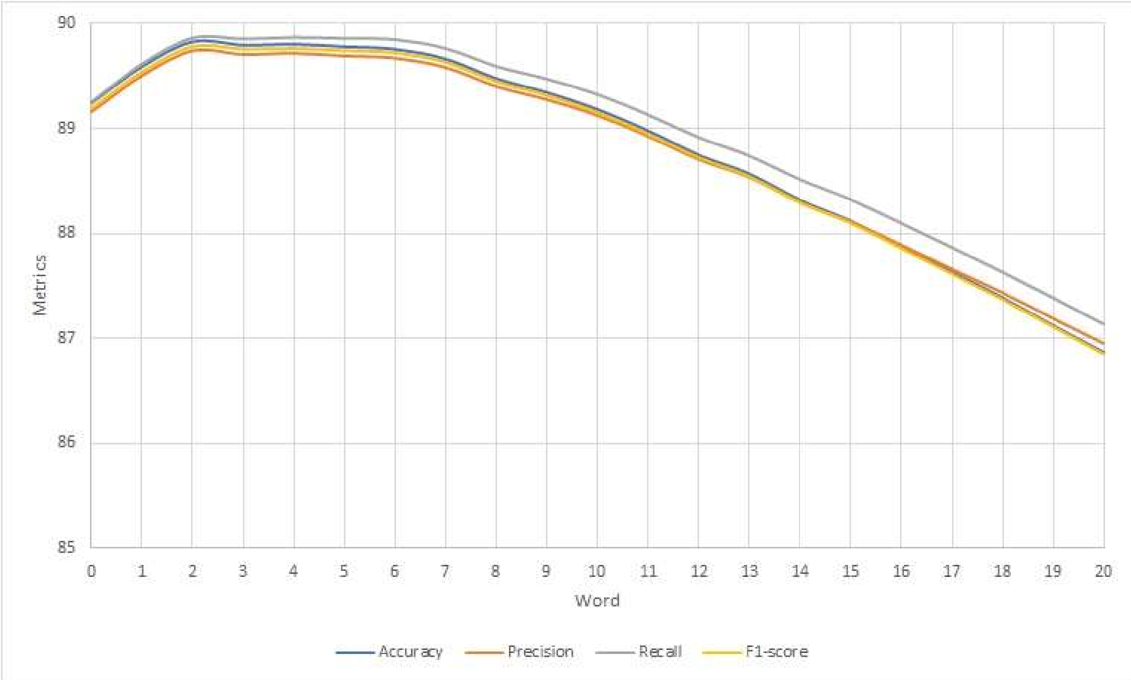
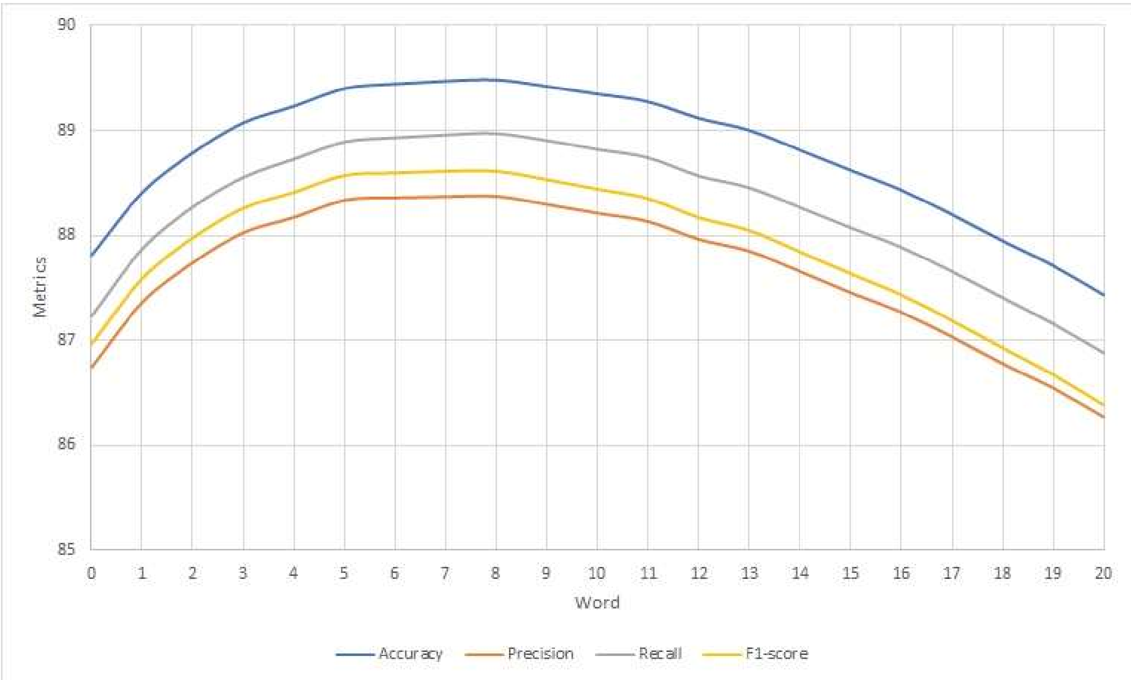


Figure 10. Metrics with $p = 12$ and $0 \leq q \leq 20$ (3 classes)



The improvement of the stepwise strategy is negligible compared to the previous strategy where we selected the same number of preceding and following words. Focusing on accuracy, the stepwise strategy reaches the maximum accuracy by adding only 2 next words for the binary classification (89.82%) and 8 next words for the classification with three classes (89.48%). In the first case the improvement compared to the mixed strategy is 0.27%, while in the second one is 0.21%.

Although the PAB classifier is designed to perform best at the word level, we can easily generalize its framework to larger levels, such as bigrams, phrases and so on. We reported in the Appendix an example of its application at the phrase level.

6. Conclusions

We proposed the PAB classifier, an adaption of the Bayes classifier for the word classification task. Its main characteristic is that the prior probabilities of topics are not constant but adapt to the posterior probabilities associated with the surrounding words. In particular, we carried out experiments on a dataset usually used to test text algorithms, showing that adapting the priors to the corresponding posteriors given that the preceding words occurred allows us to obtain a significant improvement over the original classifier. Moreover, while for the original classifier the accuracy dropped drastically by adding another class, the PAB classifier continued to maintain good performance. Finally, we observed a further improvement in terms of accuracy by considering not only the preceding but also the following words.

In contrast to other popular tools usually adopted in economics to extract quantitative information from textual data – the dictionary-based approach – the proposed classifier is more flexible, allowing us to perform a more objective analysis for tasks not necessarily related to sentiment analysis. Once the documents related to the classes to be studied have been collected, the researcher only needs to set the number of adjacent words to classify each word. Moreover, unlike other complex but less used methods, such as those based on neural networks, this classifier is not opaque in its functioning, allowing the researcher to easily understand the results obtained. Since it is neither too simple nor too complex, the proposed classifier has the potential for becoming a very useful tool for researchers of all fields in those cases where they need to extrapolate numerical information from documents only containing words.

Future refinements of the classifier may provide a built-in procedure allowing the researcher to automatically detect the optimal number of adjacent words to be considered to maximize the accuracy. Another future development of this classifier is to test a weighting scheme for the surrounding words, for example by giving more weight to the words that are closer to the word to be classified.

References

ALFANO V. and GUARINO M. (2022), A Word to the Wise Analyzing the Impact of Textual Strategies in Determining House Pricing, Journal of Housing Research, vol. 31, issue 1, pp. 88-112. doi: https://doi.org/10.1080/10527001.2021.2013058

ALSHANIK F., APON A., HERZOG A., SAFRO I. and SYBRANDT J. (2020), Accelerating Text Mining Using Domain-Specific Stop Word Lists, 2020 IEEE International Conference on Big Data (Big Data). doi: 10.1109/BigData50022.2020.9378226

APRIGLIANO V., EMILIOZZI S., GUAITOLI G., LUCIANI A., MARCUCCI J., MONTEFORTE L. (2023), The power of text-based indicators in forecasting Italian economic activity, International Journal of Forecasting, vol. 39, issue 2, pp. 791-808. doi: https://doi.org/10.1016/j.ijforecast.2022.02.006

ASH E. and HANSEN S. (2022), Text algorithms in economics, Annual Review of Economics, In press.

ATHEY S. and IMBENS G. W. (2019), Machine Learning Methods That Economists Should Know About, Annual Review of Economics, vol. 11, pp. 685-725. doi: https://doi.org/10.1146/annurev-economics-080217-053433

BATEMAN J. and JEFFREY S. (2011), What Matters about the Monument: reconstructing historical classification, Internet Archaeology, vol. 29.

BRAMER M. (2020), Principles of Data Mining, Springer, Berlin.

BREIMAN L. (2001), Random Forests, Machine Learning, vol. 45, pp. 5-32. doi: https://doi.org/10.1023/A:1010933404324

BREIMAN L., FRIEDMAN J., STONE C. J. and OLSHEN R. A. (1984), Classification and Regression Trees, Chapman and Hall/CRC, New York.

CHAPMAN W. W., NADKARNI P. M., HIRSCHMAN L., D'AVOLIO L. W., SAVOVA G. K. and UZUNER O. (2011), Overcoming barriers to NLP for clinical text: The role of shared tasks and the need for additional creative solutions, Journal of the American Medical Informatics Association, vol. 18, issue 5, pp. 540-543. doi: https://doi.org/10.1136/amiajnl-2011-000465

COHEN K. B. and DEMNER-FUSHMAN D. (2014), Biomedical Natural Language Processing, John Benjamins Pub Company, Amsterdam.

DEBOLE F. and SEBASTIANI F. (2005), An analysis of the relative hardness of Reuters-21578 subsets, Journal of the American Society for Information Science and Technology, vol. 56, issue 6, pp. 584-596. doi: https://doi.org/10.1002/asi.20147

ERCAN G. and CICEKLI I. (2012), Keyphrase extraction through query performance prediction, Journal of Information Science, vol. 38, issue 5. doi: https://doi.org/10.1177/0165551512448984

HAE-CHEON K., JIN-HYEONG P., DAE-WON K. and JAESUNG L. (2020), Multilabel naïve Bayes classification considering label dependence, Pattern Recognition Letters, vol. 136, pp. 279-285. doi: https://doi.org/10.1016/j.patrec.2020.06.021

HAN J., KAMBER M. and PEI J. (2011), Data Mining: Concepts and Techniques (3rd edition), Morgan Kaufmann Publishers, Massachusetts.

HASTIE T., TIBSHIRANI R. and WAINWRIGHT M. (2015), Statistical Learning with Sparsity: The Lasso and Generalizations, Chapman and Hall/CRC, New York. doi: https://doi.org/10.1201/b18401

HILDUM D. C. (1963), Semantic Analysis of Texts by Computer, Language, vol. 39, no. 4, pp. 649-653. doi: https://doi.org/10.2307/411960

HOERL A. E. and KENNARD R. W. (1970), Ridge regression: Biased estimation for nonorthogonal problems, Technometrics, vol. 12, pp. 55-67.

HORNIK K., STINCHCOMBE M. and WHITE H. (1989), Multilayer feedforward networks are universal approximators, Neural Networks, vol. 2, issue 5, pp. 359-366. doi: https://doi.org/10.1016/0893-6080(89)90020-8

KALAMARA E., TURRELL A., REDL C., KAPETANIOS G. and KAPADIA S. (2022), Making text count: economic forecasting using newspaper text, Journal of Applied Econometrics, vol. 37, issue 5, pp. 896-919. doi: https://doi.org/10.1002/jae.2907

LOUGHRAN T. and MCDONALD B. (2011), When is a liability not a liability? Textual analysis, dictionaries, and 10-ks, The Journal of Finance, vol. 66, issue 1, pp. 35–65. doi: https://doi.org/10.1111/j.1540-6261.2010.01625.x

MITCHELL T. M. (2019), Machine Learning, McGraw-Hill Education, New York.

PENG F., SCHUURMANS D. and WANG S. (2004), Augmenting Naive Bayes Classifiers with Statistical Language Models, Information Retrieval, vol. 7, pp. 317-345. doi: https://doi.org/10.1023/B:INRT.0000011209.19643.e2

PICAULT M. and RENAULT T. (2017), Words are not all created equal: A new measure of ECB communication, Journal of International Money and Finance, vol. 79, pp. 136-156. doi: https://doi.org/10.1016/j.jimonfin.2017.09.005

PINHEIRO R. H.W., CAVALCANTI G. D.C., CORREA R. F. and REN T. I. (2012), A global-ranking local feature selection method for text categorization, Expert Systems with Applications, vol. 39, issue 17, pp. 12851-12857. doi: https://doi.org/10.1016/j.eswa.2012.05.008

RENAULT T. (2017), Intraday online investor sentiment and return patterns in the U.S. stock market, Journal of Banking & Finance, vol. 84, pp. 25-40. doi: https://doi.org/10.1016/j.jbankfin.2017.07.002

SAHAMI M., DUMAIS S., HECKERMAN D. and HORVITZ E. (1998), A Bayesian approach to filtering junk e-mail, Learning for Text Categorization: Papers from the 1998 workshop 62, pp. 98-105.

SCACCIA J. P. (2021), Examining the concept of equity in community psychology with natural language processing, Journal of Community Psychology, vol. 49, issue 6, pp. 1718-1731. doi: https://doi.org/10.1002/jcop.22603

SINGH J. and GUPTA V. (2016), Text Stemming: Approaches, Applications, and Challenges, ACM Computing Surveys, vol. 49, issue 3, pp. 1-46. doi: https://doi.org/10.1145/2975608

STEIER J. (2019), A Characterization of Dante Alighieri: An NLP approach to the Divine Comedy, 2019 IEEE MIT Undergraduate Research Technology Conference (URTC). doi: 10.1109/URTC49097.2019.9660481

TETLOCK P. C. (2007), Giving Content to Investor Sentiment: The Role of Media in the Stock Market, The Journal of Finance, vol. 62, issue 3. doi: https://doi.org/10.1111/j.1540-6261.2007.01232.x

THORSRUD L. A. (2020), Words are the New Numbers: A Newsy Coincident Index of the Business Cycle, Journal of Business & Economic Statistics, vol. 38, issue 2, pp. 393-409. doi: https://doi.org/10.1080/07350015.2018.1506344

TIBSHIRANI R. (1996), Regression Shrinkage and Selection Via the Lasso, Journal of the Royal Statistical Society: Series B (Methodological), vol. 58, issue 1, pp. 267-288. doi: https://doi.org/10.1111/j.2517-6161.1996.tb02080.x

WANG A. H. (2010), Don't follow me: Spam detection in Twitter, 2010 International Conference on Security and Cryptography (SECRYPT), pp. 1-10.

WHITE H. (1992), Artificial Neural Networks: Approximation and Learning Theory, Blackwell Publishers, Hoboken.

ZHANG W., HU HUA, HU HAIYANG and FANG J. (2019), Semantic distance between vague concepts in a framework of modeling with words, Soft Computing, vol. 23, pp. 3347-3364. doi: https://doi.org/10.1007/s00500-017-2992-x

Appendix

Appendix A. Generalization of the framework

The PAB classifier is designed to perform best at the word level. However, we can easily generalize its framework to larger levels, such as bigrams, phrases and so on. For example, we can improve the classification of a phrase by replacing the priors of classes with the corresponding posteriors associated with the adjacent phrases. In this case the maximization problem becomes:

$$\arg\max_{j} pr\left(phrase_i \middle| c_j\right) pr\left(c_j | phrase_{i-1} \cap phrase_{i+1}\right)$$

A phrase level comparison between the original and the PAB classifier on the Reuters dataset is reported in Table A.1:

Table A.1. Comparison between the original and the PAB classifier on the Reuters dataset (phrase level)

Metric/Classifier	Original	PAB
Accuracy	86.87	92.96
Precision	84.92	91.82
Recall	85.77	91.68
F1-score	85.32	91.75

The original classifier performs well at the phrase level, with all metrics greater than or equal to 85%. However, considering the adjacent phrases yields an improvement between 6 and 7 percent, depending on the metric considered.

CHAPTER 2

An application of the Prior Adaptive Bayes classifier on the EU Recovery and Resilience Plans

Abstract

This chapter applies the PAB classifier to evaluate the alignment of the EU Recovery and Resilience Plans (RRPs) with the environmental Sustainable Development Goals (SDGs) as compared to the socioeconomic SDGs. For this purpose, we estimated for each RRPs project the number of words associated with the environmental and socioeconomic dimensions of the SDGs. Then, we built a relative index of alignment of the RRPs projects with these dimensions. Results show that the attention paid by the countries to the pro-environment SDGs increases with the funds per capita assigned, the gap in the environmental endowment and the touristic attractiveness. Finally, the environmental dimension appears associated positively with available GDP growth projections for the next few years.

Keywords: Recovery and Resilience Facility; Recovery and Resilience Plans; Sustainable Development Goals; environment; Prior Adaptive Bayes classifier

1. Introduction

In September 2015 all United Nations (UN) member states adopted the 2030 Agenda for Sustainable Development, a plan of action for people, planet and prosperity. In particular, the UN defined 17 Sustainable Development Goals (SDGs) to address global challenges by 2030, including inequality and poverty, climate change and environmental degradation, justice and peace (Sarre and Davey, 2021). Unlike the Millennium Development Goals (a set of goals defined by the UN in 2000 to reduce extreme poverty by 2015), the SDGs are addressed not only to developing countries, but also to developed ones (Fransman *et al.*, 2004; Swain and Yang-Wallentin, 2019).

A few years later, in 2019, a new coronavirus was discovered in China, which in the following months spread to the rest of the world, starting the Covid-19 pandemic (WHO, 2021). Since the new coronavirus could spread easily, people needing medical attention could rapidly increase, with the risk of causing the collapse of national health systems. To avoid this scenario, many national governments adopted unprecedented decisions, such as lockdowns, social distancing, mandatory use of masks and restrictions on economic activities (Unruh *et al.*, 2022).

To mitigate the economic and social impact of the Covid-19 pandemic and make European economies and societies more resilient and sustainable, the European Parliament and the Council of the European Union approved the regulation 2021/241, which established the Recovery and Resilience Facility (RRF). The RRF is a temporary recovery instrument that allows the European Commission to raise funds to finance member states' reforms and investments in line with the EU's priorities (Karaboytcheva, 2021). To benefit from the support of the RRF, member states submit to the European Commission their Recovery and Resilience Plans (RRPs), where the reforms and investments to be implemented by end-2026 are set out (Dias *et al.*, 2021). The guiding principle for the implementation of the RRF, and therefore for the realization of the RRPs, is the new growth paradigm of competitive sustainability, with which the SDGs are strongly associated (European Commission, 2019). Consequently, the RRPs are expected to accelerate the achievement of the SDGs.

While there are several works on the SDGs (Hák *et al.*, 2016; Sachs *et al.*, 2019; Vinuesa *et al.*, 2020), to the best of our knowledge the contributions aiming at exploring the coherence of the RRPs with the SDGs are still few and focus on specific case studies. For example, a recent work written by Rotondo *et al.* (2022) analyzed the relationships between the domains of the SDGs and the Mission 2 of the Italian RRP. Theodoropoulou *et al.* (2022) investigated the RRPs of France, Greece and Germany from the perspective of "just transition", a concept closely related to, among others, the SDGs. Sgambati (2023) analyzed the SDG 11 (Sustainable cities and communities) in the frame of the Italian RRP. More generally, recent studies not strictly related to the RRPs that tried to map the coverage of the SDGs in European documents are those realized by Borchardt *et al.* (2020) and Koundouri *et al.* (2021). In both cases, the authors manually defined some keywords associated with the SDGs and mapped their presence in some European documents. The reason there is a lack of studies attempting to investigate RRPs in relation to the SDGs is twofold. The first is a temporal reason: since the RRF was approved a few years ago, researchers are probably still investigating this topic. Second, there is a practical reason: the lack of numerical measures that univocally associate the RRPs projects with the SDGs makes difficult to perform this type of analysis. Although the projects contained in the RRPs are associated with at least one of the six pillars described by the European Commission[1], the 6 pillars and 17 SDGs are clearly two different domains. Moreover, if the classification into pillars is considered as a proxy of the impact of the SDGs, it is not possible to manipulate the interpretation of a specific dimension in which the SDGs can be grouped, by adding or removing some SDGs. Indeed, assuming we know which SDGs are included in a certain pillar, we cannot modify it by including or excluding some SDGs to test a specific SDGs model. Last, but not least, for each project the classification into pillars will be available once that project is completed, meaning that it is necessary to wait until 2026 to get all the information we need.

This chapter aims to fill an existing gap in the literature, performing a first systematic analysis of RRPs in relation to the SDGs. For this purpose, the PAB classifier discussed in Chapter 1 will be used to evaluate the alignment of the RRPs with the environmental SDGs as compared with the socioeconomic ones. Results show that the attention paid by the countries to the SDGs related to the environmental dimension increases with the

[1] The pillars are: "green transition", "digital transformation", "smart, sustainable and inclusive growth", "social and territorial cohesion", "health, social and institutional resilience" and "policies for the next generation".

funds per capita assigned, the gap in the environmental endowment and the touristic attractiveness. Finally, the environmental dimension appears associated positively with available GDP growth projections for the next few years. This chapter is structured as follows: the second section introduces the SDGs model, the third section presents the data, the fourth section tests the PAB classifier on the RRPs, the fifth section introduces an index of pro-environment relative intensity and the sixth one shows the results. The last section concludes.

2. The SDGs model

We said that the SDGs are 17 goals defined by the UN in 2015 to address global challenges by 2030, such as inequality and poverty, climate change and environmental degradation, justice and peace. These 17 SDGs can be grouped into a more compact number of categories or dimensions. In this regard, the Stockholm Resilience Centre introduced the Wedding Cake Model (Folke *et al.*, 2016), consisting of the absorption of all SDGs into three broad categories, namely biosphere protection, social cohesion, and economic growth (Figure 1).

Figure 1. The Wedding Cake Model

Source: Folke *et al.* (2016).

As SDG 17 (Partnership for the goals) is not associated with a specific dimension but shared by all three dimensions, it is excluded from the analysis.

Figure 2 shows a furtherly simplified scheme: on the one hand, the biosphere protection (environment), and, on the other hand, social cohesion and economic growth put together (socioeconomic). This scheme allows us to make a direct comparison between the SDGs related to environmental issues and those SDGs not associated with this dimension. Note that, in contradiction with the assignment of the model, this study moves SDG 2 (Zero hunger) into the environmental dimension because, in the context of the EU, SDG 2 mainly asks for policies of sustainable food creation and resilient agricultural practices (European Commission, 2021a).

Figure 2. The environmental and socioeconomic dimensions

As mentioned above, the guiding principle for the realization of the RRPs is competitive sustainability, a new growth paradigm with which the SDGs are strongly associated. Since the RRPs are written as a function of the SDGs, the alignment of each RRP with the specified dimensions of the Wedding Cake Model is an interesting research question aiming at uncovering the priorities of national governments of the EU member states. Specifically, the PAB classifier can help determine the number of words associated with the environmental and socioeconomic dimensions. Moreover, a measure of the relative intensity of the two dimensions can be used to identify the factors more intensely associated with them, including the environmental *status quo* and tourist attractiveness.

3. Data

The RRPs were assessed by the European Commission approximately two months after submission by the countries. After this assessment, the plan has been definitively approved by the European Council in an additional month. The attached document to the Council implementing decision (the annex) describes in detail the projects included in the corresponding RRP, i.e. the reforms and investments to be implemented by end-2026 (Dias *et al.*, 2022). Each annex of the RRPs contains the name, the description and the completion time of the projects. Overall, 6233 projects associated with the 27 EU countries can be univocally attributed to a specific year in the range between 2020 and 2026. The average length in terms of words and phrases of these documents is 18952 and 747, respectively, with a standard deviation of 14328 words and 486 phrases. We also used the cosine similarity to measure the similarity among the annexes (Ristanti *et al.*, 2019). The similarity for all documents is greater than or equal to 85%. The table containing the cosine similarity for each pair of annexes is reported in the Appendix.

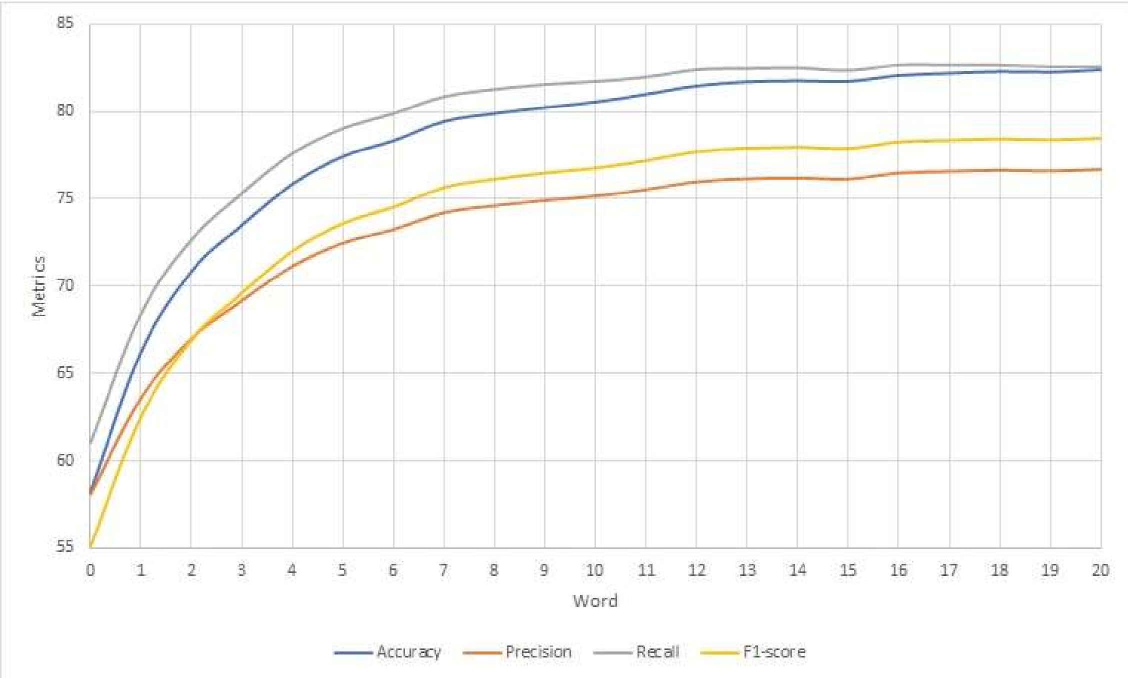
A training set of documents related to each SDG has been used to compute the likelihood necessary to execute the PAB classifier. To assure that these documents were coherent with the EU view and objectives, we considered the reading list on each SDG suggested by the statistical office of the European Union (Eurostat) in the 2020 report on progress towards the SDGs (Eurostat, 2020), selecting about 120 documents. In particular, we collected those documents that were uniquely associated with each SDGs dimension and used them to compute the probabilities of words in the vocabulary associated with the corresponding dimension. Before training the classifier, we removed stop words and numbers. Moreover, we reduced the vocabulary to the one used in the projects of the RRPs to reduce the sparsity due to words not being used in the documents to be analyzed.

4. Testing the PAB classifier on the RRPs

Before implementing the classifier on the RRPs, we tested its performance on a sample of projects: although we have already performed tests on the Reuters dataset (see Chapter 1), a test on the RRPs allows us to be sure that the results are good also on the RRPs corpus. In particular, we used systematic sampling to randomly select 500 projects, for a total of 1637 phrases (clusters of words). Then we labeled each cluster in one of two SDGs dimensions and compared the performance between the original and the PAB classifier.

Figure 3 shows the classification metrics for the mixed strategy of the PAB classifier compared to the original classifier.

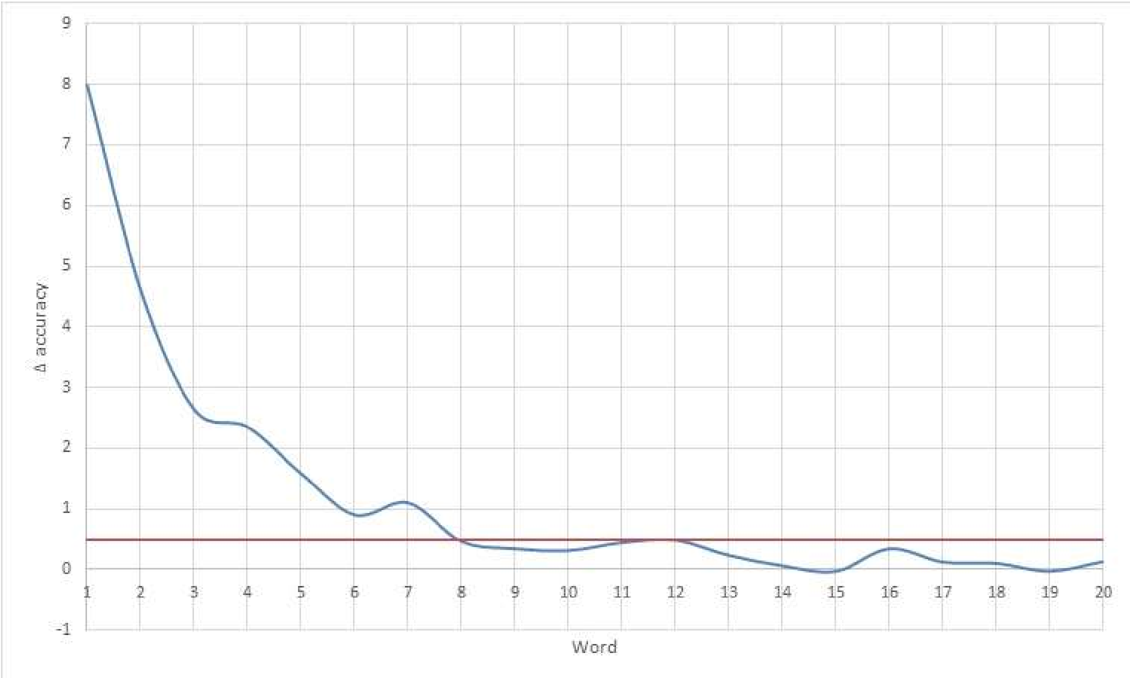
Figure 3. Metrics by number of adjacent words on the RRPs (symmetrical approach)



For all metrics, we obtained an improvement of up to more than 20% compared to the original classifier: this is a similar improvement to the one obtained using the Reuters dataset. Although the classification performance increases as the number of adjacent words increases, it is better to choose this number sparingly to avoid overfitting on the sample. As a rule of thumb, we can choose the number of adjacent words by considering the improvement in terms of classification compared to the previous number. In particular, when this improvement becomes negligible, we can stop.

In Figure 4 is reported the variation of accuracy for each number of adjacent words. Since after 7 adjacent words the improvement of accuracy becomes less than 0.5%, we chose 7 previous and 7 next words for our exercise on the RRPs.[2] In this case, the sample accuracy is about 80%.

Figure 4. Variation of accuracy by number of adjacent words (symmetrical approach)



As a further validation tool, we considered the Zipf's law, for which very few words dominate the word count distribution (Manning and Schütze, 2003). This means that analyzing the most frequent words classified by the classifier in a specific class is useful to understand if the classifier works correctly. We reported the top 75 words of the environmental and socioeconomic dimensions in the Appendix. The list appears in line with expectations as we cannot identify words that are not reasonably used in the dimension in which they are classified.

[2] As a robustness check, we performed the same exercise using the PAB classifier at the phrase level. The results are basically the same and are reported in the Appendix.

5. An index of the incidence of the environmental topics

Once the classifier estimated the number of words associated with each dimension, we built a measure of alignment of these projects with the two dimensions. In particular, for each project we calculated the relative intensity index as follows:

$$Alignment = \frac{n_{env} - n_{soceco}}{n_{env} + n_{soceco}}$$

where n_{env} and n_{soceco} are the number of words classified in the environmental dimension and the socioeconomic dimension, respectively. The index is constrained in the range –1 and 1. If alignment = –1, the project is fully aligned with the socioeconomic dimension, while if alignment = 1, the project is fully aligned with the environmental dimension.

The mean value over all projects is equal to –0.3553. The negative sign of the index may someway suggest that a relatively larger number of words are related to the socioeconomic dimension, as well as it may be simply a consequence of the fact that this dimension includes more SDGs than the environmental dimension. The standard deviation is 0.7166 suggesting that the observed series has a large variability.

As a further validation exercise, we plotted the index against the six pillars in which the RRPs are organized. Although the dimensions of the SDG model and the pillars do not overlap precisely, it is still possible to make predictions on the sign of the correlations. The figures in the Appendix display evidence in line with our expectations.

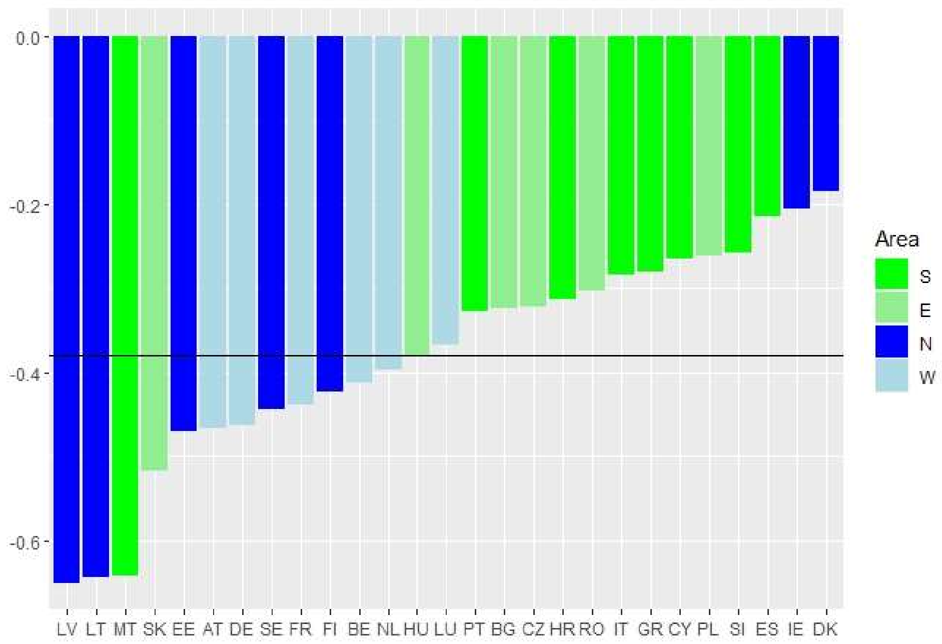
6. Results

We defined the index as a measure of alignment of the RRPs projects with the environmental dimension as compared with the socioeconomic one: the greater it is, the more the project is associated with environmental issues. In this section we will use the proposed index to test some hypotheses. In particular, we will see if the index is clustered by geographical area (section 6.1), if countries show different values of the index depending on the amount of funds received (section 6.2), some possible determinants of the index (section 6.3) and if the index is significantly associated with expected economic growth (section 6.4).

6.1. The index and the geographical area

Is the index clustered by geographical area? If so, which cluster of countries is most aligned with the environmental dimension? Figure 5 shows the sorted distribution of the index for each country in the European Union. In particular, the observations are grouped into four geographical clusters, according to the UN *geoscheme*: Northern countries (blue bars), Western countries (light blue bars), Southern countries (green bars) and Eastern countries (light green bars).

Figure 5. Sorted distribution of the index



EU countries are grouped according to the UN *geoscheme*. Northern, Western, Southern and Eastern countries are in blue, light blue, green and light green, respectively. The horizontal line indicates the mean value.

The four clusters tend not to be randomly sorted. Indeed, while on average the clusters of Eastern and especially Southern countries are usually more aligned with the environmental dimension, the opposite is true for the remaining two clusters. In particular, the clusters of Western and especially Northern countries tend to be less aligned with this dimension in favor of the socioeconomic one. If we look at the top three and bottom three countries, the only noticeable exceptions are Denmark and Ireland, Northern countries which are usually more aligned with environmental issues as the Southern and Eastern countries, and Malta, Southern country that paid more attention to socioeconomic issues. In any case, the results observed are interesting. Indeed, if we agree with the idea that each geographical cluster is a cluster of countries that share some characteristics from an economic and sociocultural point of view, this means that it makes sense to compare this index with some variables. This is what we will do in the next subsections.

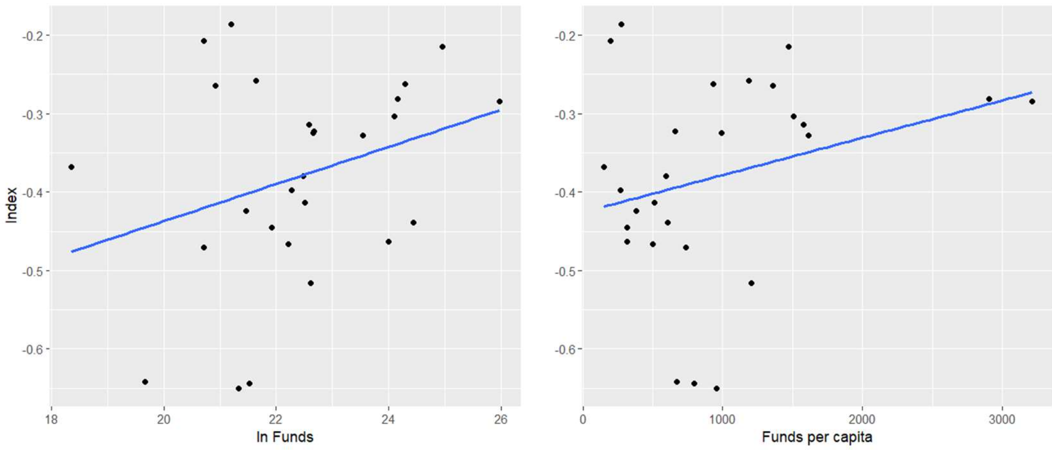
6.2. The index and the RRP funds

Are the countries that receive more funds from the RRF more interested in environmental or socioeconomic issues? We can expect that those countries receiving the larger financial support are those programming more balanced interventions across the two dimensions because they are not forced to focus only on the socioeconomic dimension that is generally considered higher on the political agenda.

Hypothesis 1: The countries receiving more funds show a higher value of the index (H1)

Both Figure 6, which reports the scatter plots of the index against the log funds and the funds per capita, and their correlation coefficients (0.31 and 0.28, respectively) give support to H1.

Figure 6. Scatter plots of the index against the log funds and the funds per capita



For each scatter plot the trend line is reported.

The positive association between the index and the funds received from the RRF, both in absolute value and per capita, reinforces the idea that the index tends to be influenced by some factors. If we read this result together with the one discussed in the previous subsection, we can state that 1) countries that receive more funds are able to pay more attention to environmental issues, which are usually perceived by governments as less urgent than socioeconomic issues; 2) net of this, the alignment with environmental issues tends to be influenced by some latent economic and sociocultural traits. In the next subsection we will discuss some of these possible traits.

6.3. The determinants of the index

The index can be a useful tool to identify the main reasons behind different cross-country mixes of environmental vs. socioeconomic projects in the RRPs. For instance, countries lagging behind from an environmental perspective might want to fill this gap, by paying more attention to the environmental dimension. Moreover, countries where tourism is a key or growing economic sector should be more interested in investing more resources in the environmental dimension.

H2: The countries where the gap in the environmental endowment is larger show a higher index value

H3: The countries where the tourism sector plays a more important role show a higher value of the index

For this analysis, we selected measures for a country's current environmental status and tourism specialization. A brief description is provided in Table 1.

Table 1. Environmental and tourist indicators

Indicator	Description
Net greenhouse gas emissions (tonnes per capita)	The indicator measures total national emissions including international aviation of the so-called 'Kyoto basket' of greenhouse gases
ln Years of life lost due to PM 2.5 exposure	The indicator measures the log of years of life lost (YLL) due to exposure to particulate matter (PM 2.5). YLL is defined as the years of potential life lost as a result of premature death
Estimated soil erosion by water (%)	The indicator estimates the area potentially affected by severe erosion by water such as rain splash, sheet wash and rills
ln Number of nights spent	It is the log number of nights spent by country of destination
ln Number of trips	It is the log Number of trips by country of

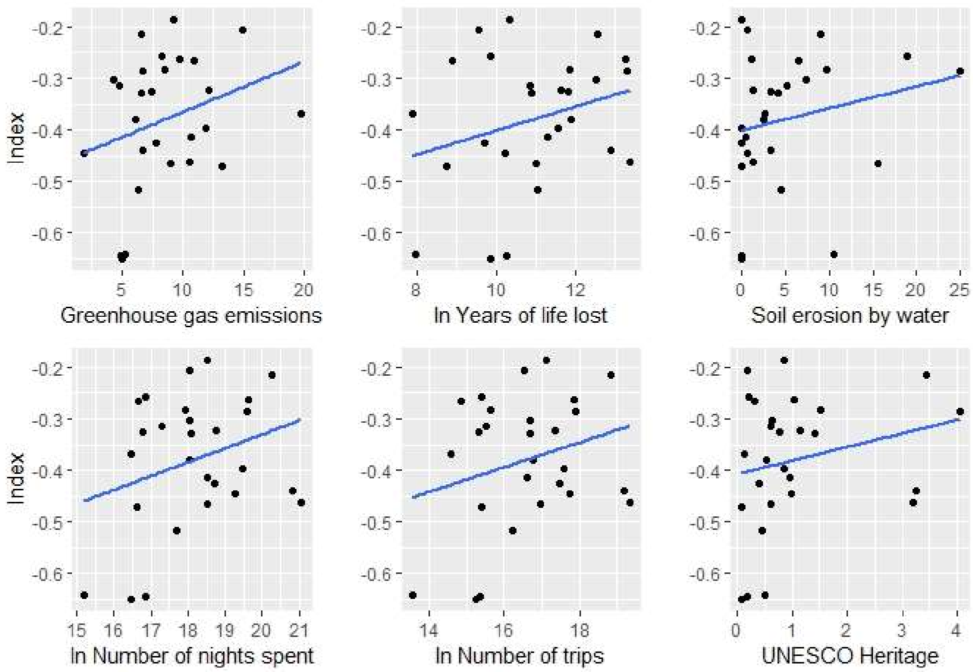
	destination
UNESCO Heritage	The indicator represents the UNESCO heritage. It is given by the ratio between the number of World Heritage Sites in a country and the surface of that country

Source: EUROSTAT and UNESCO.

While Net greenhouse gas emissions, ln Years of life lost due to PM 2.5 exposure and Estimated soil erosion by water are environmental indicators, ln Number of nights spent, ln Number of trips and UNESCO Heritage are tourist indicators. Specifically, the indicators are the averages of the period between 2015 and 2019, five years before the start of the implementation of the RRPs.

Figure 7 reports the scatter plots of each indicator against the index. Evidence is in line with H2 and H3 if we both look at the scatterplots and consider that the correlations of the index with the indicators are between 0.21 and 0.30.

Figure 7. Scatter plots of the index against the environmental and tourism indicators



Environmental and tourism indicators are shown at the top and bottom, respectively. For each scatter plot the trend line is reported.

The positive relationship between the index and each indicator suggests that those countries experiencing a delay towards the environmental objectives and those countries with a more tourism-oriented economy have put higher (and more space to) the environmental dimension on their RRPs. This means that the increase in the attention paid to environmental issues has concerned not only those countries in which a substantial part of the economy is based on tourism and, therefore, on the promotion of the cultural and environmental heritage, but also those countries in which the environment is probably not crucial for their economic development. While the first result is perhaps not surprising, the second one was not obvious. In this regard, it seems that the RRF has led the countries lagging behind from an environmental perspective to fill this gap.

6.4. The association of the index with economic growth

Ideally, we would like to investigate whether the observed annual differences across countries in the reported index can be useful to predict their economic performance. However, it is too early to measure it as we need to wait at least until the end of 2026 to assess if the different performances could be associated in someway with the different prevalence of environmental and socioeconomic projects. What we can do at this moment is to compare the index with the economic performance as predicted by the main professional forecasters. For instance, we may consider the GDP growth forecasts elaborated by the European Commission staff and included in the working document of each RRP for the period between 2020 and 2026 (European Commission, 2021b). It is worth noting that these forecasts were made available after the approval and publication of the definitive version of the RRPs, while, on the other hand, the index is based on information (RRPs) before the time the forecasts were published.

H4: A higher value of the index is associated with a better or worse expected economic performance

We consider different specifications to estimate the association between the index and the percentage change of the real GDP (Table 2).[3] In the first column we considered the following baseline regression model:

$$\dot{GDP}_{it} = \beta_0 + \beta_1 Index_{it} + \beta_2 Share\ projects_{it} + \beta_3 Trend_t + \beta_4 Covid_t + \varepsilon_{it}$$

[3] The panel dataset is unbalanced, because there are some missing values in the dependent variable. In particular, not all countries contain forecasts until 2026.

where $\dot{GDP}_{it}$ is the real GDP growth, $Index_{it}$ is the estimated alignment index, $Share\ projects_{it}$ is a variable which controls for the share of projects approved in each country over the years, $Trend_t$ is a trend control and $Covid_t$ is a time dummy control which takes 1 if the year is 2020 or 2021 and 0 otherwise. In the second and third columns we extended the baseline regression model by adding other controls. In particular, we considered the fixed effects by adding the following time-invariant variables: the average growth in real GDP five years before the start of the Covid-19 pandemic (between 2015-2019), the log GDP in 2019, the log Covid-19 deaths in 2020, the log grants and the log loans received via the RRPs (column 2). In column 3 we added another time dummy to control for the long-term time horizon (1 if the year is between 2023 and 2026 and 0 otherwise). In the remaining columns we did a similar exercise, but we considered the country effects as fixed effects. In all cases, we used robust standard errors (Wooldridge, 2010).

Table 2. The association of the index with RRP forecasts of $\dot{GDP}$

	1	2	3	4	5
Index	0.0390**	0.0361**	0.0308*	0.0490**	0.0420*
	(0.0126)	(0.0126)	(0.0130)	(0.0155)	(0.0166)
Share projects	0.1247***	0.1294***	0.1091***	0.1256***	0.1084***
	(0.0226)	(0.0222)	(0.0208)	(0.0236)	(0.0214)
Trend	-0.0002	-0.0003	0.0053	-0.0009	0.0043
	(0.0013)	(0.0014)	(0.0027)	(0.0016)	(0.0031)
Covid-19	-0.0119*	-0.0114*	-0.0142**	-0.0115*	-0.0136**
	(0.0043)	(0.0048)	(0.0045)	(0.0049)	(0.0046)
$\overline{\Delta\ \mathrm{GDP}}_{15-19}$		0.3129***	0.3100***		
		(0.0461)	(0.0440)		
$\ln(\mathrm{GDP}_{19})$		-0.0016	-0.0012		
		(0.0012)	(0.0011)		
$\ln(\text{Covid deaths}_{20})$		0.0003	-0.0001		
		(0.0021)	(0.0020)		
ln(RRP grants)		0.0000	-0.0003		
		(0.0012)	(0.0012)		
ln(RRP loans)		0.0006	0.0007		
		(0.0005)	(0.0004)		
Time horizon			-0.0227**		-0.0202**
			(0.0064)		(0.0071)

Country effects	✗	✗	✗	✓	✓
Observations	145	145	145	145	145
Adjusted R2	0.3207	0.3519	0.3790	0.4451	0.4673

Robust standard errors are reported in brackets. The constant is not reported but is included in the estimated equation. *Significant at a 5% level, **significant at a 1% level, and ***significant at a 0.1% level.

For all specifications considered, the equation shows to fit adequately the data as the adjusted R2 ranges between 32 and 47 percent. The index is statistically significant and shows a parameter stable between 0.03 and 0.05.[4] The positive association between the index and the expected growth of real GDP may reveal a positive effect of the environmental dimension on economic growth, even as compared with the socioeconomic one. The estimated economic effect suggests a small increase in growth when a country privileges the environmental dimension over the socioeconomic one, corresponding to 4 percentage points per year. This preliminary result can be considered in any case very interesting apart from surprising as the common view has always been that the socioeconomic dimension is more growth-enhancing than the environmental dimension. While several contributions in the literature show the positive impact of green policies on economic growth (Jouvet and de Perthuis, 2013; Mundaca and Markandya, 2016; Ringel *et al.*, 2016), the prevalence of the environmental policy measures as compared to the socioeconomic ones is new in the literature. If this evidence were confirmed in other empirical works focusing on observed data, it may provide support for the green policies and help mitigate the negative views of some parties and voters.

7. Conclusions

We investigated the alignment of the RRPs with the SDGs considering a validate SDGs model, the Wedding Cake Model proposed by the Stockholm Resilience Centre. For this purpose, we built a new textual dataset gathering the name, the description and the completion time of the RRPs projects. Then, we used the PAB classifier discussed in Chapter 1 to estimate the number of words associated with the environmental and socioeconomic SDGs.

[4] Robustness checks are available in the Appendix.

Once estimated for each project the number of words associated to each dimension, we built a relative index of alignment of these projects with those dimensions. Three main results emerged by plotting the index against key variables. The environmental dimension plays a more important role in those countries that: 1) receive more funds from the RRF; 2) show a major delay toward the environmental objectives; and 3) are more involved in tourism.

Finally, we estimated some panel models by regressing the index on the GDP growth forecasts elaborated by the European Commission staff and included in the working document of each RRP. The positive sign of the coefficient of the index denotes that the percentage change of the real GDP tends to be associated positively with the environmental dimension as compared to the socioeconomic one. If confirmed in future studies, such a result is really interesting because it could give support to the idea that focusing more on environmental issues is fair not only for reasons of intergenerational equity, according to which we need to leave a sustainable society, also from an environmental point of view, to the next generations, but also for economic reasons. Indeed, this result should reassure those policymakers who are afraid of implementing green policies due to their potential negative impact on economic growth, suggesting that greater environmental sustainability can coexist with greater economic growth.

References

BORCHARDT S., BUSCAGLIA D., BARBERO VIGNOLA G., MARONI M. and MARELLI L. (2020), A sustainable recovery for the EU: A text mining approach to map the EU Recovery Plan to the Sustainable Development Goals, Publications Office of the European Union, Luxembourg. doi: 10.2760/030575

COMMISSION DELEGATED REGULATION (EU) 2021/2106 of 28 September 2021 on supplementing Regulation (EU) 2021/241 of the European Parliament and of the Council establishing the Recovery and Resilience Facility by setting out the common indicators and the detailed elements of the recovery and resilience scoreboard.

DIAS C., HECSER A. and TURCU O. (2022), Recovery and Resilience Plans - public documents, Economic Governance Support Unit.

DIAS C., ZOPPÈ A., GRIGAITĖ K., SEGALL R., ANGERER J., LEHOFER W., GOTTI G., KOMAZEC K. and TURCU O. (2021), Recovery and Resilience Plans – An overview, Economic Governance Support Unit.

EUROPEAN COMMISSION (2019), Annual Sustainable Growth Strategy 2020, COM(2019) 650 final.

EUROPEAN COMMISSION (2021a), Annexes – Resilience dashboards for the social and economic, green, digital and geopolitical dimensions.

EUROPEAN COMMISSION (2021b), Commission staff working document – Guidance to member states Recovery and Resilience plans, SWD (2021) 12 final.

EUROSTAT (2020), Sustainable development in the European Union - Monitoring report on progress towards the SDGs in an EU context (2020 edition), Publications Office of the European Union, Luxembourg. doi: 10.2785/555257

FOLKE C., BIGGS R., NORSTRÖM A. V., REYERS B. and ROCKSTRÖM J. (2016), Social-ecological resilience and biosphere-based sustainability science, Ecology & Society, vol. 21, no. 3, art. 41. doi: http://dx.doi.org/10.5751/ES-08748-210341

FRANSMAN J., MACDONALD A. L., MCDONNELL I. and PONS-VIGNON N. (2004), Public Opinion Polling and the Millennium Development Goals, OECD Publishing, Paris. doi: https://doi.org/10.1787/18151949

HÁK T., JANOUŠKOVÁ S. and MOLDAN B. (2016), Sustainable Development Goals: A need for relevant indicators, Ecological Indicators, vol. 60, pp. 565-573. doi: https://doi.org/10.1016/j.ecolind.2015.08.003

JOUVET P. A. and DE PERTHUIS C. (2013), Green growth: from intention to implementation, International Economics, vol. 134, pp. 29-55. doi: https://doi.org/10.1016/j.inteco.2013.05.003

KARABOYTCHEVA M. (2021), Recovery and Resilience Facility, European Parliamentary Research Service.

KOUNDOURI P., DEVVES S. and PLATANIOTIS A. (2021), Alignment of the European green deal, the sustainable development goals and the European semester process: Method and application, Theoretical Economics Letters, vol. 11, issue 4, pp. 743-770. doi: 10.4236/tel.2021.114049

LOUGHRAN T. and MCDONALD B. (2016), Textual Analysis in Accounting and Finance: A Survey, Journal of Accounting Research, vol. 54, issue 4, pp. 1187-1230. doi: https://doi.org/10.1111/1475-679X.12123

MANNING C. D. and SCHÜTZE H. (2003), Foundations of Statistical Natural Language Processing, MIT Press, Cambridge.

MUNDACA L. and MARKANDYA A. (2016), Assessing regional progress towards a 'Green Energy Economy', Applied Energy, vol. 179, pp. 1372-1394.

OECD (2018), Economic Outlook No 103 - July 2018 - Long-term baseline projections.

OECD (2021), Economic Outlook No 109 - October 2021 - Long-term baseline projections. doi: https://doi.org/10.1787/cbdb49e6-en

RINGEL M., SCHLOMANN B., KRAIL M. and ROHDE C. (2016), Towards a green economy in Germany? The role of energy efficiency policies, Applied Energy, vol. 179, pp. 1293-1303. doi: https://doi.org/10.1016/j.apenergy.2016.03.063

RISTANTI P. Y., WIBAWA A. P. and PUJIANTO U. (2019), Cosine Similarity for Title and Abstract of Economic Journal Classification, 5th International Conference on Science in Information Technology (ICSITech) IEEE. doi: 10.1109/ICSITech46713.2019.8987547

ROTONDO F., PERCHINUNNO P., L'ABBATE S. and MONGELLI L. (2022), Ecological transition and sustainable development: integrated statistical indicators to support public policies, Scientific Reports, 12, article number 18513. doi: https://doi.org/10.1038/s41598-022-23085-0

SACHS J. D., SCHMIDT-TRAUB G., MAZZUCATO M., MESSNER D., NAKICENOVIC N. and ROCKSTRÖM J. (2019), Six Transformations to achieve the Sustainable Development Goals, Nature Sustainability, vol 2, pp. 805–814. doi: https://doi.org/10.1038/s41893-019-0352-9

SARRE A. D. and DAVEY S. M. (2021), The Sustainable Development Goals, forests, and the role of Australian Forestry, Australian Forestry, vol. 84, issue 2, pp. 41-49. doi: https://doi.org/10.1080/00049158.2021.1920207

SGAMBATI S. (2023), The interventions of the Italian Recovery and Resilience Plan: sustainable development, TeMA. Journal of Land Use, Mobility and Environment, vol. 16, no. 2, pp. 461-468. doi: http://dx.doi.org/10.6093/1970-9870/10038

SWAIN R. B. and YANG-WALLENTIN F. (2019), Achieving sustainable development goals: predicaments and strategies, International Journal of Sustainable Development & World Ecology, vol. 27, issue 2, pp. 96-106. doi: https://doi.org/10.1080/13504509.2019.1692316

THEODOROPOULOU S., AKGÜÇ M. and WALL J. (2022), Balancing Objectives? Just Transition in National Recovery and Resilience Plans, ETUI Research Paper - Working Paper 11, 2022. doi: http://dx.doi.org/10.2139/ssrn.4243412

UNRUH L., ALLIN S., MARCHILDON G., BURKE S., BARRY S., SIERSBAEK R., THOMAS S., RAJAN S., KOVAL A., ALEXANDER M., MERKUR S., WEBB E. and WILLIAMS G. A. (2022), A comparison of 2020 health policy responses to the COVID-19 pandemic in Canada, Ireland, the United Kingdom and the United States of America, Health Policy, vol. 126, issue 5, pp. 427-437. doi: https://doi.org/10.1016/j.healthpol.2021.06.012

VINUESA R., AZIZPOUR H., LEITE I., BALAAM M., DIGNUM V., DOMISCH S., FELLÄNDER A., LANGHANS S. D., TEGMARK M. and FUSO NERINI F. (2020), The role of artificial intelligence in achieving the Sustainable Development Goals, Nature Communications, vol. 11, article number 233. doi: https://doi.org/10.1038/s41467-019-14108-y

WHO (2021), Critical preparedness, readiness and response actions for COVID-19, World Health Organization, Geneva. doi: WHO/2019-nCoV/Community_Actions/2021.1

WOOLDRIDGE J. M. (2010), Econometric Analysis of Cross Section and Panel Data, MIT Press, Cambridge (Massachusetts).

Appendix

Appendix A. Validation exercises

Appendix A.1. Cosine similarity

We can use cosine similarity to measure the similarity among the annexes of the RRPs (Ristanti *et al.*, 2019):

$$Cosine\ similarity = \frac{\boldsymbol{Annex_i} \cdot \boldsymbol{Annex_j}}{\|\boldsymbol{Annex_i}\| \cdot \|\boldsymbol{Annex_j}\|}$$

where $\boldsymbol{Annex_i}$ and $\boldsymbol{Annex_j}$ are the vectors of the numbers of occurrences of each word in $Annex_i$ and $Annex_j$, respectively. In textual analysis cosine similarity is between 0 and 1: the closer cosine similarity is to 1, the more similar the annexes are. Table A.1 contains the cosine similarity for each pair of annexes:

Table A.1. Cosine similarity among the annexes of the RRPs (continues)

	Austria	Belgium	Bulgaria	Cyprus	Czechia	Germany	Denmark	Estonia	Spain
Austria	1.000								
Belgium	0.953	1.000							
Bulgaria	0.970	0.968	1.000						
Cyprus	0.945	0.966	0.955	1.000					
Czechia	0.953	0.959	0.970	0.966	1.000				
Germany	0.966	0.920	0.923	0.922	0.911	1.000			
Denmark	0.963	0.939	0.959	0.919	0.934	0.930	1.000		
Estonia	0.970	0.962	0.986	0.961	0.972	0.928	0.954	1.000	
Spain	0.962	0.971	0.968	0.979	0.969	0.939	0.941	0.970	1.000
Finland	0.971	0.964	0.979	0.950	0.964	0.934	0.961	0.978	0.967
France	0.915	0.931	0.912	0.938	0.925	0.904	0.859	0.924	0.938
Greece	0.933	0.965	0.953	0.982	0.961	0.906	0.899	0.953	0.970
Croatia	0.965	0.976	0.987	0.975	0.981	0.924	0.955	0.983	0.982
Hungary	0.967	0.956	0.987	0.946	0.968	0.922	0.962	0.979	0.963
Ireland	0.939	0.912	0.938	0.913	0.934	0.920	0.938	0.938	0.918
Italy	0.973	0.976	0.984	0.973	0.968	0.944	0.950	0.982	0.985
Lithuania	0.958	0.963	0.971	0.975	0.969	0.919	0.931	0.976	0.972

Luxembourg	0.941	0.944	0.949	0.949	0.939	0.917	0.900	0.950	0.955
Latvia	0.964	0.975	0.974	0.977	0.967	0.937	0.937	0.975	0.975
Malta	0.968	0.971	0.984	0.966	0.972	0.928	0.958	0.980	0.974
Netherlands	0.964	0.942	0.975	0.938	0.962	0.919	0.958	0.976	0.953
Poland	0.966	0.975	0.988	0.968	0.980	0.921	0.949	0.985	0.978
Portugal	0.956	0.972	0.971	0.979	0.967	0.927	0.928	0.971	0.985
Romania	0.965	0.974	0.993	0.961	0.969	0.921	0.958	0.982	0.974
Sweden	0.900	0.896	0.907	0.875	0.897	0.866	0.899	0.905	0.903
Slovenia	0.954	0.966	0.973	0.964	0.977	0.908	0.943	0.973	0.972
Slovakia	0.967	0.968	0.979	0.971	0.985	0.928	0.941	0.981	0.974

Table A.1. Cosine similarity among the annexes of the RRPs (continues)

	Finland	France	Greece	Croatia	Hungary	Ireland	Italy	Lithuania	Luxembourg
Austria									
Belgium									
Bulgaria									
Cyprus									
Czechia									
Germany									
Denmark									
Estonia									
Spain									
Finland	1.000								
France	0.902	1.000							
Greece	0.943	0.941	1.000						
Croatia	0.976	0.925	0.968	1.000					
Hungary	0.973	0.903	0.936	0.983	1.000				
Ireland	0.938	0.854	0.892	0.938	0.942	1.000			
Italy	0.978	0.943	0.968	0.985	0.976	0.927	1.000		
Lithuania	0.960	0.937	0.969	0.978	0.963	0.919	0.976	1.000	
Luxembourg	0.933	0.948	0.952	0.956	0.946	0.885	0.961	0.959	1.000
Latvia	0.964	0.952	0.976	0.982	0.963	0.920	0.982	0.980	0.966
Malta	0.974	0.923	0.955	0.988	0.984	0.940	0.983	0.973	0.954
Netherlands	0.969	0.891	0.920	0.971	0.979	0.941	0.964	0.961	0.931
Poland	0.975	0.933	0.962	0.990	0.981	0.940	0.983	0.981	0.959
Portugal	0.960	0.955	0.977	0.982	0.962	0.912	0.983	0.975	0.965
Romania	0.978	0.913	0.955	0.988	0.982	0.936	0.986	0.972	0.944

Sweden	0.903	0.872	0.850	0.909	0.922	0.882	0.907	0.895	0.889
Slovenia	0.971	0.914	0.956	0.984	0.966	0.935	0.971	0.969	0.933
Slovakia	0.970	0.947	0.963	0.986	0.975	0.931	0.982	0.979	0.961

Table A.1. Cosine similarity among the annexes of the RRPs (end)

	Latvia	Malta	Netherlands	Poland	Portugal	Romania	Sweden	Slovenia	Slovakia
Austria									
Belgium									
Bulgaria									
Cyprus									
Czechia									
Germany									
Denmark									
Estonia									
Spain									
Finland									
France									
Greece									
Croatia									
Hungary									
Ireland									
Italy									
Lithuania									
Luxembourg									
Latvia	1.000								
Malta	0.975	1.000							
Netherlands	0.949	0.973	1.000						
Poland	0.979	0.985	0.974	1.000					
Portugal	0.985	0.973	0.944	0.980	1.000				
Romania	0.973	0.985	0.973	0.989	0.973	1.000			
Sweden	0.896	0.924	0.918	0.922	0.904	0.914	1.000		
Slovenia	0.969	0.973	0.960	0.981	0.970	0.975	0.902	1.000	
Slovakia	0.979	0.981	0.969	0.987	0.978	0.978	0.912	0.976	1.000

Appendix A.2. Zipf's law

As a further validation tool, we considered the Zipf's law, for which very few words dominate the word count distribution (Manning and Schütze, 2003). Consequently, these words can potentially have a large impact on the results (Loughran and McDonald, 2016). This means that analyzing the most frequent words classified by the classifier in a specific class is useful to understand if the classifier works correctly. Figures A.1 and A.2 report the top 75 words of the two dimensions:

Figure A.1. Word count distribution for the environmental dimension

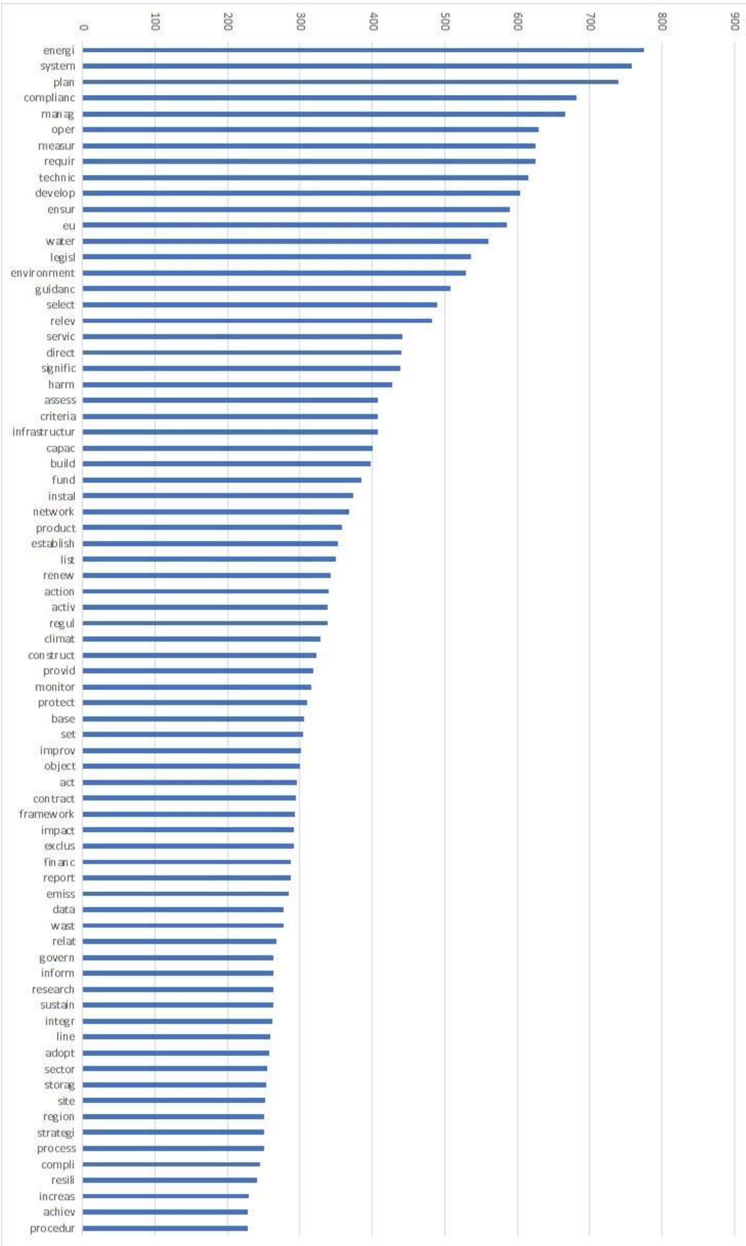
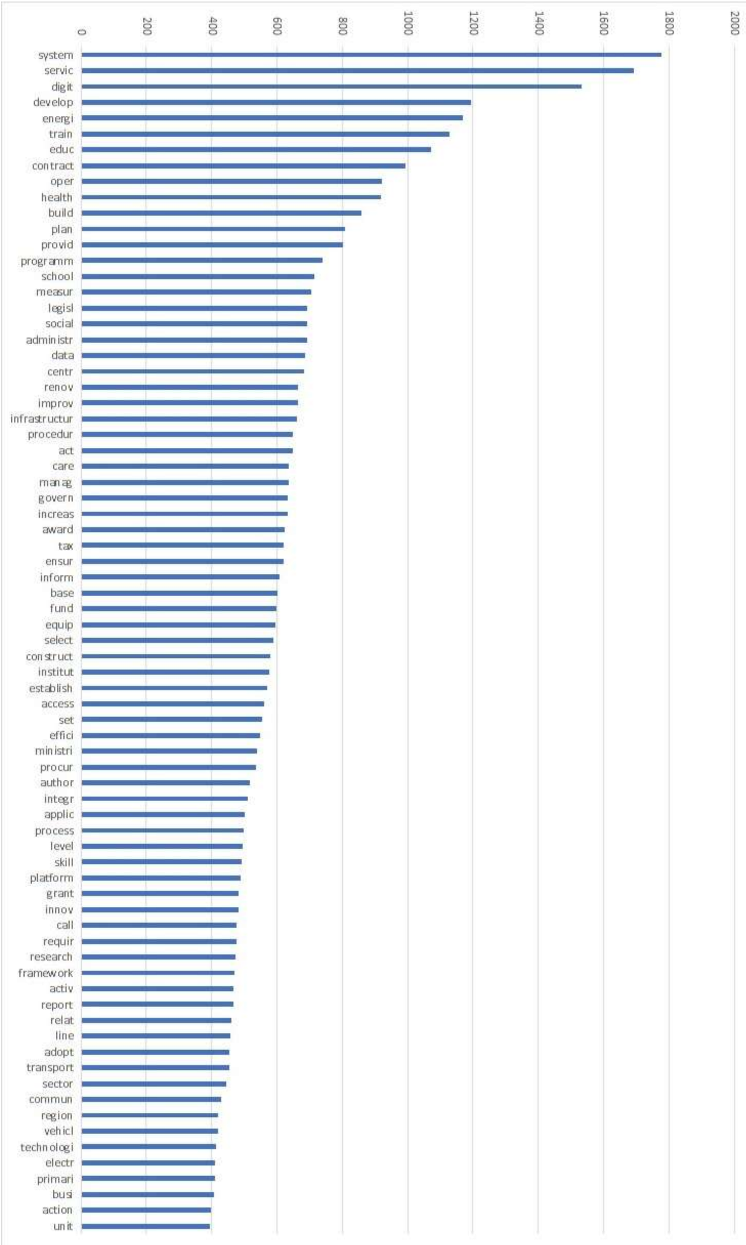


Figure A.2. Word count distribution for the socioeconomic dimension



The list appears in line with expectations as we cannot identify words that are not reasonably used in the dimension in which they are classified. Vice versa, there are some words that are clearly associated with environmental issues, such as environment, water, emissions, renewable and climate, or socioeconomic terms, such as digital, education, health, development and school.

Appendix A.3. The index and the RRP pillars

As a further validation exercise, we also plotted the index against the six pillars in which the RRPs are organized. We have already remarked that the SDGs and the pillars are different domains. The same is true if we extend the comparison to the dimensions of the Wedding Cake Model and the pillars. For example, the environmental dimension of the Wedding Cake Model does not correspond precisely to the green transition pillar.

By plotting the index against each pillar, our objective is to verify if the sign of these relationships is coherent with our expectations or not. Thus, a country deciding to allocate more funds to the green transition pillar should present a higher index, that is, more attention paid to the environmental dimension. On the other hand, funds for the pillars “digital transformation”, “health, social and institutional resilience” and “policies for the next generation” are expected to be negatively correlated with the index, because they are more intensely related to the socioeconomic dimension, such as business support for the development of digital products and services, and capacity of educational and health facilities (Commission Delegated Regulation, 2021).

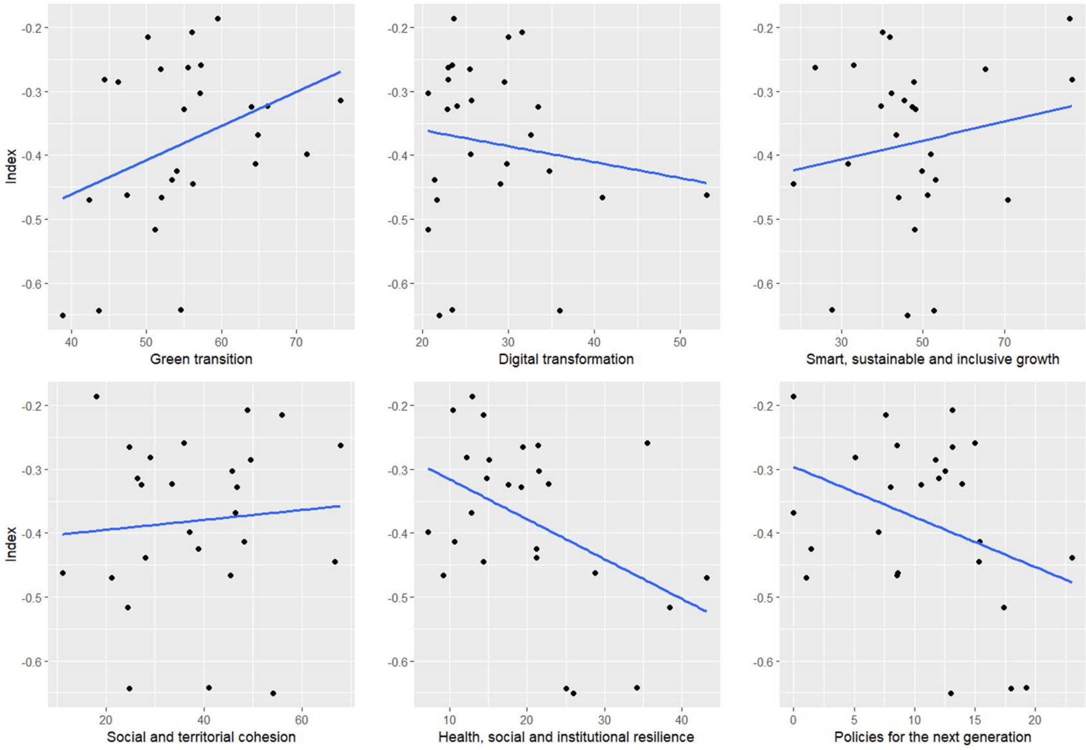
Hypothesis A.1: The countries allocating more funds to the green transition pillar show a higher index value (HA.1)

HA.2: The countries allocating more funds to the pillars “digital transformation”, “health, social and institutional resilience” and “policies for the next generation” show a lower value of the index

The relationships between the index and the pillars “smart, sustainable and inclusive growth” and “social and territorial cohesion” are not as easy to predict. These pillars deal with both environmental objectives (e.g., savings in energy consumption, renewable energy, infrastructure for alternative fuels, and benefits from protective measures against floods, wildfires and other climate-related natural disasters) and socioeconomic issues (e.g., support for firms in their activities and for people in finding a job, and inclusion of people in education or training activities) (Commission Delegated Regulation, 2021). Consequently, which of the two dimensions predominates can only be determined empirically.

Figure A.3 reports the scatter plots of the index against the percentages of funds allocated for the six pillars:

Figure A.3. Scatter plots of the index against the RRP pillars



For each scatter plot the trend line is reported.

The scatter plots show that HA.1 and HA.2 are reasonable. Specifically, there is a positive relationship between the index and the green transition pillar (correlation 0.36) and a negative relationship between the index and the pillars “digital transformation”, “health, social and institutional resilience” and “policies for the next generation” (correlations –0.14, –0.44 and –0.36, respectively). Finally, the correlations between the index and the pillars “smart, sustainable and inclusive growth” and “social and territorial cohesion”, for which we were not able to predict a sign, are positive or almost zero (0.18 and 0.09, respectively).

Appendix B. Robustness check

Appendix B.1. Estimates on OECD forecasts

To check the robustness of the estimated models, we also considered the forecasts of the growth of the real GDP made by another institution, the Organization for Economic Co-operation and Development (OECD). In particular, the data are from the long-term baseline projections made in 2021 (OECD, 2021), which take into account the effects of the Covid-19 pandemic and therefore the potential impact of the RRPs (Table B.1):

Table B.1. The association of the index with OECD forecasts (2021) of $\dot{GDP}$

	1	2	3	4	5
Index	0.0200*	0.0218*	0.0179	0.0258*	0.0213
	(0.0083)	(0.0095)	(0.0100)	(0.0103)	(0.0111)
Share projects	0.1220***	0.1196***	0.1074***	0.1157***	0.1046***
	(0.0177)	(0.0183)	(0.0172)	(0.0185)	(0.0173)
Trend	-0.0027*	-0.0028*	0.0007	-0.0031*	0.0003
	(0.0012)	(0.0013)	(0.0021)	(0.0014)	(0.0022)
Covid-19	-0.0186***	-0.0187***	-0.0223***	-0.0190***	-0.0224***
	(0.0042)	(0.0044)	(0.0043)	(0.0044)	(0.0043)
$\overline{\Delta\ \mathrm{GDP}}_{15-19}$		0.1975***	0.2017***		
		(0.0252)	(0.0261)		
$\ln(\mathrm{GDP}_{19})$		-0.0032**	-0.0029*		
		(0.0011)	(0.0011)		
$\ln(\text{Covid deaths}_{20})$		0.0021	0.0021		
		(0.0012)	(0.0011)		
ln(RRP grants)		0.0000	-0.0003		
		(0.0010)	(0.0010)		
ln(RRP loans)		-0.0001	0.0000		
		(0.0004)	(0.0003)		
Time horizon			-0.0179**		-0.0171**
			(0.0058)		(0.0058)
Country effects	✗	✗	✗	✓	✓
Observations	145	145	145	145	145
Adjusted R2	0.2699	0.2964	0.3165	0.3573	0.3783

Robust standard errors are reported in brackets. The constant is not reported but is included in the estimated equation. *Significant at a 5% level, **significant at a 1% level, and ***significant at a 0.1% level.

The results are similar to the ones based on the RRPs forecasts. Indeed, the index is usually again significant at the 5% level. The only exceptions are models 3 and 5, where the significance level of the index is at the 10%. On average, the environmental dimension leads to an increase between 2 and 3 percentage points in the growth of the real GDP.

We have carried out a final robustness check exercise. So far, we have considered the forecasts of economic growth after the start of the Covid-19 pandemic (and therefore after the realization of the RRPs). But what happens if we consider the forecasts before this shock starts? In this scenario, which does not consider the Covid-19 shock (and therefore the effects of the RRPs), it is reasonable to assume that neither the index nor the Covid-19 dummy should explain the dependent variable. To verify this hypothesis, we considered the long-term baseline projections made by the OECD in 2018 (OECD, 2018) (Table B.2):

Table B.2. The association of the index with OECD forecasts (2018) of $\dot{GDP}$

	1	2	3	4	5
Index	0.0003	0.0033	0.0033	-0.0022	-0.0028
	(0.0036)	(0.0038)	(0.0039)	(0.0031)	(0.0034)
Share projects	-0.0211*	-0.0196*	-0.0197*	-0.0160*	-0.0175*
	(0.0097)	(0.0086)	(0.0088)	(0.0067)	(0.0074)
Trend	0.0009	0.0007	0.0007	0.0012	0.0017
	(0.0007)	(0.0008)	(0.0009)	(0.0008)	(0.0010)
Covid-19	-0.0011	-0.0014	-0.0015	-0.0010	-0.0015
	(0.0012)	(0.0012)	(0.0012)	(0.0009)	(0.0011)
$\overline{\Delta\ \mathrm{GDP}}_{15-19}$		0.0389	0.0389		
		(0.0843)	(0.0846)		
$\ln(\mathrm{GDP}_{19})$		-0.0002	-0.0002		
		(0.0019)	(0.0019)		
$\ln(\mathrm{Covid\ deaths}_{20})$		-0.0020	-0.0020		
		(0.0034)	(0.0034)		
ln(RRP grants)		0.0029	0.0029		
		(0.0027)	(0.0027)		
ln(RRP loans)		-0.0013	-0.0013		
		(0.0007)	(0.0007)		
Time horizon			-0.0001		-0.0024

			(0.0011)		(0.0015)
Country effects	✗	✗	✗	✓	✓
Observations	145	145	145	145	145
Adjusted R2	0.0081	0.1296	0.1231	0.6659	0.6679

Robust standard errors are reported in brackets. The constant is not reported but is included in the estimated equation. *Significant at a 5% level, **significant at a 1% level, and ***significant at a 0.1% level.

The estimated models confirm our hypothesis, that is the index and the Covid-19 dummy do not affect the economic growth forecasts made before the start of the pandemic. This evidence is very useful to draw conclusion on the nature of the relationship between the index and the GDP growth forecasts. Indeed, we would have found a significant coefficient on the index if the positive association between these two variables had been driven by third unobserved factors that were already known at the time of the projections made by the OECD in 2018.

Appendix B.2. Estimates at the phrase level

A phrase level comparison between the original and the PAB classifier on the RRPs is reported in Table B.3:

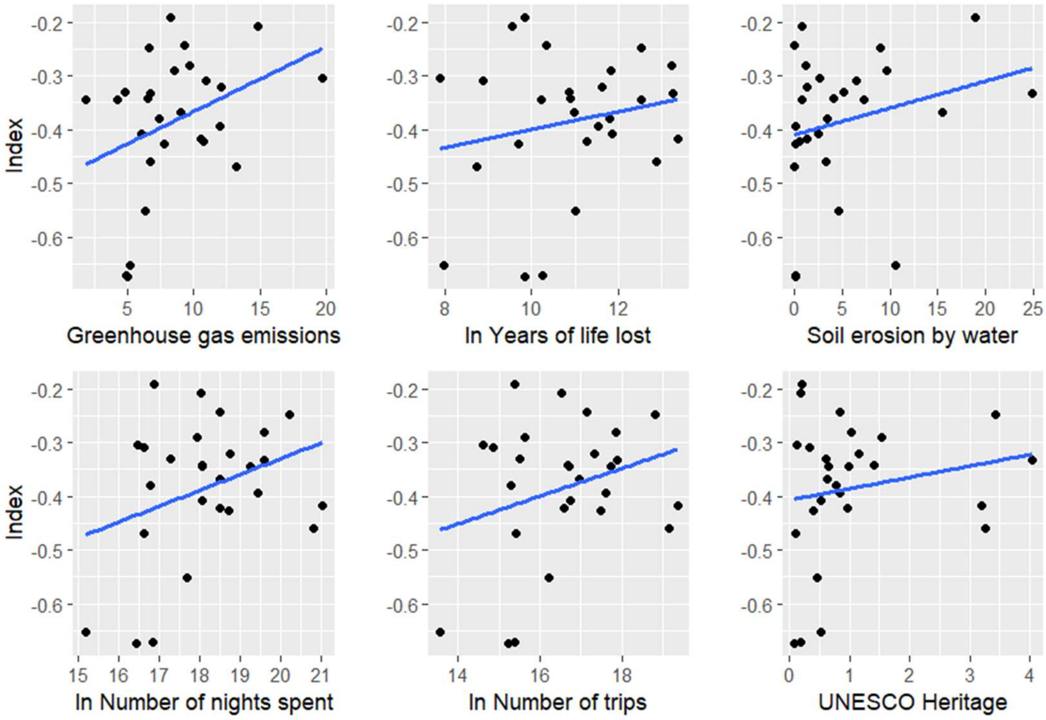
Table B.3. Comparison between the original and the PAB classifier on the RRPs (phrase level)

Metric/Classifier	Original	PAB
Accuracy	78.31	84.97
Precision	73.27	79.59
Recall	80.59	87.38
F1-score	74.52	81.76

For all metrics, we obtained an improvement of about 7% compared to the original classifier. The overall performance of the PAB classifier is good, with all metrics greater than or equal to 80%.

We performed the same exercise on the RRPs using the PAB classifier at the phrase level. The results are basically the same to the ones obtained at the word level. For reasons of synthesis, we only reported the scatter plots of each environmental and tourism indicator against the index (Figure B.1) and the regression analysis on the RRP forecasts of the growth of the real GDP (Table B.4):

Figure B.1. Scatter plots of the index against the environmental and tourism indicators (phrase level)



For each scatter plot the trend line is reported.

Table B.4. The association of the index with RRP forecasts of $\dot{GDP}$ (phrase level)

	1	2	3	4	5
Index	0.0328**	0.0322**	0.0273*	0.0433**	0.0370*
	(0.0108)	(0.0108)	(0.0116)	(0.0126)	(0.0140)
Share projects	0.1336***	0.1371***	0.1158***	0.1357***	0.1173***
	(0.0207)	(0.0199)	(0.0189)	(0.0205)	(0.0189)
Trend	-0.0003	-0.0004	0.0052	-0.0011	0.0041
	(0.0013)	(0.0014)	(0.0027)	(0.0015)	(0.0030)
Covid-19	-0.0115*	-0.0109*	-0.0138**	-0.0111*	-0.0132**
	(0.0042)	(0.0047)	(0.0045)	(0.0048)	(0.0045)
$\overline{\Delta\,\mathrm{GDP}}_{15-19}$		0.3259***	0.3213***		
		(0.0501)	(0.0463)		
$\ln(\mathrm{GDP}_{19})$		-0.0021	-0.0016		

		(0.0012)	(0.0012)		
$\ln(\text{Covid deaths}_{20})$		-0.0007	-0.0009		
		(0.0022)	(0.0021)		
ln(RRP grants)		0.0007	0.0003		
		(0.0014)	(0.0013)		
ln(RRP loans)		0.0006	0.0007		
		(0.0004)	(0.0004)		
Time horizon			-0.0228**		-0.0200**
			(0.0064)		(0.0070)
Country effects	✗	✗	✗	✓	✓
Observations	145	145	145	145	145
Adjusted R2	0.3103	0.3497	0.3767	0.4446	0.4664

Robust standard errors are reported in brackets. The constant is not reported but is included in the estimated equation. *Significant at a 5% level, **significant at a 1% level, and ***significant at a 0.1% level.

CHAPTER 3

The impact of Special Economic Zones on Southern Italy

Abstract

This chapter proposes a first analysis of the impact of Italian Special Economic Zones (SEZs) on firms in Southern Italy. To do this, we built a panel dataset of Italian businesses and analyzed the impact of being a SEZ firm or a firm adjacent to a zone on its number of employees. Preliminary results suggest that SEZs have been successful, because SEZ businesses and businesses adjacent to a zone have significantly increased their number of employees. Moreover, the SEZ program has induced economic specialization: while businesses in the agricultural sector have not made significant changes to employment, the opposite is true for firms in the industrial and service sectors, where the number of employees has increased significantly.

Keywords: Special Economic Zones; Southern Italy; Italian dualism; employment; economic specialization

1. Introduction

Special Economic Zones (SEZs) are geographically delimited area in which governments establish special rules for businesses and investors, through tax breaks and administrative simplifications (Bost, 2019; UNCTAD, 2019).

A SEZ program is a place-based policy that finds its roots in the new economic geography theory (Krugman, 1991). According to this theory, economic forces tend to influence the location of economic activities in the core or the periphery. In this theoretical framework, we have two opposing forces: centripetal forces, which tend to agglomerate economic activities in the core, and centrifugal forces, which operate in the opposite direction, trying to favor a more balanced distribution of economic activities across space. However, centripetal forces usually overcome centrifugal forces, generating an uneven distribution of economic activities across space and, therefore, regional disparities. For those who share these theoretical assumptions, place-based policies, such as SEZs, should be implemented to reduce these territorial inequalities. Moreover, supporters of place-based policies state that these policies should be implemented not only for reasons of equity, but also for reasons of economic efficiency. In this regard, Duranton and Venables (2021) highlighted that uncontrolled development of regions leads to market failures, because it produces congestion in major cities, due to the choice of most economic agents to locate their economic activities in the same area, and poverty in lagging regions, whose communities remain trapped in low-level economic development.

From a practical point of view, there are three main reasons why policymakers create SEZs. The first is investment attraction (Davies and Mazhikeyev, 2019). Attracting domestic investment and foreign investment is necessary for both developing and developed countries to boost the economic and social development of lagging regions. A study realized by Wang (2013) on Chinese SEZs found that the SEZ program significantly increased foreign direct investment in treated municipalities, generating wage increases for workers more than the increase in the local cost of living. A second reason strictly related to the previous one is the creation of jobs (Lu *et al.*, 2019). Indeed, investment attraction in existing or new firms generates an increase in employment, directly and indirectly. Directly for those firms in which investments are made, indirectly for those firms whose activity is closely linked to the firms affected by investments. Zheng (2021) recently studied the impact of Chinese SEZs on job creation, showing that zones increased local jobs due to investments in the creation of new businesses and the expansion of existing ones. The combination of investment attraction and job creation leads to the last reason: economic growth (Moberg, 2015). In this regard, SEZs are expected to increase the GDP of the treated areas and, consequently, of the country as a whole. For example, Huang *et al.* (2017) found that the Shanghai pilot free trade zone positively affected Shanghai's economic growth.

The first modern SEZs were created in the 1960s, and then their number increased exponentially in the following decades: while in 1975 there were just 79 zones in the world, in 2019 this number increased to 5,383. The creation of SEZs is a phenomenon usually linked to developing countries, and in particular to Asian ones. Indeed, 4,046 zones are placed in Asia. China is the Asian country with the largest number of SEZs (2,543). Despite this, SEZs also exist in developed countries (374 zones), most of which are in the United States (262). In the European Union, SEZs are usually located in former socialist economies. Indeed, the top three EU countries by number of SEZs include Poland, Lithuania and Croatia. This is because the zones were used to sustain employment in undeveloped areas during the economic transition of the 1990s (Jensen, 2018).

Despite SEZs have a long history, they are a new policy tool in Italy. Indeed, the Italian government approved the law which establishes SEZs (*Zone Economiche Speciali* – ZES in Italian) in 2017 (law decree n. 91). Stimulating economic growth of Southern Italy is the reason why this tool was introduced in Italy. Indeed, Italy has been affected by an economic dualism since the proclamation of the Kingdom of Italy in 1861. On the one hand we have Northern Italy whose economy was gradually integrating with the developed European economies, on the other hand the economy of Southern Italy lagged behind. To solve this problem, several interventions were implemented in the following decades, both at the national and European level.

The most important intervention implemented by the Italian government after the Second World War was the Fund for the South, which was established with the law n. 646 in 1950 to promote the realization of public works and infrastructure in rural areas of Southern Italy. The Fund operated until 1984 and was supposed to contribute to "the economic and social progress of Southern Italy" (law 1950/646). In the meantime, the European Union started cohesion policy in the 1980s, an investment policy delivered through several funds aimed at supporting economic and social growth among member states. For the 2021-2027 cohesion policy, Southern Italy was financed by the European Social Fund Plus, which supports employment and aims to create a fair and socially inclusive society in EU countries, and by the European Regional Development Fund, which invests in social and economic development of all EU regions and cities.

Despite the use of these tools, the Italian dualism remains unsolved (Banca d'Italia, 2022). Indeed, several macroeconomic indicators suggest that both the Fund for the South before and the cohesion policy after have not eliminated, or at least significantly reduced, the historical gap between Northern and Southern Italy. In this regard, we can see SEZs as the new intervention tool aimed at reducing the Italian dualism. Although it is too early to judge whether SEZs have been successful in achieving this long-term goal, we can make a preliminary assessment of their effectiveness.

This study proposes a quantitative analysis of the impact of SEZs on Southern Italy. To the best of our knowledge, this is the first study that attempts to evaluate the effectiveness of this policy tool in Italy using quantitative methods. Since the Italian SEZ program has only recently become fully operational, the few existing studies on Italian SEZs are descriptive studies aimed at evaluating the strengths and weaknesses of SEZs, providing suggestions to policy makers on how to improve the current regulatory framework of the Italian SEZ program. For example, Ferrara *et al.* (2022), after a broad review of the existing literature on the impact of SEZs on countries that have already implemented this tool, highlighted that the regulatory framework of Italian SEZs should be improved considering: 1) SEZ development strategies fully integrated into the general Italian economic development strategies; 2) the SEZ program as a place-based approach, which takes into account the needs of the different territories in which the SEZs reside; 3) institutional strengthening actions to be integrated into territorial development strategies to facilitate the planning, operation and continuous monitoring of these strategies.

While most of the literature has studied the impact of zones at the aggregate level, in this paper we study this impact on entities directly affected by the Italian law on SEZs, i.e. Italian businesses. To do this, we constructed a panel dataset of hundreds of thousands of Italian firms observed between 2014 and 2022, the year in which the SEZ policy became fully operational. Then we carried out a regression analysis where we analyzed the impact of SEZs on the number of employees. Although not all firms eligible for SEZ benefits have already received these benefits, investigating whether the SEZ program led to an increase in their number of employees or not is an interesting research question. This is because announcement effects may have led many of these firms to start an investment program to access SEZ benefit. Moreover, we also verified whether SEZs generated positive or negative spillovers on businesses located in municipalities adjacent to zones. Results suggest that SEZ firms and firms located in a municipality adjacent to zones increased their number of employees.

This chapter is structured as follows: section 2 presents a summary of previous findings on the effects of SEZs and describes the policy background of Italian zones. The third section illustrates data e methods used for the empirical analysis. Section 4 discusses the obtained results. The role of Italian SEZs in solving the dualism between Northern and Southern Italy is discussed in section 5. The sixth section concludes.

2. Literature review

Several studies have assessed the impact of SEZs policies. Busso *et al.* (2013) estimated causal impacts of American Empowerment Zones, basically SEZs aimed at encouraging economic and social investment in the neediest urban and rural areas of the United States. To do this, they applied an adjusted difference-in-differences estimator on a dataset of households and establishments from the 1980, 1990 and 2000 Decennial Censuses of Population and Housing. Their findings show that these zones generated jobs in affected areas and increased wages of residents working in the zones, without causing dramatic changes in the local cost of living. Ambroziak and Hartwell (2018) analyzed the impact of Polish zones on regional development. For this purpose, they used a counterfactual evaluation method to evaluate the economic and social consequences of Polish SEZs at the *powiat* level (Polish entities equivalent to the Local Administrative Units (LAU) level 1) between 2005 and 2013. In particular, they identified *powiats* for the experimental and control groups (*powiats* affected and not affected by the SEZ policy, respectively) which are statistically equivalent, i.e. *powiats* with similar characteristics in terms of GDP per capita. Their results show that SEZs have increased investment attractiveness and job creation. Ciżkowicz *et al.* (2017) estimated a set of panel models for employment and capital outlays of Polish *powiats* over the period 2003–2012. Their results suggest that SEZs had a strong positive effect on employment and a weak positive effect on investment. Jensen (2018) assessed the employment impact of the Poland's SEZs policy using the Polish databank. She collected economic data at the *gmina* level (basically, Polish municipalities equivalent to the LAU level 2) for the period 1995-2014. Then, she used a difference-in-differences approach adjusted for panel data to assess the impact of zones on employment, finding that SEZs have been successful in increasing employment after the economic transition of 1990s. A comparison of SEZ programs among EU countries was realized by Arbolino *et al.* (2023), which investigated the impact of European incentive zones (IZs), a generic term which covers different types of policy incentives, including SEZs. To this end, they implemented a two-step methodology on a panel dataset of administrative regions located in seven EU countries (Croatia, Estonia, France, Germany, Lithuania, Poland and Spain) observed between 2006 and 2018. First, they constructed two composite indicators using the principal component analysis to assess the benefits obtained by IZ regions during the implementation of IZ programs. Second, they compared IZ regions with other regions using the counterfactual analysis to verify the ability of public policy to steer the conditions of a target population in a desired direction. Their findings show significant positive results achieved by the various industrial policy instruments with differing levels of success.

Focusing on other studies not strictly related to SEZs policies, Martin *et al.* (2011) adopted a GMM approach for analyzing the impact of the French cluster policy. They used French annual business surveys data from 1996 to 2004, finding that neither workers nor profits captured the gains from localization economies. Kline and Moretti (2014) studied the long-term effects of the Tennessee Valley Authority (TVA), an American regional development program established in 1933 to modernize the economy of the Tennessee Valley region through investments in infrastructure. For this purpose, they estimated Oaxaca-Blinder regressions to compare the economic performance between TVA counties and non-TVA counties with similar characteristics to the treated counties before the program started, finding that the TVA led to large gains in agricultural and manufacturing employment between 1940 and 1960. However, between 1960 and 2000, when federal transfers were reduced, the gains in agricultural employment were reversed, while the gains in manufacturing employment continued to increase. Since the manufacturing sector paid higher wages than the agricultural sector, the TVA generated a positive net effect for an extended period.

Focusing on developing countries, Alkon (2018) investigated whether SEZs have induced developmental spillovers in India. He created an original dataset by matching SEZs to SEZs to the nearest Indian villages. Then, he tested the spillover effects of SEZs policy using 2001 and 2011 Indian census data (four years before and six years after the Indian law on SEZs was approved). For this purpose, he applied the Covariate Balancing Propensity Score methodology to several indicators associated with economic and social development. His findings show that Indian SEZs have failed to achieve socioeconomic development, suggesting that this result is due to the political economy framework of India, in which high levels of corruption lead politicians to privilege rent-seeking instead of long-term economic and social growth. On the contrary, Chinese SEZs are seen as a case study of successful SEZs in developing countries. Indeed, there are many studies that state that SEZs in China have increased the economic development of affected areas, for example in terms of investment attractions and employment generation (Zeng, 2010; Wang, 2013; Alder *et al.*, 2016). As an example, a recent study realized by Lu *et al.* (2019) investigated the effects of the SEZ program in China using a panel dataset of manufacturing firms from the economic censuses conducted by China's National Bureau of Statistics at the end of 2004 and 2008. In particular, they used a difference-in-differences estimation to compare village and county performance before and after the establishment of SEZs, finding that zones have increased employment and productivity in the designated areas. Case studies of successful SEZs can also be found in Latin America. Defever *et al.* (2019) analyzed the reform of Dominican Republic's SEZs, which involved the staggered removal of export share requirements in the zones to align the law on SEZs with the World Trade Organization agreement on subsidies. The authors carried out panel regressions on customs data using international trade transactions between 2006 and 2014, finding that the reform made SEZs more attractive locations for exporters. A more comprehensive study of how SEZs impacted developing economies was realized by Frick *et al.* (2019). The authors collected nightlight data from the Defense Meteorological Satellite Program and used them to proxy the performance of SEZs in developing economies. In particular, they regressed SEZs growth between 2007 and 2012 on SEZs factors, finding that SEZs growth is difficult to sustain over time, zones rarely lead to economic specialization and larger SEZs have an advantage in terms of growth potential.

Table 1 reports a summary of the recent literature on SEZ programs, including the authors, the country analyzed, the period considered, the methodology applied and the effectiveness of the SEZ program:

Table 1. Summary of the recent literature on SEZ programs

Authors	Country	Period	Method	Effective SEZs?
Alkon (2018)	India	2001 and 2011	CBPS	✗
Ambroziak and Hartwell (2018)	Poland	2005-2013	Counterfactual analysis	✓
Arbolino *et al.* (2023)	EU countries	2006-2018	PCA and counter-factual analysis	✓
Busso *et al.* (2013)	United States	'80, '90 and '00	DiD	✓
Ciżkowicz *et al.* (2017)	Poland	2003-2012	Panel regression	✓
Defever *et al.* (2019)	Dominican Republic	2006-2014	Panel regression	✓
Frick *et al.* (2019)	Developing countries	2007 and 2012	Panel regression	✗
Jensen (2018)	Poland	1995-2014	DiD	✓
Kline and Moretti (2014)	United States	1940-2000	Oaxaca-Blinder regressions	✓
Lu *et al.* (2019)	China	2004 and 2008	DiD	✓
Martin *et al.* (2011)	France	1996-2004	GMM	✗

2.1. The Italian Special Economic Zones

The law on SEZs and the related regulation were approved by the Italian government with the law decree 2017/91 ("Urgent measures for the economic growth of Southern Italy") and the decree of the prime minister 2018/12, respectively. According to article 2 of the regulation, SEZs are established to promote favorable conditions in economic, financial and administrative terms to allow the development of existing and new firms in the zones. Article 4 of the law establishes that a SEZ is a geographically delimited area which includes at least one port.[5] In this area, existing or new firms can benefit from special economic conditions. Each less developed or transition region can propose to the Italian government the establishment of maximum two zones, provided that there are two or more ports in its territory. Less developed or transition regions that do not have ports can apply for the establishment of an interregional SEZ with less developed or transition regions that have ports. Each SEZ is administered by an authority (*Comitato di indirizzo*, in Italian), presided by a Special Commissioner appointed by the Italian government. The SEZ authority has to ensure the proper functioning of the zone, supporting existing and new firms and promoting the attraction of investments. The monitoring of the implementation of the SEZ program is carried out by the Territorial Cohesion Agency, a public agency supervised by the Italian government. According to article 7 of the regulation, the minimum and maximum duration of SEZs is 7 and 21 years, respectively.

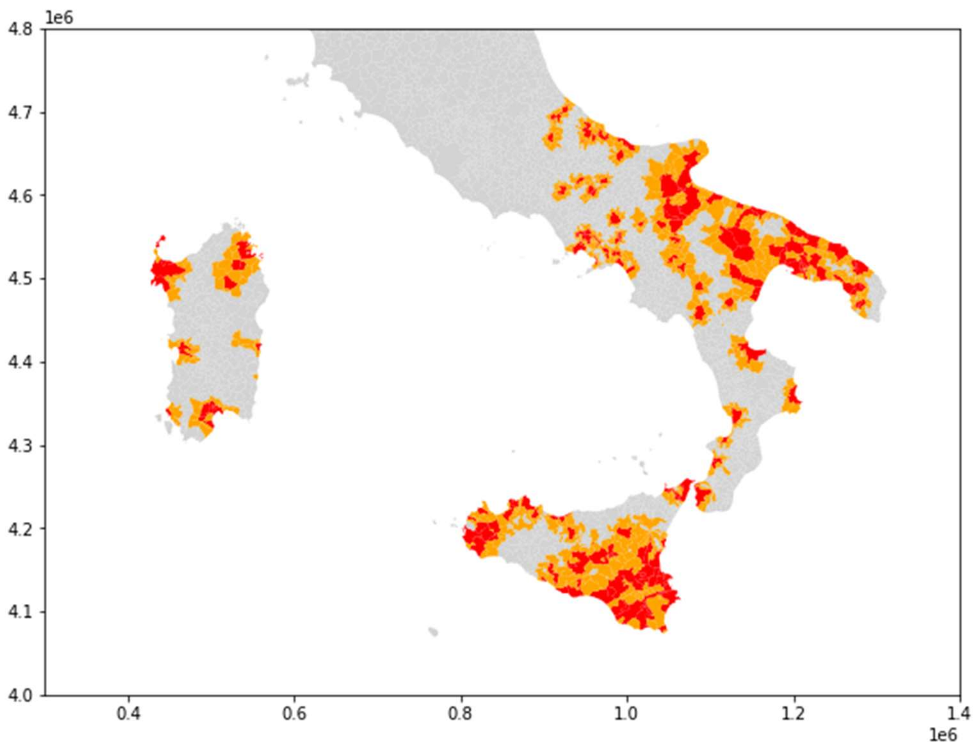
Article 5 of the law defines the package of benefits for businesses located in a SEZ, basically administrative simplifications, a special customs regime and fiscal incentives. With reference to the administrative simplifications, existing or new firms can benefit from the streamlining of administrative procedures. In particular, for these businesses the time for these procedures is reduced by a third or even half, depending on the procedure. A zone can also include a special customs regime. Indeed, in a SEZ can be established customs free zones, where firms can import goods at a reduced tariff. Focusing on the fiscal incentives, businesses can benefit from the tax credit of up to 100 million euros for goods (machineries, lands and buildings) purchased by 2023. According to this article, the firms eligible for the fiscal incentives are the ones described starting from paragraph 98 of article 1 of law 2015/208 ("Budget Law 2016"). In particular, small, medium and big businesses that invest in existing and new production structures can benefit from the tax credit, provided that they do not belong to the following sectors: steel industry, coal industry, shipbuilding industry, synthetic fiber industry, transport industry and related infrastructure, energy production and distribution industry, energy infrastructure industry, as well as the credit, financial and insurance sector. Agricultural, fishing and aquaculture sectors are also excluded from

[5] Ports must have the characteristics defined by the EU regulation 2013/1315.

the benefits. Firms in a SEZ that want to access these benefits have to continue their activities in the zone for at least seven years after receiving the benefits. Paragraph 174 of article 1 of law 2020/178 ("Budget Law 2021") extended this period to ten years, specifying that firms have to preserve "the jobs created in the SEZ activity for at least ten years".

The Italian government established eight SEZs between 2018 and 2021: SEZ Abruzzo (2020), SEZ Calabria (2018), SEZ Campania (2018), SEZ Apulia-Basilicata (2019), SEZ Apulia-Molise (2019), SEZ Sardinia (2021), SEZ Western Sicily (2020) and SEZ Eastern Sicily (2020). Although these zones have been established since 2018, they became fully operational in 2022. Indeed, the appointment of the Special Commissioners, who preside the SEZ authorities, took place from the end of 2021. Figure 1 shows the map of Italian municipalities that fall within a SEZ or are adjacent to a SEZ:

Figure 1. Map of SEZ municipalities



Municipalities that fall within a SEZ and those that are adjacent to a SEZ are in red and orange, respectively.

3. Data and methods

We gathered data from the Computerized analysis of Italian companies database (*Analisi informatizzata delle aziende italiane* – Aida in Italian). The Aida database contains detailed information on the financial statements of Italian businesses. The constructed dataset contains firms active between 2014 and 2022. Collected variables include municipalities, provinces and regions where business headquarters are located, and assets, number of employees and revenues of businesses. Since for each firm we have the municipality where business headquarters are located, we constructed a dummy variable which captures whether the i-th firm is in an operational SEZ:

$$Operat.SEZ_{it} = \begin{cases} 1 \; if \; i \in SEZ \; municipality \; and \; t \geq year \; in \; which \; SEZ \; started \\ 0 \; otherwise \end{cases}$$

We considered 2022 as the year in which zones actually started, because SEZs became fully operational in this year.

We said that only small, medium and big firms that do not belong to some sectors can benefit from the tax credit. Focusing on the size of firms, this aspect is defined according to the Commission recommendation of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises. In particular, since the tax credit refers to small, medium and big firms, we can consider all firms that are not micro businesses, that is those firms whose number of employees is less than 10 and its revenues or assets are less than 2 million euros. Consequently, we can create a dummy variable which captures whether the i-th firm belongs to the size eligible for the fiscal incentives as follows:

$$Eligible \; size_i = \begin{cases} 1 \; if \; i \in small, medium \; or \; big \; firm \\ 0 \; otherwise \end{cases}$$

With reference to the sectoral aspect, we can identify the sector wherein each firm operates using ATECO 2007, the classification system of economic activities adopted by the Italian National Institute of Statistics (ISTAT, 2009). Table 2 shows the sectors that cannot benefit from the tax credit and their ATECO 2007 codes:

Table 2. Sectors not eligible for the fiscal incentives

Sector	ATECO 2007 codes
Agricultural, fishing and aquaculture sectors	A.01.1; A.01.2; A.01.3; A.01.5; A.01.6; A.03
Coal industry	B.05
Credit, financial and insurance sector	K
Energy infrastructure industry	D.35.11; D.35.12; D.35.13; D.35.21; D.35.22
Energy production and distribution industry	F.42.22
Shipbuilding industry	C.30.1
Steel industry	C.24.1
Synthetic fiber industry	C.20.6
Transport industry and related infrastructure	H

Consequently, a dummy variable which captures whether the i-th firm belongs to the sector eligible for the fiscal incentives can be constructed in the following way:

$$Eligible\ sector_i = \begin{cases} 1\ if\ i \in sector\ eligible\ for\ the\ fiscal\ incentives \\ 0\ otherwise \end{cases}$$

The product among the aforementioned dummies gives us the variable of our interest, that is a dummy variable that tells us whether the i-th business is a small, medium or big firm that belongs to an eligible sector and is in an operational SEZ (value 1) or not (value 0):

$$SEZ_{it} = Eligible\ size_i * Eligible\ sector_i * Operat. SEZ_{it}$$

We also created a dummy variable which captures whether the i-th firm is in a municipality adjacent to an operational SEZ as follows:

$$Adj\ SEZ_{it} = \begin{cases} 1\ if\ i \in mun. adjacent\ to\ a\ SEZ\ and\ t \geq year\ in\ which\ SEZ\ started \\ 0\ otherwise \end{cases}$$

We have seen in the literature review section that employment is a key variable for evaluating the effectiveness of a SEZ program. Consequently, we used the log number of employees as dependent variable in an econometric model based on a fixed effects strategy, allowing us to mitigate omitted-variable bias. In particular, we built the following econometric model:

$$\ln(Employees_{it}) = \beta_0 + SEZ_{it}\beta_1 + Adj\ SEZ_{it}\beta_2 + \boldsymbol{Size}'_{it}\boldsymbol{\beta}_3 + \boldsymbol{Sector}'_i\boldsymbol{\beta}_4 + \boldsymbol{SEZ}'_i\boldsymbol{\beta}_5 + \boldsymbol{X}'_i\boldsymbol{\beta}_6 + \boldsymbol{T}'_t\boldsymbol{\beta}_7 + \varepsilon_{it}$$

The model includes the variables of our interest (SEZ_{it} and $Adj\ SEZ_{it}$) as well as several controls. A summary description of all regressors is reported in Table 3:

Table 3. Description of the regressors included in the model

Variable name	Description
SEZ_{it}	Dummy variable which captures whether the i-th firm is a small, medium or big firm that belongs to an eligible sector and is in an operational SEZ
$Adj\ SEZ_{it}$	Dummy variable which captures whether the i-th firm is in a municipality adjacent to an operational SEZ
$\boldsymbol{Size}'_{it}$	Row of dummies which capture the size effect (micro, small or medium-big businesses). We made this classification using the definition of small and medium-sized enterprises adopted by the European Commission (European Commission, 2020). In particular, we have a micro business whether its number of employees is less than 10 and its revenues or assets are less than 2 million euros. Small businesses have less than 50 employees and less than 10 million euros in revenues or assets. We defined medium-big businesses all other businesses that were neither micro nor small businesses
$\boldsymbol{Sector}'_i$	Row of dummies which capture the sectoral effect (agricultural, industrial or service sector). To classify a business in one of these three macro sectors, we used its ATECO 2007 code (ISTAT, 2009). In particular, we classified each business in the agricultural, industrial or service sector
$\boldsymbol{SEZ}'_i$	SEZ businesses effects: it is a row of dummies which capture firms eligible for SEZ benefits or firms adjacent to SEZ municipalities regardless of the year. These controls should cancel out the impact of SEZ_{it} and $Adj\ SEZ_{it}$ if the increase in jobs in these firms occurs regardless of the

	operation of the SEZ program
$\boldsymbol{X}_i'$	Row of dummies which capture fixed effects. Each firm has unique characteristics. Fixed effects are used to absorb these heterogeneous traits
$\boldsymbol{T}_t'$	Row of dummies which capture time effects. Time effects are useful for absorbing common shocks which occurred in a given year

The main descriptive statistics associated with the dependent variable and the regressors are reported in Table 4:

Table 4. Descriptive statistics of the regressors included in the model

Variable	Mean ± SD or N. observations = 1
$\ln(Employees_{it})$	1.42 ± 1.31
SEZ_{it}	8713
$Adj\ SEZ_{it}$	18624
Micro business	3700413
Small business	1041182
Medium-big business	445863
Agricultural sector	88101
Industrial sector	1741748
Service sector	3357609

Total observations observed between 2014 and 2022: 5187458.

The average log number of employees is 1.42, with a standard deviation of 1.31, denoting that there is not high variability around the mean value. Focusing on the SEZ regressors, in 2022 we observed 8713 SEZ businesses, i.e. small, medium or big businesses located in SEZ municipalities that belong to sectors eligible for SEZ incentives. On the other hand, in 2022 the number of businesses located in municipalities adjacent to a SEZ is 18624. These numbers, which are small if compared to the total number of firms observed in a specific year, are not surprising because 1) being a SEZ business means meeting specific geographical, dimensional and sectoral criteria; 2) municipalities adjacent to a SEZ are usually municipalities with few inhabitants and, therefore, businesses. With reference to the size, the majority of firms observed between 2014 and 2022 are micro firms, followed by small firms and medium-big firms. This result is in line with our expectations since the Italian economy is characterized by a large number of micro-small firms. Finally, most businesses observed in the 2014-2022 time interval belong to the service sector. The industrial sector is also a relevant sector, while few companies belong to the agricultural sector.

We launched our model on a balanced panel of firms observed over the period considered. We used robust standard errors (Wooldridge, 2010).

4. Results and discussions

Do SEZs affect the number of employees? Do SEZs induce spillovers on adjacent municipalities? Do SEZs lead to economic specialization? In this regard, we can make some hypotheses. As we have seen in the literature review section, most of the contributions on SEZs state that this tool has been successful in increasing the employment of treated areas. For example, the study of Jensen (2018) on the impact of Poland's SEZs showed that SEZs have been able to sustain employment in the consolidation phase after the economic transition of the 1990s. Moreover, the regulation of Italian SEZs (decree of the prime minister 2018/12) states that SEZs are established to promote favorable conditions in economic, financial and administrative terms to allow the development of existing and new firms in the zones.

Hypothesis 1: SEZ businesses increased their number of employees (H1)

Before illustrating the other hypotheses, we have to clarify a crucial point. In the previous section we said that SEZ_{it} is a dummy variable which captures whether the i-th firm is small, medium or big firm that belongs to an eligible sector and is in an operational SEZ. Although not all firms eligible for SEZ benefits have already received these benefits (this information is not publicly available), it is reasonable that many of these firms have started an investment program aimed at increasing their number of employees, regardless of whether they have already received SEZ benefits. This phenomenon can be explained by the theoretical framework of announcement effects, according to which the announcement of a new policy produces effects on the subjects affected by that policy. A such theoretical framework has been studied extensively in the context of financial markets, where current prices reflect publicly available information (Fama, 1970; Cornell, 1982; McQueen and Roley, 1993; Andersen *et al.*, 2003). The most famous case study of announcement effects is probably the Outright

Monetary Transactions (OMT) program announced in July 2012 by the president of the European Central Bank (ECB) Mario Draghi (Acharya *et al.*, 2019). During the Global Investment Conference in London, at the peak of the European debt crisis, Draghi anticipated this program by stating that "the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough". Even though the OMT program has not been activated yet, the sole announcement of its introduction has lowered spreads of sovereign bonds issued by the distressed European countries. The theoretical framework of announcement effects can be adapted to any economic context, even when we talk about SEZs. Knowing about the start of the SEZ policy may have led several firms eligible for SEZ benefits to make investment decisions aimed at increasing their number of jobs, even if they have not received these benefits yet.

SEZs are also expected to generate positive spillovers on neighboring areas (Alder *et al.*, 2016; Frick and Rodríguez-Pose, 2019). This is because firms whose activities are closely related to firms that operate in zones should benefit from the growth of these partners (for example, consider how deep the economic relationship can be between a supplier operating outside a zone and its customer operating in the zone). In this regard, the United Nations estimated that globally SEZs have indirectly generated between 50 and 200 million jobs (UNCTAD, 2019).

H2: businesses adjacent to an operational SEZ increased their number of employees

We have seen that the Italian government established eight SEZs. Consequently, it can monitor, through the Territorial Cohesion Agency, the implementation of the SEZ program in different parts of the country. Indeed, it could happen that not all zones have been successfully implemented, allowing the Italian government to adopt targeted interventions to solve the issues encountered in a SEZ. This means that we can analyze the performance of each SEZ to verify whether the results observed at the aggregate level are confirmed at smaller levels.

H3: not all SEZs have been successful

Economic specialization is a crucial point for a successful SEZ program (UNCTAD, 2019). Indeed, policymakers should use zones not only as an investment promotion tool, i.e. as a tool only used to attract investments, but also and foremost as an industrial policy tool, i.e. SEZs should lead to the specialization of economies. This is usually what happens in developed economies, where SEZs have developed specific branches of economies. As a consequence, we can reasonably assume that SEZs do not affect all sectors equally: some sectors may be positively affected by zones, other sectors may be unaffected or even negatively affected by a SEZ program.

H4: the effects of SEZs on firms depend on their economic sector

While it is reasonable to assume that the effects of the SEZ program on firms may depend on their economic sector, the economic literature does not seem to suggest that there may be valid reasons why such effects may depend on the size of the firm. Consequently, we can assume that the number of employees increased regardless of the size of the business.

H5: SEZs affected firms regardless of their size

We will test these hypotheses in the next subsections. To check the robustness of our estimates, we will consider different intervals of years for our panel dataset, from 2014-2022 to 2020-2022, two years before the actual implementation of the SEZ program. Indeed, on the one hand, considering shorter time intervals allows us to expand the sample of firms observed, reducing the risk that the estimates are influenced by a specific sample of firms. On the other hand, removing more remote years reassures us that the observed results are not influenced by years that, due to their distance from the year of implementation of the policy, are less interesting.

4.1. Have SEZs been successful?

To test the first two hypotheses empirically, we regressed the panel model discussed in section 3 (Table 5):

Table 5. The impact of SEZs and their spillovers on the log Number of employees

	14-22	15-22	16-22	17-22	18-22	19-22	20-22
SEZ	0.0638***	0.0577***	0.0527***	0.0490***	0.0427***	0.0389***	0.0330***
	(0.0062)	(0.0058)	(0.0054)	(0.0051)	(0.0048)	(0.0045)	(0.0042)
Adjacent SEZ	0.0653***	0.0632***	0.0617***	0.0639***	0.0611***	0.0529***	0.0410***
	(0.0052)	(0.0049)	(0.0046)	(0.0042)	(0.0038)	(0.0036)	(0.0033)
Industrial sector	0.0840	0.0725	0.0653	0.0689	0.0611	0.0358	0.0537
	(0.0543)	(0.0492)	(0.0470)	(0.0460)	(0.0432)	(0.0429)	(0.0398)

Service sector	-0.0111	0.0027	-0.0013	0.0159	0.0170	-0.0039	0.0010
	(0.0549)	(0.0498)	(0.0473)	(0.0465)	(0.0438)	(0.0434)	(0.0402)
Small business	0.6802***	0.6562***	0.6400***	0.6235***	0.6071***	0.5814***	0.5415***
	(0.0024)	(0.0024)	(0.0026)	(0.0028)	(0.0030)	(0.0034)	(0.0041)
Medium-big business	0.6109***	0.5764***	0.5456***	0.5151***	0.4793***	0.4373***	0.3805***
	(0.0036)	(0.0037)	(0.0038)	(0.0040)	(0.0042)	(0.0046)	(0.0052)
SEZ businesses effects	✓	✓	✓	✓	✓	✓	✓
Fixed effects	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓
Observations	1688445	1604688	1504328	1385940	1253125	1077864	857364
R-squared	0.3037	0.2908	0.2821	0.2720	0.2608	0.2469	0.2288

Robust standard errors are reported in brackets. The constant is not reported but is included in the estimated equation. *Significant at a 5% level, **significant at a 1% level, and ***significant at a 0.1% level.

Both H1 and H2 are supported. Indeed, SEZ and Adjacent SEZ are significant at the 0.1% level in all models. The positive sign of their coefficients denotes that there is a positive association between these regressors and the dependent variable. In particular, being a SEZ firm or a firm adjacent to an operational SEZ leads to an average increase in the number of employees between 3 and 7 percentage points.[6]

4.2. Have *all* SEZs been successful?

Now we will verify whether all zones have been successfully implemented or not. For this purpose, we modified the proposed model as follows:

$$\ln(Employees_{it}) = \beta_0 + \boldsymbol{SEZ}'_{it}\boldsymbol{\beta}_1 + \boldsymbol{Size}'_{it}\boldsymbol{\beta}_2 + \boldsymbol{Sector}'_{i}\boldsymbol{\beta}_3 + \boldsymbol{SEZ}'_{i}\boldsymbol{\beta}_4 + \boldsymbol{X}'_{i}\boldsymbol{\beta}_5 + \boldsymbol{T}'_{t}\boldsymbol{\beta}_6 + \varepsilon_{it}$$

where $\boldsymbol{SEZ}'_{it}$ represents a row of dummies which capture small, medium and big firms that belong to eligible sectors in each operational SEZ (SEZ Abruzzo, SEZ Calabria, SEZ Campania, SEZ Apulia-Basilicata, SEZ Apulia-Molise, SEZ Sardinia, SEZ Western Sicily and SEZ Eastern Sicily). The estimates are reported in Table 6:

[6] Since we used a model where the dependent variable is log-transformed, the beta coefficients must be interpreted as follows: $(e(\beta) - 1) * 100 = x$. The result indicates that for every one-unit increase in the regressor, the dependent variable increases by about x%.

Table 6. The impact of individual SEZs on the log Number of employees

	14-22	15-22	16-22	17-22	18-22	19-22	20-22
SEZ Abruzzo	0.0450	0.0409	0.0419	0.0390	0.0358	0.0396	0.0428
	(0.0375)	(0.0336)	(0.0297)	(0.0302)	(0.0288)	(0.0262)	(0.0248)
SEZ Calabria	0.0499	0.0403	0.0433	0.0645	0.0556	0.0305	0.0039
	(0.0472)	(0.0426)	(0.0380)	(0.0343)	(0.0317)	(0.0296)	(0.0271)
SEZ Campania	0.0703***	0.0598***	0.0533***	0.0645***	0.0380***	0.0329***	0.0283***
	(0.0102)	(0.0094)	(0.0088)	(0.0343)	(0.0079)	(0.0074)	(0.0070)
SEZ Apulia-Basilicata	0.0238	0.0162	0.0178	0.0205	0.0164	0.0316	0.0267
	(0.0236)	(0.0221)	(0.0205)	(0.0202)	(0.0187)	(0.0180)	(0.0171)
SEZ Apulia-Molise	0.0717***	0.0688***	0.0636***	0.0592***	0.0502***	0.0495***	0.0419***
	(0.0123)	(0.0115)	(0.0108)	(0.0101)	(0.0093)	(0.0085)	(0.0079)
SEZ Sardinia	0.0491	0.0588*	0.0561*	0.0504*	0.0437	0.0248	0.0452*
	(0.0272)	(0.0263)	(0.0255)	(0.0242)	(0.0230)	(0.0219)	(0.0198)
SEZ Western Sicily	0.0269	0.0277	0.0287	0.0347*	0.0314*	0.0273*	0.0224
	(0.0189)	(0.0176)	(0.0170)	(0.0159)	(0.0149)	(0.0138)	(0.0125)
SEZ Eastern Sicily	0.0685***	0.0587***	0.0477**	0.0402**	0.0412**	0.0385**	0.0266*
	(0.0165)	(0.0158)	(0.0149)	(0.0139)	(0.0136)	(0.0127)	(0.0118)
Industrial sector	0.0836	0.0720	0.0638	0.0671	0.0587	0.0339	0.0521
	(0.0542)	(0.0492)	(0.0472)	(0.0461)	(0.0431)	(0.0427)	(0.0398)
Service sector	-0.0118	0.0020	-0.0032	0.0141	0.0146	-0.0059	-0.0004
	(0.0549)	(0.0498)	(0.0476)	(0.0467)	(0.0436)	(0.0432)	(0.0402)
Small business	0.6805***	0.6565***	0.6403***	0.6239***	0.6075***	0.5818***	0.5419***
	(0.0024)	(0.0024)	(0.0026)	(0.0028)	(0.0030)	(0.0034)	(0.0041)
Medium-big business	0.6110***	0.5765***	0.5458***	0.5153***	0.4796***	0.4376***	0.3807***
	(0.0036)	(0.0037)	(0.0038)	(0.0040)	(0.0042)	(0.0046)	(0.0052)
SEZ businesses effects	✓	✓	✓	✓	✓	✓	✓
Fixed effects	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓
Observations	1688445	1604688	1504328	1385940	1253125	1077864	857364
R-squared	0.3037	0.2909	0.2820	0.2720	0.2608	0.2468	0.2287

Robust standard errors are reported in brackets. The constant is not reported but is included in the estimated equation. *Significant at a 5% level, **significant at a 1% level, and ***significant at a 0.1% level.

Results support H3. The SEZs Abruzzo, Calabria and Apulia-Basilicata have not affected the number of employees, while there is weak evidence in the increase in this number for the SEZs Sardinia and Western Sicily. Finally, the number of employees is increased in the remaining SEZs for all models. Focusing on SEZs that have influenced business employment, although the sign of SEZ coefficients is positive, denoting a positive relationship between being a business located in an operational zone and its number of employees, it is interesting to look at the magnitude of these coefficients. Indeed, this allows us to understand if some zones have been more successful than others. For this purpose, we tested linear constraints on pairs of SEZ coefficients, whose detailed results are reported in the Appendix. Tests suggest that there are not significant differences in the impact of each SEZ on firm employment.

The different impact of the SEZ program among the eight SEZs may have led the Italian government to modify the current regulatory framework on SEZs by introducing the Single SEZ (law decree 2023/124), which will come into force on 1 January 2024. This reform entails that the current eight SEZs, which correspond to different administrative structures, are unified into a single entity from an administrative point of view, allowing the Italian government to implement the SEZ program more effectively in all regions through clearer coordination between government and regions.

4.3. Have SEZs induced economic specialization?

We can test H4 by analyzing the interaction between SEZ firms or firms adjacent to an operational SEZ and each economic sector. In this case, the proposed model becomes:

$$\ln(Employees) = \beta_0 + SEZ_{it} * \boldsymbol{Sector}'_i\boldsymbol{\beta}_1 + Adj\ SEZ_{it} * \boldsymbol{Sector}'_i\boldsymbol{\beta}_2 + \boldsymbol{Size}'_{it}\boldsymbol{\beta}_3 + \boldsymbol{Sector}'_i\boldsymbol{\beta}_4 + \boldsymbol{SEZ}'_i\boldsymbol{\beta}_5 + \boldsymbol{X}'_i\boldsymbol{\beta}_6 + \boldsymbol{T}'_t\boldsymbol{\beta}_7 + \varepsilon_{it}$$

If all interactions have the same impact on the dependent variable, i.e. there is a significant and positive association between these regressors and the dependent variable, we can conclude that the SEZ program did not lead to the specialization of specific economic sectors. If otherwise, the program has induced economic specialization. Table 7 includes the estimates with the interactions:

Table 7. The impact of SEZs and their spillovers by economic sector on the log Number of employees

	14-22	15-22	16-22	17-22	18-22	19-22	20-22
SEZ*Agricultural sector	-0.1468	-0.1529*	-0.1574**	-0.1314**	-0.0773	-0.0540	-0.0380
	(0.0803)	(0.0664)	(0.0600)	(0.0502)	(0.0874)	(0.0747)	(0.0381)
SEZ*Industrial sector	0.0990***	0.0897***	0.0831***	0.0755***	0.0653***	0.0536***	0.0394***
	(0.0090)	(0.0084)	(0.0079)	(0.0075)	(0.0070)	(0.0065)	(0.0061)
SEZ*Service sector	0.0385***	0.0351***	0.0314***	0.0307***	0.0271***	0.0295***	0.0290***
	(0.0084)	(0.0078)	(0.0073)	(0.0069)	(0.0065)	(0.0061)	(0.0057)
Adj. SEZ*Agricultural sector	0.0102	-0.0025	0.0065	0.0055	0.0233	0.0242	0.0192
	(0.0355)	(0.0329)	(0.0304)	(0.0265)	(0.0238)	(0.0220)	(0.0196)
Adj. SEZ*Industrial sector	0.1060***	0.1049***	0.1053***	0.1060***	0.1045***	0.0931***	0.0766***
	(0.0083)	(0.0080)	(0.0075)	(0.0070)	(0.0065)	(0.0061)	(0.0058)
Adj. SEZ*Service sector	0.0408***	0.0392***	0.0367***	0.0405***	0.0366***	0.0303***	0.0211***
	(0.0067)	(0.0062)	(0.0057)	(0.0052)	(0.0047)	(0.0044)	(0.0041)
Industrial sector	0.1041*	0.0919*	0.0949*	0.0914*	0.0707	0.0463	0.0630
	(0.0512)	(0.0463)	(0.0434)	(0.0442)	(0.0426)	(0.0426)	(0.0397)
Service sector	0.0106	0.0216	0.0273	0.0373	0.0250	0.0041	0.0082
	(0.0519)	(0.0470)	(0.0439)	(0.0448)	(0.0432)	(0.0432)	(0.0401)
Small business	0.6802***	0.6562***	0.6400***	0.6234***	0.6070***	0.5813***	0.5414***
	(0.0024)	(0.0024)	(0.0026)	(0.0028)	(0.0030)	(0.0034)	(0.0041)
Medium-big business	0.6108***	0.5763***	0.5455***	0.5150***	0.4792***	0.4372***	0.3803***
	(0.0036)	(0.0037)	(0.0038)	(0.0040)	(0.0042)	(0.0046)	(0.0052)
SEZ businesses effects	✓	✓	✓	✓	✓	✓	✓
Fixed effects	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓
Observations	1688445	1604688	1504328	1385940	1253125	1077864	857364
R-squared	0.3035	0.2907	0.2821	0.2720	0.2608	0.2470	0.2288

Robust standard errors are reported in brackets. The constant is not reported but is included in the estimated equation. *Significant at a 5% level, **significant at a 1% level, and ***significant at a 0.1% level.

H4 is also confirmed. Indeed, SEZ and Adjacent SEZ do not have the same impact in all economic sectors. While in the industrial and service sectors both regressor are significant at the 0.1% level and the sign of their coefficients is positive, the same is not true for the agricultural sector: indeed, both regressors are usually not significant, denoting that the SEZ program did not affect this sector. A possible reason for this outcome is that in Italy the agricultural sector is a low added value sector, which grows at low or even negative rates. For example, according to a recent report on the Italian economy, in 2021 the value added of this sector decreased by 1.3% (ISTAT, 2022). Vice versa, the number of employees has increased significantly in SEZ firms or firms adjacent to a zone of the industrial and service sectors. If confirmed in the long term, these results are interesting for two reasons. First, the service sector has always been crucial for the *current* development of the South. Indeed, the current economy of Southern Italy is mostly based on businesses operating in this sector (Bripi *et al.*, 2023). Second, a development of the industrial sector could be important for the *future* development of this area. Southern Italy has always suffered from the lack of a developed industrial sector (Prezioso and Servidio, 2011), which usually has higher growth margins than the other sectors. Going back to previous report on the Italian economy, in 2021 the value added of the industrial sector increased by 16.6% against 4.7% of the service sector.

4.4. Have SEZs affected firms of all size?

A last hypothesis that we will verify for the number of employees is whether SEZs have affected this number in firms of all size or not. To this end, we will consider the interaction between the SEZ businesses or businesses adjacent to a zone and their size class, obtaining the following model:

$$\ln(Employees) = \beta_0 + SEZ_{it} * \boldsymbol{Size}'_{it}\boldsymbol{\beta}_1 + Adj\ SEZ_{it} * \boldsymbol{Size}'_{it}\boldsymbol{\beta}_2 + \boldsymbol{Size}'_{it}\boldsymbol{\beta}_3 + \boldsymbol{Sector}'_{i}\boldsymbol{\beta}_4 + \boldsymbol{SEZ}'_{i}\boldsymbol{\beta}_5 + \boldsymbol{X}'_{i}\boldsymbol{\beta}_6 + \boldsymbol{T}'_{t}\boldsymbol{\beta}_7 + \varepsilon_{it}$$

The estimated models are reported in Table 8:

Table 8. The impact of SEZs and their spillovers by size class on the log Number of employees

	14-22	15-22	16-22	17-22	18-22	19-22	20-22
SEZ*Small business	0.0583***	0.0562***	0.0542***	0.0536***	0.0510***	0.0463***	0.0374***
	(0.0064)	(0.0061)	(0.0058)	(0.0055)	(0.0052)	(0.0049)	(0.0045)
SEZ*Medium-big business	0.0759***	0.0606***	0.0491***	0.0379***	0.0239*	0.0234*	0.0251**
	(0.0131)	(0.0122)	(0.0114)	(0.0108)	(0.0101)	(0.0093)	(0.0086)
Adj. SEZ*Micro business	0.0504***	0.0503***	0.0536***	0.0608***	0.0615***	0.0538***	0.0422***
	(0.0065)	(0.0061)	(0.0056)	(0.0051)	(0.0047)	(0.0043)	(0.0040)
Adj. SEZ*Small business	0.0608***	0.0605***	0.0529***	0.0526***	0.0485***	0.0420***	0.0280***

	(0.0084)	(0.0079)	(0.0075)	(0.0070)	(0.0066)	(0.0062)	(0.0058)
Adj. SEZ*Medium-big business	0.0928***	0.0732***	0.0647***	0.0499**	0.0341*	0.0292*	0.0190
	(0.0202)	(0.0191)	(0.0181)	(0.0167)	(0.0153)	(0.0140)	(0.0126)
Industrial sector	0.0837	0.0724	0.0649	0.0686	0.0604	0.0352	0.0531
	(0.0544)	(0.0492)	(0.0470)	(0.0462)	(0.0433)	(0.0430)	(0.0400)
Service sector	-0.0111	0.0029	-0.0016	0.0154	0.0161	-0.0046	0.0004
	(0.0549)	(0.0497)	(0.0473)	(0.0467)	(0.0439)	(0.0435)	(0.0404)
Small business	0.6716***	0.6465***	0.6300***	0.6143***	0.5989***	0.5739***	0.5334***
	(0.0024)	(0.0025)	(0.0027)	(0.0029)	(0.0031)	(0.0035)	(0.0043)
Medium-big business	0.6070***	0.5713***	0.5400***	0.5094***	0.4740***	0.4340***	0.3772***
	(0.0037)	(0.0038)	(0.0040)	(0.0041)	(0.0044)	(0.0048)	(0.0054)
SEZ businesses effects	✓	✓	✓	✓	✓	✓	✓
Fixed effects	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓
Observations	1688445	1604688	1504328	1385940	1253125	1077864	857364
R-squared	0.3027	0.2896	0.2809	0.2709	0.2598	0.2461	0.2279

Robust standard errors are reported in brackets. The constant is not reported but is included in the estimated equation. *Significant at a 5% level, **significant at a 1% level, and ***significant at a 0.1% level.

Note that while for the SEZ regressor we did not consider the interaction with micro businesses, for the Adj. SEZ regressor we considered this interaction. This is because a SEZ firm can be a small, medium or big business, while Adj. SEZ is a variable that simply captures whether the firm is in a municipality adjacent to an operational SEZ or not, regardless of its sector and size. Focusing on the estimates, results give support to H5, because all interactions are significant at the 0.1% level in most models, suggesting that the SEZ program positively affected the number of employees of SEZ firms and firms adjacent to a zone regardless of their size.

4.5. Have revenues increased?

Businesses SEZ firms benefit from special rules that allow them to be more competitive in the market and, therefore, increase their revenues (Lu, 2011; Li *et al.*, 2021). Revenues represent a crucial element for assessing the sustainability of employment growth in businesses. Indeed, benefits for SEZ firms are not enough to sustain their employment, especially in the medium-long term. To offset this cost, revenues should also increase. Given this premise, we should highlight two aspects: first, the SEZ program impact directly the number of employees and indirectly the revenues: if this occurred, the increase in revenues would be driven by the increase in the number of employees due to the SEZ policy. This means that the increase in revenues could occur later. The second aspect, probably linked to the first one, is that the Italian legislator required firms to preserve the jobs created in the SEZ activity for at least ten years (see Section 2.1): the rationale for this requirement is that the final impact of the SEZ policy can be observed only in the medium-long term, and for this reason businesses should not withdraw their investments due to, for example, the initial failure to increase their revenues. To test whether SEZs have indirectly affected the revenues,[7] we estimated the model proposed in section 3 using the log revenues as the dependent variable (Table 9):

Table 9. The impact of SEZs and their spillovers on the log Revenues

	14-22	15-22	16-22	17-22	18-22	19-22	20-22
SEZ	-0.0004	-0.0052	-0.0110	-0.0240	-0.0407***	-0.0400***	-0.0361***
	(0.0138)	(0.0134)	(0.0128)	(0.0124)	(0.0118)	(0.0111)	(0.0107)
Adjacent SEZ	0.1289***	0.1282***	0.1322***	0.1286***	0.1305***	0.1200***	0.0902***
	(0.0154)	(0.0144)	(0.0136)	(0.0128)	(0.0125)	(0.0123)	(0.0122)
Industrial sector	0.0850	0.1191	0.0657	0.2802	0.2245	0.2117	0.2067
	(0.1115)	(0.0909)	(0.0771)	(0.1740)	(0.1407)	(0.1318)	(0.1557)
Service sector	0.0133	0.0167	-0.0603	0.1342	0.0686	0.0072	-0.0452
	(0.1092)	(0.0903)	(0.0778)	(0.1743)	(0.1416)	(0.1351)	(0.1605)
Small business	0.8121***	0.7950***	0.7915***	0.7760***	0.7845***	0.7813***	0.7232***
	(0.0068)	(0.0071)	(0.0077)	(0.0082)	(0.0093)	(0.0106)	(0.0131)
Medium-big business	1.2720***	1.2473***	1.2264***	1.1987***	1.1843***	1.1676***	1.0903***
	(0.0102)	(0.0107)	(0.0113)	(0.0122)	(0.0136)	(0.0155)	(0.0188)
SEZ businesses effects	✓	✓	✓	✓	✓	✓	✓
Fixed effects	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓
Observations	1688445	1604688	1504328	1385940	1253125	1077864	857364
R-squared	0.2133	0.2134	0.2143	0.2113	0.2102	0.2098	0.2046

Robust standard errors are reported in brackets. The constant is not reported but is included in the estimated equation. *Significant at a 5% level, **significant at a 1% level, and ***significant at a 0.1% level.

[7] The revenues variable refers to revenues deriving from the sale of products and the provision of services, net of returns and discounts (see article 2425-*bis* of the Italian civil code).

There is evidence that the increase in the number of employees is not sustainable over time. Indeed, the SEZ regressor is not statistically significant in most specifications, while it is even negative in the remaining models. In any case, it is too early to draw definitive conclusions in this regard, because the time horizon that we are analyzing is short. A clearer picture can only be depicted in a medium-long term analysis, which should be performed when new data will be available.

With reference to the Adjacent SEZ regressor, it is statistically significant at the 0.1% level for each model. At first glance it could seem like a surprising and counterintuitive result: some would have expected the description of a strong positive significance for the SEZ regressor rather than for the Adjacent SEZ one. Actually, the explanation is simple if it is clear to us which phenomena the two regressors describe. We defined the SEZ regressor as a dummy variable that tells us whether the i-th business is a small, medium or big firm that belongs to an eligible sector and is in an operational SEZ or not. In other words, it is a regressor that indicates firms that can potentially benefit from the SEZ policy. For this purpose, these firms have to invest in existing and new production structures in order to create new jobs: the increase in jobs, which we have seen to be statistically significant in the previous estimates, is not due to an increase in the wealth of businesses, for example in their revenues, but is determined exogenously by a policy. Then, this increase in jobs could also lead to an increase in revenues later. The Adjacent SEZ regressor, vice versa, is simply a dummy variable which captures whether the i-th firm is in a municipality adjacent to an operational SEZ or not. These firms do not directly benefit from the SEZ policy, the increase in jobs is caused exclusively by the firms themselves based on their economic performance, for example their revenues. The increase in revenues, however, could be influenced by a more competitive market created indirectly, at least in part, by the SEZ policy.

4.6. And what about the remaining businesses?

The estimates described so far are based on balanced panels. This means that we investigated the impact of the SEZ program on the log Number of employees considering firms that existed in the entire time intervals considered, for example 2014-2022, 2015-2022, and so on. In this subsection we extend our analysis by considering all businesses observed in the panel constructed between 2014 and 2022, including for example businesses that, given the dimensional and sectoral criteria discussed previously, may have been attracted to an operational SEZ. For this purpose, we performed the same estimates discussed in the previous subsections using all firms contained in the observed panel, thus getting estimates based on an unbalanced panel (Table 10):

Table 10. The impact of SEZs on the log Number of employees (unbalanced panel)

	I	II	III	IV
SEZ	0.0263***			
	(0.0058)			
Adjacent SEZ	0.0858***			
	(0.0041)			
SEZ Abruzzo		0.0198		
		(0.0348)		
SEZ Calabria		-0.0230		
		(0.0377)		
SEZ Campania		0.0211*		
		(0.0097)		
SEZ Apulia-Basilicata		-0.0257		
		(0.0245)		
SEZ Apulia-Molise		0.0221*		
		(0.0117)		
SEZ Sardinia		0.0217		
		(0.0250)		
SEZ Western Sicily		0.0108		
		(0.0178)		
SEZ Eastern Sicily		0.0461**		
		(0.0154)		
SEZ*Agricultural sector			-0.0345	
			(0.1036)	
SEZ*Industrial sector			0.0646***	
			(0.0086)	
SEZ*Service sector			0.0021	
			(0.0078)	
Adj. SEZ*Agricultural sector			0.0950***	
			(0.0267)	

Adj. SEZ*Industrial sector			0.1173***	
			(0.0068)	
Adj. SEZ*Service sector			0.0665***	
			(0.0050)	
SEZ*Small business				0.0429***
				(0.0061)
SEZ*Medium-big business				-0.0178
				(0.0130)
Adj. SEZ*Micro business				0.1023***
				(0.0047)
Adj. SEZ*Small business				0.0388***
				(0.0077)
Adj. SEZ* Medium-big business				-0.0098
				(0.0194)
Industrial sector	0.1305	0.1272	0.1559*	0.1312
	(0.0691)	(0.0692)	(0.0683)	(0.0690)
Service sector	0.0460	0.0424	0.0688	0.0463
	(0.0685)	(0.0686)	(0.0678)	(0.0684)
Small business	0.8838***	0.8840***	0.8838***	0.8748***
	(0.0017)	(0.0017)	(0.0017)	(0.0018)
Medium-big business	0.8237***	0.8236***	0.8236***	0.8150***
	(0.0029)	(0.0029)	(0.0029)	(0.0031)
Fixed effects	✓	✓	✓	✓
Time effects	✓	✓	✓	✓
SEZ businesses effects	✓	✓	✓	✓
Observations	5187458	5187458	5187458	5187458
R-squared	0.3662	0.3662	0.3663	0.3654

Robust standard errors are reported in brackets. The constant is not reported but is included in the estimated equation. *Significant at a 5% level, **significant at a 1% level, and ***significant at a 0.1% level.

In particular, models I, II, III, and IV are the same models discussed in subsections 4.1, 4.2, 4.3, and 4.4, respectively. Even considering all firms contained in the observed panel, the estimates are similar to the ones discussed in the previous subsections. The only notable difference concerns the models that consider the interaction between SEZ businesses and their sector or size (models III and IV). For model III it is worth noting that the number of employees increased only in the industrial sector, while in model IV the interaction between SEZ firms or firms located in a municipality adjacent to a SEZ and the medium-big class is no longer significant.

5. Towards the end of the Italian dualism?

In the previous section we saw that SEZs have been successful in increasing the number of employees in Southern Italy, as well as they have led to economic specialization in this macro-region. Even if an increase in revenues has not been observed at the moment, the Italian legislator required firms to preserve the jobs created in the SEZ activity for at least ten years. But can we state that SEZs will lead to the end of the Italian dualism? The short answer is it depends. This is because the Italian SEZ program started a few years ago. Consequently, it is too early to make predictions about a problem that has afflicted the Italian economy since the 19^{th} century. However, we can make some hypotheses based on what the literature says about the long-term effects of successful SEZ programs and the previous interventions that tried to address the Italian dualism. Most of the literature is optimistic about the positive effects of SEZs over time, suggesting that successful SEZ programs lead to economic development and structural transformation (Zeng, 2021). For example, Alder *et al.* (2016) analyzed the long-term effects of Chinese SEZs on the economic development of Chinese cities, finding a GDP increase of about 20% in cities where SEZs are established. However, if we pay our attention to the previous interventions carried out at the national and European level, we are not optimistic that the Italian SEZ program can solve the problem of two-speed Italy. Indeed, several studies suggested that programs such as the Italian Fund for the South and the European cohesion policy did not lead to positive structural changes in the economic growth of Southern Italy (Milio, 2010; Felice and Lepore, 2013). According to these studies, these interventions failed because of their poor implementation. For example, d'Adda and de Blasio (2017) showed that the Fund for the South suffered from low quality of governance and was driven by political considerations rather than by efficiency ones. Citarella and Filocamo (2017) explained that the cohesion policy failed in reducing the gap between Northern and Southern Italy because of the inefficiency of the EU financing system in terms of programming, co-financing and conditionality.

Going back to our question about the possibility of SEZs to eliminate, or at least to significantly reduce, the Italian dualism, the answer is: SEZs can reduce the gap between Northern and Southern Italy, provided that they will be implemented correctly. The SEZ program is an economic tool whose effectiveness depends on *how* it is implemented. In this regard, there are three factors for a successful SEZ program (UNCTAD, 2019). First, SEZs need a strategic focus, i.e. policymakers have to keep a development strategy in mind during the realization of the SEZ program. Indeed, SEZs are not only an investment tool (they provide incentives in limited geographical areas), but also and foremost an industrial policy tool (they should lead to the specialization of economies). Second, a SEZ program needs an adequate regulatory framework. In this regard, policymakers have to create an independent zone regulator, which must be shielded from political pressure and adequately funded to effectively implement the program. Moreover, an adequate regulatory framework has to include monitoring mechanisms, in order to verify whether the SEZ program needs adjustments during its implementation. Third, it is important the value proposition in the SEZs, i.e. the package of benefits that zones provide. This package should include at least three benefits: the choice of location, support for infrastructure and services, and administrative simplifications. With reference to the first benefit, we said that SEZs are usually created to support the economic development of underdeveloped areas. However, underdeveloped areas should not be confused with remote areas. Although a remote area is usually an underdeveloped area, an underdeveloped area is not necessarily a remote area. A remote area is an area away from key infrastructure and/or large cities. If we want to attract businesses and investors to the zone, we need a zone that is well connected to the rest of the world, for example through ports and airports, and/or close to labor pools. Indeed, studies have shown a negative correlation between the distance of a SEZ from ports and large cities and its performance (Frick *et al.*, 2019). The second benefit that a zone should include is adequate support for infrastructure and services, for example by providing access to at least two modes of transportation and services for businesses and investors. The last benefit is the facilitation of administrative procedures, which is considered more important than fiscal incentives (UNCTAD, 2019). Studies suggest that excessive bureaucracy has significantly affected failed SEZ programs (Moberg, 2015).

The Italian SEZ program seems to satisfy all the factors to be a successful program. First, preliminary analyses realized in section 4.3 suggest that SEZs have induced economic specialization in Southern Italy (strategic focus factor). Second, the Italian law on SEZs described in section 2.1 includes an independent zone regulator, whose power is divided among different institutions, and a monitoring mechanism (regulatory framework factor). Third, this law provides many benefits for investors and businesses, from the choice of location of SEZs, which by law must be close to at least a port, to the administrative simplifications, thanks to which businesses can benefit from the streamlining of administrative procedures (value proposition factor).

6. Conclusions

This chapter proposed a first analysis of the impact of Italian SEZs on firms in Southern Italy. To do this, we built a panel dataset of Italian businesses and analyzed the impact of being a firm eligible for SEZ incentives or being a firm adjacent to a zone on its number of employees. Preliminary results suggest that SEZs have been successful, because SEZ businesses and businesses adjacent to a zone have significantly increased their number of employees. This evidence is confirmed on some individual SEZs, and in particular SEZ Campania, Apulia-Molise and Eastern Sicily. Moreover, it seems that the SEZ program has not affected all economic sectors. In particular, while businesses in the agricultural sector have not made significant changes to employment, the opposite is true for firms in the industrial and service sectors, where the number of employees has increased significantly. The SEZ program, on the other hand, has affected businesses of any size. However, an increase in revenues has not been observed at the moment.

This analysis was carried out over a short time horizon, and for this reason further studies are needed to understand whether the SEZ program is actually an effective policy tool to eliminate, or at least significantly reduce, the historical gap between Northern and Southern Italy. For example, we need to understand whether what we have observed will persist over the years or not. In other words, we have to understand if the increase in employment in businesses is only a temporary boost or if it represents the beginning of a radical structural change. Only a medium-long term analysis will be able to suggest whether the SEZ program could lead to the definitive closure of the chapter of Italian dualism. In this regard, the Italian government will play a crucial role in ensuring the effective implementation of this policy tool, especially after the introduction of the Single SEZ, which will be operational from 2024. On the one hand, the government should implement the SEZ program in agreement with the SEZ regions, thus ensuring the implementation of a true place-based policy that promotes the specialization of territories. On the other hand, it should verify that the program is implemented effectively in all regions, introducing corrective measures in those areas that present critical issues. In this case, understanding why some SEZs have worked better than others could be useful for maintaining the positive aspects of the current governance, discarding what has not worked.

References

ACHARYA V. V., EISERT T., EUFINGER C. and HIRSCH C. (2019), Whatever It Takes: The Real Effects of Unconventional Monetary Policy, The Review of Financial Studies, vol. 32, issue 9, pp. 3366–3411. doi: https://doi.org/10.1093/rfs/hhz005

ALDER S., SHAO L. and ZILIBOTTI F. (2016), Economic reforms and industrial policy in a panel of Chinese cities, Journal of Economic Growth, vol. 21, pp. 305–349. doi: https://doi.org/10.1007/s10887-016-9131-x

ALKON M. (2018), Do special economic zones induce developmental spillovers? Evidence from India's states, World Development, vol. 107, pp. 396-409. doi: https://doi.org/10.1016/j.worlddev.2018.02.028

AMBROZIAK A. A. and HARTWELL C. A. (2018), The impact of investments in special economic zones on regional development: the case of Poland, Regional Studies, vol. 52, issue 10, pp. 1322-1331. doi: https://doi.org/10.1080/00343404.2017.1395005

ANDERSEN T. G., BOLLERSLEV T., DIEBOLD F. X. and VEGA C. (2003), Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange, American Economic Review, vol. 93, no. 1, pp. 38-62. doi: 10.1257/000282803321455151

ARBOLINO R., LANTZ T. L. and NAPOLITANO O. (2023), Assessing the impact of special economic zones on regional growth through a comparison among EU countries, Regional Studies, vol. 57, issue 6, pp. 1069-1083. doi: https://doi.org/10.1080/00343404.2022.2069745

BANCA D'ITALIA (2022), Il divario Nord-Sud: sviluppo economico e intervento pubblico, Divisione editoria e stampa della Banca d'Italia, Rome.

BOST F. (2019), Special Economic Zones: Methodological Issues and Definition, Transnational Corporations Journal, vol. 26, no. 2, pp. 141-153. doi: https://ssrn.com/abstract=3623051

BRIPI F., BRONZINI R., GENTILI E., LINARELLO A. and SCARINZI E. (2023), Structural change and firm dynamics in the South of Italy, Structural Change and Economic Dynamics, In press. doi: https://doi.org/10.1016/j.strueco.2023.02.003

BUSSO M., GREGORY J. and KLINE P. (2013), Assessing the Incidence and Efficiency of a Prominent Place Based Policy, American Economic Review, vol. 103, no. 2, pp. 897-947. doi: 10.1257/aer.103.2.897

CITARELLA A. and FILOCAMO A. (2017), The Process of European Integration: Market Economy, Budgetary Constraints and Failed Objectives of the Cohesion Policy, Rivista economica del Mezzogiorno, issue 1-2, pp. 117-134. doi: 10.1432/87100

CIŻKOWICZ P., CIŻKOWICZ-PĘKAŁA M., PĘKAŁA P., and RZOŃCA A. (2017), The effects of special economic zones on employment and investment: a spatial panel modeling perspective, Journal of Economic Geography, vol. 17, issue 3, pp. 571–605. doi: https://doi.org/10.1093/jeg/lbw028

COMMISSION RECOMMENDATION of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises (2003/361/EC) (https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2003:124:0036:0041:en:PDF).

CORNELL B. (1982), Money supply announcements, interest rates, and foreign exchange, Journal of International Money and Finance, vol. 1, pp. 201-208. doi: https://doi.org/10.1016/0261-5606(82)90015-8

D'ADDA G. and DE BLASIO G. (2017), Historical Legacy and Policy Effectiveness: The Long-Term Influence of Preunification Borders in Italy, Journal of Regional Science, vol. 57, issue 2, pp. 319-341.

DAVIES R. B. AND MAZHIKEYEV, A. (2019), The impact of special economic zones on exporting behavior, Review of Economic Analysis, vol. 11, no.1, pp. 145–174. doi: 10.15353/rea.v11i1.1520

DECREE OF THE PRIME MINISTER 2018/12 of 25 January 2018 on Regulation establishing Special Economic Zones (SEZs) (https://www.gazzettaufficiale.it/eli/id/2018/2/26/18G00033/sg)

DEFEVER F., REYES J. D., RIAÑO A. and SÁNCHEZ-MARTÍN M. E. (2019), Special Economic Zones and WTO Compliance: Evidence from the Dominican Republic, Economica, vol. 86, issue 343, pp. 532-568. doi: https://doi.org/10.1111/ecca.12276

DURANTON G. and VENABLES A. J. (2021), Placed-based Policies: Principles and Developing Country Applications, in Handbook of Regional Science, Springer Berlin, Heidelberg. doi: https://doi.org/10.1007/978-3-642-23430-9

EUROPEAN COMMISSION (2020), User guide to the SME Definition, Publications Office of the European Union, Luxembourg.

FAMA E. F. (1970), Efficient Capital Markets: A Review of Theory and Empirical Work, Journal of Finance, vol. 25, no. 2, pp. 383-417. doi: https://doi.org/10.2307/2325486

FELICE E. and LEPORE A. (2013), Reviewed development policies in the South of Italy: history of enterprises and regional accounts related to the "Cassa per il Mezzogiorno" interventions, Rivista economica del Mezzogiorno, issue 3, pp. 593-634. doi: 10.1432/75849

FERRARA A. R., NISTICÒ R. and PROTA F. (2022), Special Economic Zones: Their Potentialities and Limits, Rivista economica del Mezzogiorno, issue 4, pp. 875-902. doi: 10.1432/107769

FRICK S. A. and RODRÍGUEZ-POSE A. (2019), Are special economic zones in emerging countries a catalyst for the growth of surrounding areas?, Transnational Corporations Journal, vol. 26, no. 2, pp. 75-94. doi: https://ssrn.com/abstract=3623043

FRICK S. A., RODRÍGUEZ-POSE A. and WONG M. D. (2019), Toward Economically Dynamic Special Economic Zones in Emerging Countries, Economic Geography, vol. 95, issue 1, pp. 30-64. doi: https://doi.org/10.1080/00130095.2018.1467732

HUANG D., VAN V. T., HOSSAIN M. E. and HE Z. (2017), Shanghai pilot free trade zone and Its effect on economic growth: A counter-factual approach, Open Journal of Social Sciences, vol. 5, no. 09, pp. 73–91. doi: 10.4236/jss.2017.59006

ISTAT (2009), Classificazione delle attività economiche Ateco 2007, Servizio produzione editoriale Istat, Rome.

ISTAT (2022), Report sui conti economici territoriali. Anni 2019-2021, Servizio produzione editoriale Istat, Rome.

JENSEN C. (2018), The employment impact of Poland’s special economic zones policy, Regional Studies, vol. 52, issue 7, pp. 877-889. doi: https://doi.org/10.1080/00343404.2017.1360477

KLINE P. and MORETTI E. (2014), Local Economic Development, Agglomeration Economies, and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority, The Quarterly Journal of Economics, vol. 129, issue 1, pp. 275–331. doi: https://doi.org/10.1093/qje/qjt034

KRUGMAN P. (1991), Increasing Returns and Economic Geography, Journal of Political Economy, vol. 99, no. 3. doi: https://doi.org/10.1086/261763

LAW 1950/646 of 1 September 1950 on Establishment of the Fund for the South (https://www.gazzettaufficiale.it/eli/id/1950/09/01/050U0646/sg#:~:text=Istituzione%20della%20Cassa%20per%20opere,(Cassa%20per%20il%20Mezzogiorno).).

LAW 2015/208 of 28 December 2015 on Budget Law 2016 (https://www.gazzettaufficiale.it/eli/id/2015/12/30/15G00222/sg).

LAW 2020/178 of 30 December 2020 on Budget Law 2021 (https://www.gazzettaufficiale.it/eli/id/2021/01/18/21A00174/sg).

LAW DECREE 2017/91 of 20 June 2017 on Urgent measures for the economic growth of Southern Italy (https://www.gazzettaufficiale.it/eli/id/2017/06/20/17G00110/sg).

LAW DECREE 2023/124 of 19 September 2023 on Urgent measures for cohesion policies, for the relaunch of the economy of Southern Italy, as well as for immigration (https://www.gazzettaufficiale.it/eli/id/2023/09/19/23G00137/sg)

LI X., WU X. and TAN Y. (2021), Impact of special economic zones on firm performance, Research in International Business and Finance, vol. 58, article number 101463. doi: https://doi.org/10.1016/j.ribaf.2021.101463

LU R. (2011), Building Engines for Growth and Competitiveness in China: Experience with Special Economic Zones and Industrial Clusters, Regional Studies, vol. 45, issue 9, pp. 1292-1293. doi: https://doi.org/10.1080/00343404.2011.608259

LU Y., WANG J. and ZHU L. (2019), Place-Based Policies, Creation, and Agglomeration Economies: Evidence from China's Economic Zone Program, American Economic Journal: Economic Policy, vol. 11, no. 3, pp. 325-60. doi: 10.1257/pol.20160272

MARTIN P., MAYER T. and MAYNERIS F. (2011), Spatial concentration and plant-level productivity in France, Journal of Urban Economics, vol. 69, issue 2, pp. 182-195. doi: https://doi.org/10.1016/j.jue.2010.09.002

MCQUEEN G. and ROLEY V. V. (1993), Stock Prices, News, and Business Conditions, The Review of Financial Studies, vol. 6, issue 3, pp. 683-707. doi: https://doi.org/10.1093/rfs/5.3.683

MILIO S. (2010), Twenty years of European funding: Italy is still struggling with implementation, in Italy Today. The Sick Man of Europe, Routledge, London. doi: https://doi.org/10.4324/9780203859636

MOBERG L. (2015), The political economy of special economic zones, Journal of Institutional Economics, vol. 11, issue 1, pp. 167–190. doi: https://doi.org/10.1017/S1744137414000241

PREZIOSO S. and SERVIDIO G. (2011), Southern Industry and Industrial Policy from the Unification of Italy to this Day, Rivista economica del Mezzogiorno, issue 3, pp. 561-624. doi: 10.1432/36157

UNCTAD (2019), World Investment Report 2019 - Special Economic Zones, United Nations Publications, New York.

WANG J. (2013), The economic impact of Special Economic Zones: Evidence from Chinese municipalities, Journal of Development Economics, vol. 101, pp. 133-147. doi: https://doi.org/10.1016/j.jdeveco.2012.10.009

WOOLDRIDGE J. M. (2010), Econometric Analysis of Cross Section and Panel Data, MIT Press, Cambridge (Massachusetts).

ZENG D. Z. (2010), How Do Special Economic Zones and Industrial Clusters Drive China's Rapid Development?, in Building Engines for Growth and Competitiveness in China: Experience with Special Economic Zones and Industrial Clusters, World Bank, Washington, D. C.

ZENG D. Z. (2021), The Past, Present, and Future of Special Economic Zones and Their Impact, Journal of International Economic Law, vol. 24, issue 2, pp. 259–275. doi: https://doi.org/10.1093/jiel/jgab014

ZHENG L. (2021), Job creation or job relocation? Identifying the impact of China's special economic zones on local employment and industrial agglomeration, China Economic Review, vol. 69, article number 101651. doi: https://doi.org/10.1016/j.chieco.2021.101651

Appendix

Appendix A. Linear constraints on individual SEZs

In section 4.2 we analyzed the impact of each SEZ on the log Number of employees, finding that most SEZs have positively influenced business employment. Now we will test whether the magnitude of the coefficients is the same for all SEZs or not, allowing us to understand if some zones have been more successful than others. For this purpose, we used the Wald test to verify the following linear constraint on each pair of SEZ coefficients:

$$H_0: \beta_{SEZ_i} - \beta_{SEZ_j} = 0$$

where β_{SEZ_i} and β_{SEZ_j} are the coefficients of the i-th SEZ and j-th SEZ, respectively. If this null hypothesis is rejected, the difference between β_{SEZ_i} and β_{SEZ_j} is significantly different from zero, denoting that the two coefficients are not the same; while the opposite is true if the null hypothesis is not rejected. Results of the linear constraint for models where we considered 2014-2022 and 2020-2022 as time intervals are reported in Table A.1:

Table A.1. Linear constraints on SEZ coefficients

Couple observed	2014-2022			2020-2022		
	β_{SEZ_i}	β_{SEZ_j}	p-value	β_{SEZ_i}	β_{SEZ_j}	p-value
Campania-Apulia Molise	0.0703	0.0717	0.9288	0.0283	0.0419	0.1939
	(0.0102)	(0.0123)		(0.0070)	(0.0079)	
Campania-East. Sicily	0.0703	0.0685	0.9262	0.0283	0.0266	0.9029
	(0.0102)	(0.0165)		(0.0070)	(0.0118)	
Apulia Molise- East. Sicily	0.0717	0.0685	0.8758	0.0419	0.0266	0.2802
	(0.0123)	(0.0165)		(0.0079)	(0.0118)	

Robust standard errors are reported in brackets.

Tests suggest that there are not significant differences in the impact of each SEZ on firm employment, because the linear constraint is never rejected.

Conclusions

This thesis investigated several topics of interest for the economic field, from textual analysis to the assessment of new public interventions, and in particular the European Recovery and Resilience Plans and the Italian Special Economic Zones. The first chapter proposed the Prior Adaptive Bayes (PAB) classifier, a new classifier adapted for the word classification task whose main characteristic is that the priors of classes are not constant, but they adapt to the corresponding posteriors associated with the surrounding words. We tested the PAB classifier on a dataset usually used to evaluate the performance of textual classifiers, showing that it achieves a significant improvement over the standard Bayes classifier.

The second chapter implemented the PAB classifier to investigate the alignment of the European Recovery and Resilience Plans (RRPs) with the environmental Sustainable Development Goals (SDGs) as compared to the socioeconomic SDGs. In particular, once we estimated for each project contained in the RRPs the number of words associated with each dimension, we built a relative index of alignment of these projects with the two SDGs dimensions. Then, we analyzed this index in relation to several variables. Among the results obtained, countries that receive more funds are able to pay more attention to environmental issues. Net of this, we analyzed some possible determinants of the index, finding that the increase in the attention paid to environmental issues has concerned both countries in which a substantial part of the economy is based on tourism and those countries that show a major delay toward the environmental objectives. Finally, we estimated some panel models by regressing the index on the GDP growth forecasts elaborated by the European Commission. Estimates suggest that the percentage change of the real GDP tends to be associated positively with the environmental SDGs.

Finally, the third chapter performed a first quantitative analysis aimed at evaluating the impact of Special Economic Zones (SEZs) on firms in Southern Italy, and in particular on firms eligible for SEZ incentives, as well as the spillovers of the Italian SEZ program on firms located in municipalities adjacent to SEZs. Preliminary results suggest that SEZs have been successful so far, because SEZ businesses and businesses adjacent to a zone have significantly increased their number of employees. This evidence is confirmed on SEZ Campania, Apulia-Molise and Eastern Sicily. Moreover, the SEZ program has not affected all economic sectors equally: while businesses in the agricultural sector have not made significant changes to employment, the opposite is true for firms in the industrial and service sectors, where the number of employees has increased significantly. Despite these promising results, further studies are needed in the medium-long term to understand if the observed increase in employment is only a temporary boost or if it represents the beginning of a radical structural change aimed at significantly reducing the historic economic gap between Northern and Southern Italy.

Acknowledgments

I would like to thank those who supported me during this wonderful journey, and in particular my family, from my parents to my brothers and their families, from my in-laws to the sister I never had, Mary. A special thanks goes to my beloved Lilly: thank you for always being by my side, in good times and especially when I doubted I could do it. Thanks also to my historical friends with whom I spent these years – Davide, Loredana, Valentina and Nicolò – and to my colleagues with whom I shared this journey.

I want to thank my supervisor, Professor Emanuele Millemaci, a man with a great human side and scientific rigor that taught me how to do research. I also thank Professor Giorgio Liotti for giving me the opportunity to broaden my research horizons at the Technical University of Košice. Thanks finally to all those who helped me to improve the quality of this work with their invaluable suggestions, and in particular Professor Michele Limosani and Alessandra Insana.