A Mining Driven Decision Support System for Joining the European Monetary Union

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***Abstract*—The European Monetary Union (EMU) is a result of an economic integration of European Union member states into a unified economic system. The literature is divided on whether the EMU members benefit from this monetary unification. Considering costs and benefits, a fiscal authority may ask whether it is a good decision to join the EMU. We introduce and develop a decision support system to answer the proposed question using a historical dataset of twelve Macroeconomic Outcomes (MOs) obtained for 31 European countries and for 18 years (1999-2016). The system meets the three-prong goal of: (1) identifying highly relevant MOs for a given year, y_i, using the data from years y_1 to y_i; (2) deriving decision of "join/not-join" the EMU along with its certainty factor using the relevant MOs for y_i; and (3) examining the accuracy of the derived decision using the data from y_{i+1} to y_{18}. The performance analysis of the system reveals that (a) the number of relevant MOs has declined nonlinearly over time, (b) the relevant MOs and decisions are significantly changed before and after the European debt crisis, and (c) the derived decisions by the system has 79% accuracy**.

Keywords- Mining Features; Mining-based Decision Support System; The European Monetary Union; Bayesian Theorem

I. INTRODUCTION

The European Monetary Union (EMU) is an agreement among the European countries to join together for creating one functioning monetary system with one currency. The idea of the EMU was given by the European Council in the Dutch city of Maastricht in December of 1991. Later the formation of this union was declared in the Treaty on European Union or as it is better known the Maastricht Treaty (1992). In January of 1999, eleven countries adopted the single currency—euro. For joining the European Monetary Union, a country must adhere to the following entry conditions: price stability, sound and sustainable public finances, durability of interest rate convergence, and exchange rate stability.

The advantages of joining the EMU have been enumerated by many sources including the European central bank that is in charge of stabilizing inflation by implementing a common monetary policy across the Eurozone [1]. Rogers [2] has shown that joining the EMU leads to more stable prices. Alesina and Barro [3] and also Frankel and Rose [4] have indicated that the trade costs among European countries have reduced and the credibility of monetary policy has enhanced. Kim *et al.* [5] and also Bernoth *et al.* [6] have claimed separately that the members have experienced a lower default risk premium. (Risk premium is defined as the spread between member's yield and the yield on the German Bund). Rose and Engle [7] have empirically shown that due to the trade volume, the volatility of exchange rate has declined in the Eurozone.

However, the disadvantages of joining the EMU have also been enumerated by many resources. Feldstein [8] expresses that the loss of monetary independence of the members is counted as one of the major disadvantages. Codongo *et al.* [9] have argued that credit risk has been greater in the euro area. After the European Sovereign Debt Crisis started in 2009, the disadvantages were more pronounced: Government debt increased due to massive tax cuts and increase in the government spending [10][11]. Banking crises became evident among some members that led to deep and prolonged asset market collapses associating with declines in total output measured by Gross Domestic Product (GDP) [12][13].

Considering the advantages and disadvantages of joining the EMU, a fiscal authority may ask: is it a good decision to join the EMU. We try to answer the proposed question using historical Macroeconomic Outcomes (MOs) obtained for 31 European countries and for 18 years [1999-2016]. The binary attribute of *membership* divides the 31 countries into two groups of member and non-member of the EMU. For a given year, y_i, the curtailed historical data will include all the records from year 1999 up to year y_i (y_i year data is not included.)

The goal of this research effort has three prongs: (1) Identifying the highly relevant MOs to the membership attribute for a given year, y_i, using the curtailed historical data for the year, (2) Deriving a decision of "join/not-join" the EMU along with a certainty factor, at the year y_i using the relevant attributes, and (3) Examining the accuracy of the derived decision by assessing the behavior of the MOs

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of those countries that joined the EMU at year y_i for the years of y_i to y_{2016}.

The rest of the paper is organized as follows. The Previous Works is the subject of Section 2. The Methodology is presented in Section 3. The Empirical Results are covered in Section 4. The Conclusions and Future Research are covered in Section 5.

II. PREVIOUS WORKS

The literature presents a body of work for determining whether membership in the EMU is beneficial using MOs. Frankel and Rose have used trade volume and GDP (two MOs) to find the effects of monetary unification [4]. They applied a two-stage approach to the problem. In the first stage, trade between any two countries was estimated using a gravity model. In the second stage, the Ordinary Least Squares method was used to find how joining the EMU affects trade and GDP. Gomez-puig tested the existence of causal relationships between the bond yield and government debt and joining the EMU [14]. The Granger's causality test was used which is based on the concept of the causal ordering. The causal relationship was estimated using the first difference and lagged variables regression. Rose and Engle used a linear regression model to determine whether the MOs of openness, exchange rates, and price integration statistically changed within the EMU members compared to the non-EMU members [7]. Codongo et al. [9] and Bhatt *et al.* [15] separately and by different methodologies have determined the effects of joining the EMU on yield and yield spread as two MOs.

In all reported studies, the number of MOs used is limited and extremely small. However, we use a large set of MOs (twelve of them) and that is the major point of departure from the similar works reported in literature. As the second point of departure, we consider our dataset as a snapshot of the twelve MOs at a point in time and then we say knowing what we know from the snapshot, is it advisable to join the EMU. In addition we verify the accuracy of the advice.

III. METHODOLOGY

Let D be a dataset with N independent attributes of $A_1, ..., A_n$ and one dependent attribute of E. As a preprocessing step, we keep only one copy of the attributes that are correlated. The Pearson method is used to compute the correlation coefficients among every two attributes, Ai, A_j using formula (1)

$$\rho_{A_i,A_j} = \frac{cov(A_i,A_j)}{\sigma_{A_i}\sigma_{A_j}} \quad (1)$$

Where, ρ_{A_i,A_j} denotes the Pearson coefficient. $cov(A_i,A_j)$ is the covariance and $\sigma_{A_i}, \sigma_{A_j}$ are the standard deviations. The correlation test calculates the S-statistics defined by

$$S = (n^3 - n)\frac{1-\rho_{A_i,A_j}}{6} \quad (2)$$

Where, n is the sample size. The S-statistics is compared to its critical value to reject the null hypothesis of no correlation between the two attributes.

The details of the methodology for meeting the three prongs of the goal are covered in the following three subsections

A. *Identifying the Most Relevant Attributes*

The first sub-goal is to identify the relevant attributes among the independent attributes of ($A_1 ... A_n$) that are indicative of E (the dependent variable in dataset D). We assume the possible values for E are $d_1, ..., d_g$. To meet this sub-goal, we use the Naïve Bayesian classification approach which is encapsulated as follows.

Let r be a new record with ($A_1 ... A_n$) attributes for which a predicted value of E is sought using D as a training set. The predicted value of E for r is determined by the highest probability amongst P(E=d_j | r), for j = 1 to g. The P(E=dj | r) is defined by formulas (3):

$$P(E = d_j \mid r) = \frac{p(E=d_j)\prod_{i=1}^{n} p(A_i = v \mid E = d_j)}{p(r)} \quad (3)$$

Since the denominator is the same for all probabilities of $P(E = d_j \mid r)$, we need to calculate only the numerator.

Two algorithms Core (Fig. 1) and Relevant (Fig. 2) are used for determining the *relevance degree* of each independent attribute in reference to the dependent attribute. The Core algorithm accepts a dataset Φ with k attributes of $A_1, ..., A_k$ as independent variables and the binary attribute of Z as dependent variable.

Algorithm Core (Φ, se, sp)
Given: Dataset Φ with independent attributes of ($A_1, ..., A_k$) and a binary dependent attribute of Z. S_1 and S_2 that are the set of all the record numbers in Φ with Z = 1 and Z =0, respectively.
Objective: Predict the Z value for every record in Φ and return sensitivity (se) and specificity (sp) for the overall prediction.
Method:
Step1- Repeat for each record, r_j, in Φ and in presence of the rest of the records
Step2- Treat r_j as the test set and Φ-r_j as the training set;
Step3- Apply the Naïve Bayesian classification to predict a Z value for r_j;
End;
Step4- W_1 and W_2 that are the set of all the record numbers in Φ with predicted values of Z = 1 and Z =0, respectively.
Step5- se = $|S_1 \cap W_1|/|S_1|$;
sp = $|S_2 \cap W_2|/|S_2|$;
Return (se, sp);
End;

Figure 1. The Algorithm Core

Core algorithm: (a) treats every record of the dataset Φ, individually, as a test set of one record while treating the remaining records as a training set (Steps 1 and 2), (b) applies the Naïve Bayesian classifiers to predict the Z value for the record in the test set (Step3), (c) upon completion of predicting a Z value for every record in Φ, Core algorithm returns sensitivity and specificity of the classification as two parameters of $se = T^1/(T^1+F^0)$ and $sp = T^0/(T^0+F^1)$, where T^1 and T^0 are the number of records that truly predicted 1 and 0, respectively. F^1 and F^0 are the number of records that falsely predicted 1 and 0, respectively (Step5).

To explain the algorithm Relevant, the dataset D which is similar to dataset Φ and has n attributes of $A_1 \ldots A_n$ is given. Let us make n subsets out of dataset D, $(D_1, \ldots, D_n)$, such that D_i is composed of the attribute A_i and a copy of the attribute Z (Steps 1 and 2.) Let us also apply Core algorithm on each subset, D_i, separately and calculate se_i and sp_i, (Step 3.) The prediction of Z values by A_i is as good as $\alpha_i = \text{Min}(se_i, sp_i)$, (Step4). Therefore, we consider α_i as the relevancy measure of A_i to Z (named the *relevance degree* of A_i in reference to Z.) The Relevant algorithm delivers a list of attributes and their corresponding relevance degrees such that each relevance degree in the list is greater than a given threshold (Step 5.) The list is the response to the first sub-goal.

Algorithm Relevant
Given: Dataset D with independent attributes of $(A_1 \ldots A_n)$ and a binary dependent attribute of Z. A Relevance Degree matrix, RD, of the size n X 2. A threshold value of T_v.
Objective: Determining the most relevant independent attributes to Z.
Method:
Step1- Repeat for every attribute, A_i, in D.
Step2- D_i is the projection of D over attributes of (A_i, Z);
Step3- Invoke Core(D_i, se_i, sp_i);
Step4- $\alpha_i = \text{Min}(se_i, sp_i)$.
Step5- If $(\alpha_i > T_v)$
Then Insert the pair of (A_i, α_i) into RD.
End;
End;

Figure 2. The Algorithm Relevant

B. *Deriving a Decision*

Considering the dataset D given above and the outcome of the algorithm Relevant, deriving a decision is completed in three stages. In the first stage, a subset of D is chosen, D_r, that includes only the relevant attributes obtained from RD along with a copy of Z

In the second stage, the matrix RD is sorted in descending order of the relevance degree values and the attribute in the top row of matrix RD is selected as the *seed*, A_s. The attribute A_s is used as a root of a *search* tree with q-1 branches at the first level, where q is the number of the relevant attributes in D_r, as shown in Fig. 3.

To minimize the cost of building the search tree, we apply a filtering process at each level of the tree such that only the best leaf survives. Through the filtering process, "tie" cases may happen in selecting a node for expansion. Such cases are resolved by randomly choosing one node among the tied nodes.

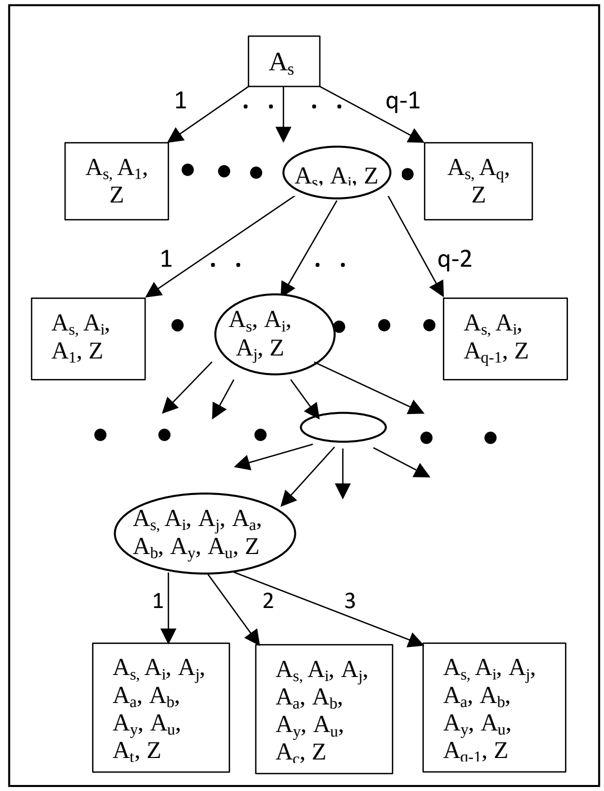

Figure 3. A search tree: The winner node at each level is designated by an oval shape and there is not any winner node at the last level

To explain it further, the i-th leaf of the first level is a projection of D_r over the Z, root of its subtree, and the attribute A_i (A_i cannot be the same as the root of its subtree.) Only one leaf from the first level is chosen as the winner and expanded (the condition for being a winner node are introduced shortly.) In the second level there are q-2 branches from the winner node of the first level. The j-th leaf of the second level is a projection of D_r over the Z, attributes in the path from the root to the winner node, and the attribute A_j (A_j is not the root of any subtree.) This process continues until the subtree cannot be expanded either because all the attributes in D_r are exhausted or there is not any winner node in the current level. Reader needs to be reminded that each node of the search tree has its own dataset which is a subset of the dataset D_r. Selecting a node as the winner of a given level is done by taking the following steps:

a. The Core algorithm is applied on each one of the node's datasets separately to obtain sensitivity and specificity, and relevance degree for the dataset.
b. The winner node is the one with the highest relevance degree among the nodes' datasets and it is greater than a set threshold.

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The search tree delivers the most relevant attributes to the attribute Z which is considered feature extraction from D.

In the third stage, the last winner node of the search tree with sensitivity of se_l and specificity of sp_l is examined one more time. If ($se_l > sp_l$) it means the node's dataset more reflects those countries that are members of the EMU. Therefore, the suggested decision by the system is "join". Using the same argument, if ($se_l < sp_l$) then the suggested decision is "Not-Join". In the case that ($se_l = sp_l$), the weighted average (WA) for all the records in the winner node's dataset with Z =0 and Z =1 are calculated separately.

If ($WA_1 > WA_0$) Then decision is "join"
If ($WA_1 < WA_0$) Then decision is "not-join"
If ($WA_1 = WA_0$) Then no decision can be made.

A *certainty factor, CF*, ($0 \le CF \le 1$) is associated with any driven decision, which simply expresses the level of confidence that the decision support system has in the suggested decision. A higher value for CF means higher confidence in the decision. The CF is simply the average of sensitivity and specificity for last winner node.

C. Examining the Derived Decision

We examine the accuracy of the derived decision for a given year, y_i, by (a) identifying those countries that joined the EMU at year y_i, (b) assessing the behavior of their MOs for years of y_i to y_{18}, in reference to the average of their MOs behavior prior to joining the EMU, and (c) determining whether the assessment results support the derived decision. The assessing process is done by performing a trend analysis which is encapsulated as follows:

Let C = {C_a, . . ., C_p} be a set of countries that joined the EMU at year y_i and {A_1, . . ., A_n} be the set of attributes (MOs) that are the same for every country, C_j, in C. Let also G^{i-1} be the set of the average values for each one of the n attributes of C_j from year 1 to year y_{i-1}, G^{i-1} = {(g_1^{i-1}, . . ., g_n^{i-1}), that is used as the *baseline* during the trend analysis. In addition, let the values for the n attributes of C_j for the k[th] year after y_i be (v_1^{i+k}, . . ., v_n^{i+k}.) The trend of attribute A_m for the year i+k is denoted by Trend(A_m^{i+k}) and it is computed by formula (4).

$$Trend(A_m^{i+k}) = \frac{v_m^{i+k} - g_m^{i-1}}{g_m^{i-1}} * 100 \quad (4)$$

The *overall trend* of A_m for the period of q years for C_j is:

$$ot(A_m^q)_{C_j} = \frac{\sum_i^q Trend(A_m^{i+q})}{q} \quad (5)$$

For the same period, the *overall trend* of A_m for the countries in C, OTC, is:

$$otc(A_m^q) = \frac{\sum_a^p ot(A_m^q)_{C_a}}{|C|} \quad (6)$$

The interpretation of the $otc(A_m^q)$ value depends on the nature of the attribute. For example, a negative overall trend value for the attribute "inflation" is considered an improvement whereas a negative trend value for GDP is considered deterioration. The same can be argued for a positive value. Table 1 is used to remove the duplicity of the interpretation. As a result, a positive/negative trend value is considered an improvement/deterioration trend, for any attribute, respectively.

The formula (6) delivers the overall trend for attribute A_m (m=1 to n) for a period of q years considering all countries in C. The *overall trend for the countries* in C given all the attributes and for the same period of q is calculated using formula (7).

$$Trend(C) = \frac{\sum_{m=1}^n OCT(A_m^q) * \beta_m}{n} \quad (7)$$

Where, $OCT(A_m^q)$ is the $oct(A_m^q)$ after its duplicity removed, β_m is the average of the relevance degrees of the attribute A_m for the period of q years and for all the countries in C.

TABLE I. ACTIONS FOR DUPLICITY REMOVAL

Trend Value: $otc(A_m^q)$	**Negative (Improvement)**	**Positive (Improvement)**
Negative	$otc(A_m^q)$*(-1)	$otc(A_m^q)$
Positive	$otc(A_m^q)$*(-1)	$otc(A_m^q)$

The architecture of the Mining Driven Decision Support System is summarized as a collection of three major modules: Feature Extractor, Decision Driver, and Trend Analyzer, Fig. 4. The dataset D goes to a pre-processing step to be cleaned and a subset of D is selected, Y, for years in the range of [1- y) which includes those countries that were adopted into the Eurozone in year y. The feature extractor module accepts Y as input. The module extracts a subset, K, of the attributes in D such that the K attributes are highly relevant to the dependent variable Z for the years of [1- y). The extraction is done by applying the algorithm Core, algorithm Relevant, and creation of search tree. The outcome of the module helps to make two different projections of D over the K attributes, Y' and Y", for the years [1-y) and [y+1, 18], respectively.

The decision Driver Module accepts the Y' as the input dataset and, in reference to Z, calculates the sensitivity (se) and specificity (sp) for Y' using a naïve Bayesian approach. A decision of "join" or "not-join" is suggested by the module using the values for se and sp.

The trend analyzer module accepts the dataset Y" and delivers an overall trend of the behavior of MOs for the countries (adopted into the EMU in year y) during the years of [y, 18]. The support of the overall trend for the suggested decision is used to confirm the validity of the suggested decision.

IV. EMPIRICAL RESULTS

Currently, the European Union consists of 31 members of which 19 countries have adopted the euro, Table 2. The Master Dataset used has the measurements of twelve MOs for every country in Table 2 and for the duration of 1999-2016. The short and expanded names of the MOs in the Master Dataset are given in Table 3.

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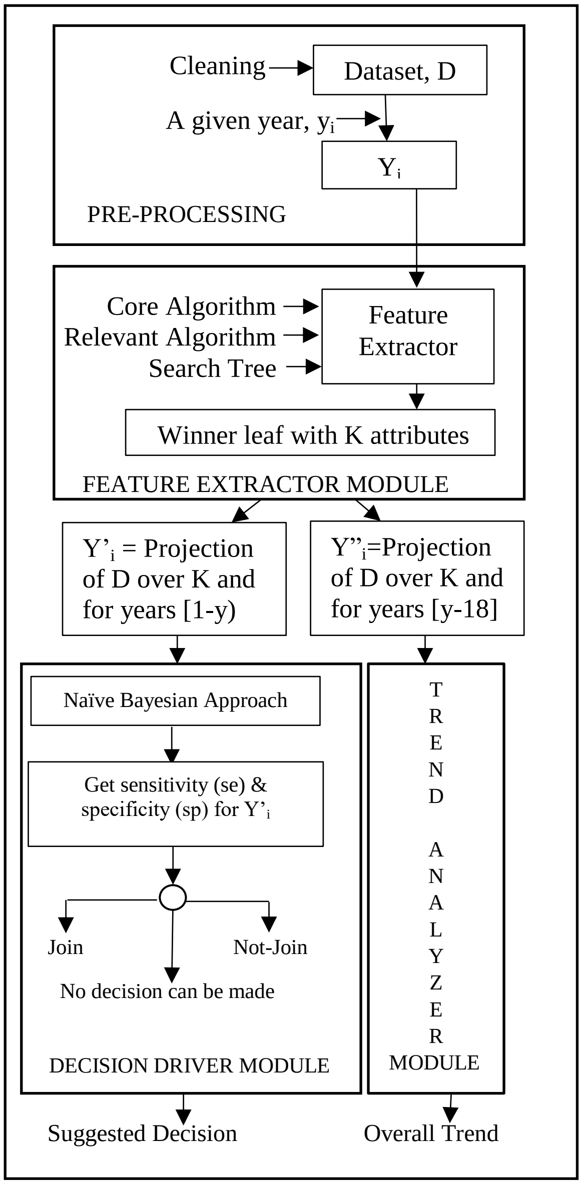

Figure 4. The architecture of the Mining Driven Decision Support System

Table 2 has eight unique adoption dates for the current members of the EMU (1999, 2001, 2007, 2008, 2009, 2011, 2014, and 2015.) We divided the Master Dataset into eight triplets of new datasets as follows (Y_{99}, Y'_{99}, Y''_{99}), (Y_{00}, Y'_{00}, Y''_{00}), (Y_{06}, Y'_{06}, Y''_{06}), (Y_{07}, Y'_{07}, Y''_{07}), (Y_{08}, Y'_{08}, Y''_{08}), (Y_{10}, Y'_{10}, Y''_{10}), (Y_{13}, Y'_{13}, Y''_{13}), and (Y_{14}, Y'_{14}, Y''_{14}.) The dataset Y_i ($i \neq 99$) held only those records of the Master Dataset for which the adopted year is i+1. The reason for choosing data up to one year prior to each one of the eight-unique adoption dates stems from the fact that we assume the decision of “join” or “not-join” is based on the historical data prior to the date of adoption. For the year 1999, however, there is no prior data and as a remedy we use the data for year 1999 itself as the historical data.

TABLE II. MEMBERS AND NON-MEMBERS OF THE EMU FROM 1999 TO 2016

EMU Members			
Country	***Adoption Date***	***Country***	***Adoption Date***
Austria	1999	Latvia	2014
Belgium	1999	Lithuania	2015
Cyprus	2008	Luxembourg	1999
Estonia	2011	Malta	2008
Finland	1999	Netherlands	1999
France	1999	Portugal	1999
Germany	1999	Slovakia	2009
Greece	2001	Slovenia	2007
Ireland	1999	Spain	1999
Italy	1999		
Non Members			
Bulgaria	Denmark	Romania	Iceland
Croatia	Hungary	Sweden	Norway
Czech Rep.	Poland	UK	Switzerland

In addition, two attributes of Treat and Year were added to the Master Dataset to reflect the membership of the country in the EMU and the year for which data was collected, respectively. The Treat was a binary attribute where the values of zero and one for a country meant “member” and “non-member” of the EMU, respectively. The Year values were 1 to 18, where value = 1 means year 1999 and value = 18 means year 2016. The total number of records was 31 * 18 = 558. The MOs were considered as independent variables and the Treat attribute was considered as the dependent attribute.

TABLE III. THE SHORT AND EXPANDED NAMES OF THE “MO”S

MO’s Short Name	**MO’s Expanded Name**
ldebt	First lag of the government-debt ratio
lgdpg	First lag of GDP growth
lrmg	First lag of real money growth
lpi	First lag of inflation
lopen	First lag of trade
lrer	First lag of real exchange rate
bndyld	10-year government bond yield
lspread	First lag of the spread between bndyld and average of French and German yields
bndvol	Volatility of the bond yield
gdpgvol	Volatility of GDP growth
pivol	Volatility of inflation
spreadvol	Volatility of the spread

The dataset Y'_i held only those records of Y_i that were non-members but became members in the year i+1, and Y''_i held only those records of the Master Dataset for which the year values ≥ i and country names were the same as the ones in Y'_i.

For a triplet of (Y_i, Y'_i, Y''_i), the dataset Y_i was used to determine the relevant attributes and derive the decision of “join/not-join” along with its certainty factor. The dataset Y'_i was used to provide a baseline for the trend analysis and Y''_i was used to study the trends in reference to the baseline.

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The following process was repeated for each triplet of (Y_i, Y'_i, Y''_i). (This means the process repeated only for those years that one or more countries joined the EMU.):

Step1: Correlated attributes in Y_i were identified and from each group of correlated attributes only one attribute remained in Y_i (generating a cleaned Y_i.) The maximum calculated correlation among any two MOs was 0.3. Therefore, none of the MOs was dismissed.

Step2: The cleaned Y_i was used to identify the most relevant independent attributes of Y_i with regard to dependent attribute, Treat (using the Relevant algorithm) and the rest of the independent attributes were dismissed (generating a scrubbed Y_i.)

Step3: The independent attributes in Y'_i and Y''_i that were not found in the scrubbed Y_i were removed. A baseline was established using Y'_i by averaging the values for each attribute separately.

Step4: A decision of "join/not-join" was derived from scrubbed Y_i using the relevant attributes and the search tree outcome. The certainty factor for each decision was also calculated.

Step5: The derived decision for Yi was considered as the derived decision for the countries C = {Ca, . . ., Cp} joining the EMU at the year Y_{i+1}. The Y'_i was used as a baseline to verify the accuracy of the derived decision using overall trend for C in Y''_i.

In reference to the first sub-goal of the research, the list and rank of the relevant MOs produced by Step 2 of the process are shown in Table 4. (Rank of an MO is its importance to the derived decision and Rank equal to 1 is the highest rank.) The derived decisions along with the certainty factor produced by Step 4 of the process were also shown in Table 4.

TABLE IV. THE RELEVANT "MO"S AND THEIR RANKS ALONG WITH THE DERIVED DECISION AND THEIR CERTAINTY FACTOR FOR EACH ADOPTION DATE

Rank	**Y_{99}**	**Y_{00}**	**Y_{06}**	**Y_{07}**
(1)	spreadvol	spreadvol	lspread	lspread
(2)	lrmg	lrmg	lrer	lrer
(3)	ldebt	ldebt	bndyld	bndyld
(4)	bndyld	lspread	bndvol	
(5)	lrer	lrer		
(6)	lspread	bndyld		
(7)	gdpgvol	gdpgvol		
Derived Decision	*Join CF:0.93*	*Not-Join CF:0.98*	*Not-Join CF:0.84*	*Not-Join CF:0.79*
Rank	**Y_{08}**	**Y_{10}**	**Y_{13}**	**Y_{14}**
(1)	lopen	lopen	lopen	ldebt
(2)	lrer	bndvol	pivol	lopen
(3)		lrer	lrer	lrer
(4)		ldebt	ldebt	
Derived Decision	*Join CF:0.77*	*Join CF:0.79*	*Join CF:0.73*	*Join CF:0.69*

The trend analysis delivered by Step 5 of the process is shown in Table 5 in which the improvement/deterioration of the overall trend of the MOs were expressed by the notations of (+)/(–), respectively. The overall trend of (+) and the derived decision of "join" are in agreement and so the overall trend of (–) and derived decision of "not-join".

TABLE V. DERIVED DECISIONS AND OVERALL TRENDS FOR EACH UNIQUE ADOPTION DATE

Adoption Date	**No. of Countries**	**Derived Decision**	**Overall trend**
1999	11	Join	(+)
2001	1	Not-Join	(–)
2007	1	Not-Join	(+)
2008	2	Not-Join	(+)
2009	1	Join	(–)
2011	1	Join	(+)
2014	1	Join	(+)
2015	1	Join	(+)

VI. CONCLUSIONS AND FUTURE RESEARCH

The same procedure may be applied to only one of the countries for a given date of adoption as long as Y'_i and Y''_i include the past and ongoing economic performance of that one country. It is also true that the same procedure may be applied for any given year, but it is not necessary. To explain it further, the purpose is to compare the past and ongoing economic performance of a given country (captured in two datasets of Y'_i and Y''_i.) If the year i be any year then, the comparison of the two datasets Y'_i and Y''_i does not have any meaning. Therefore, framing the past and ongoing economic performance into the years of (1999-i) and (i+1- 2016) is relevant as well as adequate. As another point of clarification, the time(year)-lag effects are not the same over all MOs. We use the first lag for all MOs except bndyld, and volatility attributes (bndvol, gdpvol, pivol, and spreadvol.) The reason for using the first lag is that economic theories suggest that today's decisions by central banks are made with a one-period lag. This is not true for volatility variables and bndyld. Readers need to be reminded that our study is a longitudinal framework, which includes time (year) and unit (country).

The findings for our decision support system were presented in Tables 4 and 5. Table 4 indicates the relevant MOs for the years prior to the adoption dates and the derived decisions. The relevance of MOs has changed over time. A greater set of MOs determines whether the country must join the EMU for the years closer to the introduction of the euro, 1999. As time goes on, the relevant MOs set shrinks nonlinearly. For the years before the European sovereign debt crisis the MOs of, spreadvol, spread, lrmg, and lrer play significant roles in the decision making process; however, after the crisis other outcomes such as lopen, ldebt, bndvol, and pivol become pertinent.

The MO of lrer is the only one that was identified as the relevant attribute in all Y_i datasets. One possible reason is that the EMU members link their currency to the euro which protects them from currency fluctuations. This linkage makes the lrer a significant factor for all the samples. The MOs, bndyeld and lspread identified as relevant only for countries that joined the EMU prior to 2009. The reason stems from the fact that bond yield convergence is one of the goals of monetary unification and members had benefited from joining the EMU through the bond yield channel [16]. However, the bond yields have reduced to nearly zero after the crisis due to expansionary monetary policy. Thus, the bond market attributes have become irrelevant in the post crisis era. In contrast, lopen was observed as a relevant MO for only countries that joined the EMU subsequent to 2009. The attempt of the EMU members to overcome the turmoil of the banking crisis by increasing trade within the monetary union was completely aligned with the observation of lopen as a relevant MO.

The derived decision is “join” for the year 1999 when 11 countries adopted the euro corroborating evidence that it is beneficial to join at the beginning of the European monetary union. However, the findings reveal that the decisions made by European countries to “join” the EMU in adoption dates of 2001, 2007, and 2008 (years prior to crisis), are not beneficial. In contrast, the findings provide evidence that joining would be beneficial after the crisis.

Table 5 shows the derived decisions and overall trends for each adoption date. Considering the last two columns of Table 5, four possible combinations of (Join, +), (Join, –), (Not-Join, +), and (Not-Join, –) may exist. Only the combinations of (Join, +) and (Not-Join, –) are evidence of the support for the derived decision by the actual trends in the behavior of the MOs. Based on Table 5, for five out of the eight groups of countries that joined the EMU on the unique adopted dates, the derived decision and trend analysis agreed. The five groups included 15 countries. To summarize, the accuracy of our decision support system was 15/19 = 0.79% with the false positive of 3/19 = 16% and false negative of 1/19 = 5%.

The certainty factor for the derived decision declines with time. One explanation for such decline is that the size of the Y''_i datasets reduce with time. The reduced sample size is a potential threat to the validity.

It is worth mentioning that the proposed methodology can be applied to other policy making questions such as whether adopting a specific monetary policy strategy (e.g., Inflation Targeting) is effective.

The discussed mining driven decision support system is designed to suggest a decision of “join” or “not-join” the EMU to a fiscal authority. As a future research, we plan to investigate another popular/political question. The question is under what circumstances is it beneficial for a given country to leave the EMU? This issue has become significantly important for both policy makers and researchers after the recent talk of Brexit. Also, the development of a Bayesian belief system to support the casual relationships among MOs, if any, is in progress.

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