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A Multidimensional Analysis of Socioeconomic Factors in Housing Policy in the Eurozone Countries (2010–2014)

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SUMMARY

The latest global economic and financial crisis has had adverse social consequences in many areas, including income and the social situation of households and their living conditions, especially when the housing phenomenon is addressed. The reality of this uncertainty has made the study of the housing phenomenon even more relevant, in particular from the perspective of an analysis of its evolution. In this context, we revisit EUROSTAT's databases. This analysis was done for twelve Euro Area countries over five years, using the HJ-BIPLOT method developed by Galindo (1986). This multidimensional approach identified and represented twelve Eurozone sample countries in latent constructs of reduced dimensionality related to the housing policy problem. The simultaneous factorial representation identified (a) the most relevant variables to characterize these countries, (b) their trajectories during the period in analysis, and (c) the relations between variables, between countries, and between variables and countries. This approach also identified the most significant factors contributing to the countries' performance. This methodological approach can be useful in housing research, when studying data of a multivariate nature, and is also, by its visual interpretation, a potential tool for producing richer information not only for academia but also for policy makers.

Key words: housing policy, housing affordability, BIPLOT

1. Introduction

Since the beginning of the mortgage crisis in the United States in 2007, with its origins in the collapse of the sub-prime mortgage boom and housing prices bubble (MARTIN, 2011), and after the financial crisis in the European Union and Eurozone countries in 2008, there has been growing concern about the housing issue. This concern has been focused on the framework of public policy, which has made changes and adaptations and has specific characteristics for the behaviour of housing demand. Given the growth of housing affordability problems, the decrease in disposable income, the reorganization of households' behaviour and their adjustment to a new social and economic paradigm, this concern still persists. It has therefore become essential to recognize the institutional intervention of economic operators in the market, in particular from the state, owners and households (NEWMANN et al., 2000; DEWILDE et al., 2015; HAFFNER et al., 2011).

In the period 2010–2014, the state played an on-the-go role in the housing sector, legislating and promoting the purchase of housing owning and renting. Indeed, from early in the decade, and up to 2014, concerns of a more social nature were added to these housing policy guidelines, and rehousing programmes were created in urban areas, with support for leasing with incentives particularly for young people and stimulus for the recovery of degraded properties. The purchase of homes by households, house renting on the open market – and specifically by young people – pushed the state forward as a stimulating element in the housing market and urban regeneration, theoretically through an equity-based redistribution of income for households (ANDREWS et al., 2011).

However, the problem of housing cannot be reduced only to a perspective of supply and demand. In fact, the specific characteristics of this problem led to the creation of inefficiencies in the market, in particular due to the inadequacy of market argument as a resolution mechanism for housing in lower-income households. The strengthening of housing programmes for the most insolvent populations had the effect of partially solving housing needs, but it was not enough (SANTOS, 2014). In the general European case (DEWILDE, 2016), the housing reality was mainly constructed by the acquisition of one's own housing, given the comparative low expression of the rental market. Nonetheless, it only provided a housing solution for relatively solvent households. Consequently, in this period, the housing credit supply matured, interest rates had a significant downward trend, access to credit for households stabilized, and new opportunities arose for the financial institutions (ARESTIS et al., 2013).

Therefore, a new relative extension of housing credit and a fresh attitude towards the rental alternative in these years was a rational response of economic agents to favourable changes in financing conditions, and not only in southern European countries. On the other hand, the development of a more dynamic rental market was another goal of housing policies in this period.

We take it as relevant to characterize the Eurozone countries, on a housing policy perspective and in a post-crisis context, incorporating ten variables considered to be the most pertinent, based on data from Eurostat. We used five groups of indicators: general economics, housing stocks, housing affordability, population and social conditions, and housing quality (EUROSTAT, 2014), to relate WEALTH and LIVING STANDARDS with AFFORDABILITY.

The use of the HJ-BIPLOT method developed by GALINDO (1986), an evolution of the classical BIPLOT introduced by GABRIEL (1971, 1981), allows a better simultaneous representation of the effects of political, economic and social decisions on the Eurozone countries, by identifying their similarities and dissimilarities concerning wealth, living standards and affordability.

Traditionally, descriptive statistics allow only an analysis of the average country on an individual level. On the other hand, the HJ-BIPLOT identifies relationships between the individuals (countries per year), between the variables and between individuals and variables, allowing the identification of hidden patterns in the data, facilitating and enriching the interpretation of the results.

Thus, we highlight four major objectives:

(1) To generate a methodological approach, with the use of the HJ-BIPLOT method in order to achieve a richer diagnosis, for the 2010–2014 period, of the effects of political, economic and social decisions on the twelve Eurozone Countries, by identifying their similarities and dissimilarities;

(2) To identify relationships between wealth, living standards and affordability in the housing situation in twelve Eurozone countries for the period 2010–2014;

(3) To recognize behavioural typologies in the twelve Eurozone countries linked to Wealth and Living Standards associated with Housing Affordability;

(4) To distinguish clusters of countries with divergences and/or convergences in the housing sector.

2. Methodology and data

2.1. BIPLOT methods

BIPLOT analysis is a multivariate technique proposed by GABRIEL (1971) which has the main objective of performing an approximated graphical representation, with reduced dimension, of a data matrix X_{nxp}. It is done in such a way that the representation allows visualization in the same plane of the relations and interrelations between rows and columns of matrix X. According to GABRIEL (1971), "*Every rank two matrix can be graphically represented by a BIPLOT that consists of a vector for each line and a vector for each column, chosen so that each element of the matrix is exactly these vectors' internal product. If the matrix has a rank greater than two, this matrix can be represented in an approximated way, by a BIPLOT of a matrix of rank two.*"

The original data matrix X is to be represented as the product of two matrices performed by Singular Value Decomposition of the matrix in Singular Values – SVD, which contains the row and column vectors and which constitutes the elements considered in the graphical representation.

In the BIPLOT representation of X_{nxp}, there are simultaneously two sets of vectors a_1, a_2, ..., a_n for the lines from X, representing the individuals (observations of countries for years), and b_1, b_2, ... , b_p for the columns of X, representing the variables, in such a way that the internal product a_i^T b_j, approximated to element x_{ij} of the original matrix, is as good as possible.

If the rank of matrix X_{nxp} (r = min (n,p)) is greater than three, the BIPLOT representation will always be a data approximation. Nonetheless, when the rank of X_{nxp} is two or three, the representation of the data in bifactorial or trifactorial planes is exact.

BIPLOT methods are used as a data visualization tool essentially due to two properties: the internal product property, which originates an exact or approximated representation of the individuals in space, and the property of equality between the cosine of the angle formed by the vectors which represent two variables and the correlation coefficient between these same variables. The properties of BIPLOT are detailed in GABRIEL (1971).

As result of the BIPLOT properties it is possible to identify:

1) The relations between column vectors (individuals);
2) The relations between line vectors (variables);
3) The interrelations between line vectors and column factors.

Therefore the BIPLOT representation gives a more complete picture of the data matrix than any scatter plot. Also the identification of the relations and interrelations of individuals and variables is of value, as it facilitates multivariate analysis of data. The seminal works in BIPLOT Methods, known as Classical BIPLOTS, were developed by GABRIEL (1971, 1981) and are designated JK-BIPLOT, GH-BIPLOT and SQRT-BIPLOT.

An HJ-BIPLOT (GALINDO, 1986) for a data matrix X_{nxp} is defined as the multivariate graphical representation by means of vectors $j_1, j_2,\dots,j_n$ for the lines (individuals) and $h_1, h_2,\dots,h_p$ for the columns of X, selected so that row and column representations can be projected in the same reference system with the same maximum quality of representation. The rows are represented by points and the columns by vectors. The advantages and properties of BIPLOT (GABRIEL, 1971) apply to the HJ-BIPLOT developed by GALINDO (1986).

2.2. Ward's method

The general principle of classification used in this research is based on building a table of similarities between the series data. For this purpose, Ward's method was used (WARD, 1963), considering the Euclidean distance for hierarchical clustering. In Ward's method, the total variance is equal to the sum of the internal variance of the class and inter-class variance. It is therefore necessary to find a homogeneity within each class (thus minimizing the variation of inter-class variance), and a heterogeneity between classes. Thus, at each step of the computation, the algorithm either clusters or combines observations, minimizing the results of error from the squares or alternatively maximizing the determination *coefficient* value, in order to maximize the similarity within the groups and differences between groups.

2.3. The individuals – observations

The observations used in this research comprise the first twelve countries of the Eurozone which first used the euro currency, for the period of 2010–2014. The sample countries are presented in Table 1.

Table 1. 12 Euro Area countries

COUNTRIES	COD
Austria	AT
Belgium	BE
Finland	FI
France	FR
Germany	DE
Greece	EL
Ireland	IE
Italy	IT
Luxembourg	LU
Netherlands	NL
Portugal	PT
Spain	ES

Source: own elaboration

2.4. The variables

The variables used in this research are indicators collected from EUROSTAT databases and are of various types: economic, housing stock, affordability and quality. The variables used in this investigation are presented in Table 2. We consider them appropriate to study the effects of political, economic and social decisions on the housing problem in Eurozone countries, identifying their similarities and dissimilarities, for the period 2010–2014.

Table 2. 10 indicators

TYPE	COD	DESIGNATION	EUROSTAT database
General Economic Indicator	GDPPC	GDP per capita	nama_10_pc
General Economic Indicator	UNP	Unemployment rate - annual average (%)	une_rt_a
Housing Stock Indicator	OML	Owner with mortage or loan (%)	ilc_lvho02
Housing Stock Indicator	TEN	Tennant	ilc_lvho02
Housing Affordability Indicator	SHCI	Share of housing cost in disposable income (%)	ilc_mded01
Housing Affordability Indicator	OBD	Housing cost overburden rate (as % of population)	ilc_lvho07a
Housing Affordability Indicator	HWEG FI	Annual average index-housing, water, electricity, gas and other fuels	prc_hicp_aind
Housing Affordability Indicator	HPI	House prices index	tipsho20
Population and Social Condition	RPSE	Population at risk of poverty (%)	ilc_peps01
Housing Quality Indicator	OCD	Housing overcrowding rate	ilc_lvho05a

Source: own elaboration

2.5. The methodological procedure

The methodological options used in this research are presented in Table 3.

Table 3. BIPLOT and Segmentation procedure by MultBiplot (2015)

Type of BIPLOT	HJ-BIPLOT
Transformation of the raw data	Column Standardization (z-s cores)
Estimation Method	Singular Value Decomposition
Segmentation Process	Hierarchical Cluster with the Euclidean distance using the HJ-BIPLOT scores – Ward's Method

Source: own compilation

The statistical software used for the data treatment was MultBiplot, version 15.1412 (VILLARDON, 2015).

3. Results

Table 4 (see APPENDIX) presents the EUROSTAT database, for the period 2010–2014, used for the production of the results that support this research.

Through the application of HJ-BIPLOT with the MultBiplot software, we were able to attain a two-dimensional solution that captured about 63% of the variability of the original data, with 44.71% of the information retained on the first axis (Table 5).

Table 5. Explanation level of Inertia

A xis	Eigenvalue	Inertia Explained Variance	Accumulated Interia
1	268 286	44 714	44 714
2	109 209	18 201	62916
3	90 118	15.02	77 935

Source: MultBiplot (2015) output

In Table 6 (see APPENDIX), we observe the relative contributions of the 12 Eurozone countries (2010–2014), distributed in three dimensions, where the most significant contributions for the construction of the factorial axes can be distinguished. Table 6 (see APPENDIX) also shows the factorial coordinates of the 60 observations that allow a projection in Euclidean space (Figure 1) of the 12 Eurozone countries for the period 2010–2014. Thus a cloud of observations can be observed spread over the four quadrants of this factorial structure.

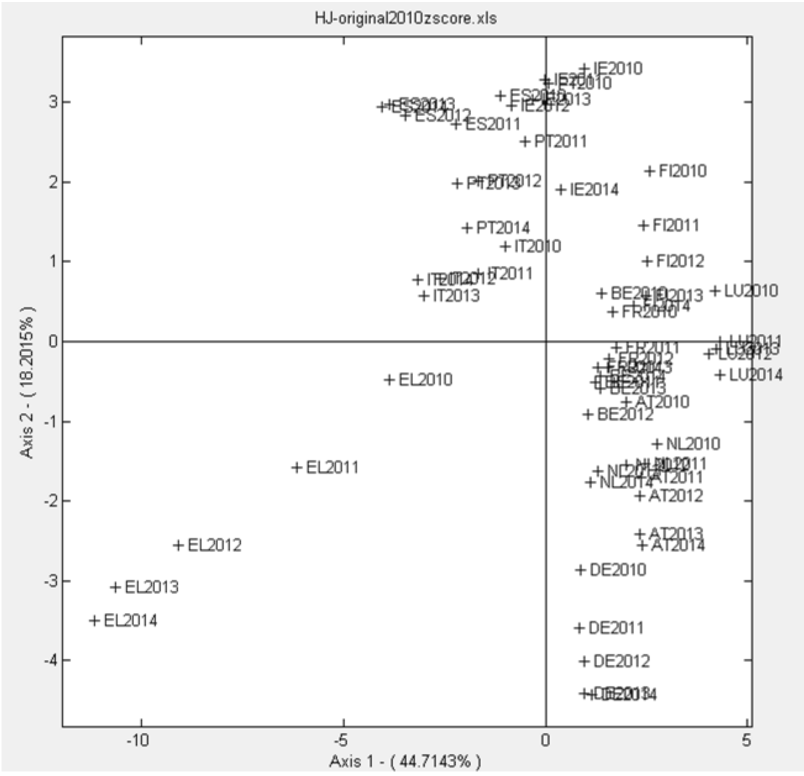
Also from Figure 1 and according to the most relevant contributions, it becomes possible to interpret the trajectories of the countries linked to the two axes (Table 7).

Table 7. Contributions interpretation (rows)

Axis1 (73%)	**EL (2010-2014)**	Declining
	LU (2010-2014) **FI (2010-2014)**	Stable
	FR (2011-2013) ES (2012-2014) BE (2010-2011) IT (2013-2014) PT (2014) AT (2012)	
Axis2 (74%)	**DE (2010-2014)**	Declining
	IE (2010-2014)	Stable
	PT (2010-2013) ES (2010-2011) AT (2013-2014)	

Source: own elaboration

Thus, the full paths of EL, LU and FI with the incomplete trajectories of FR, ES, BE, IT, PT and AT contribute 73% to the total explicability of the first axis. Also,

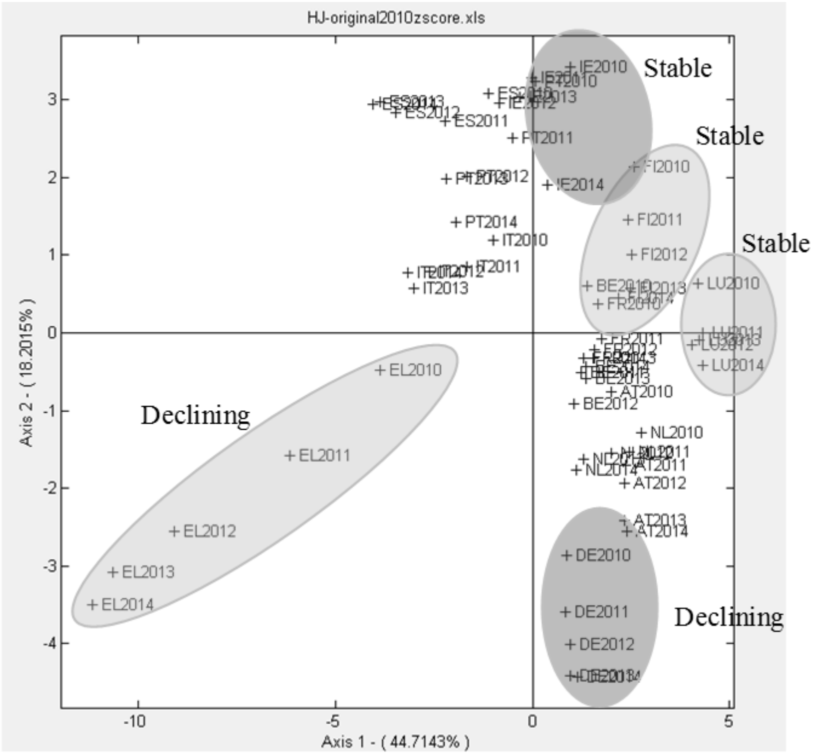


Source: MultBiplot (2015) output

Figure 1. HJ-BIPLOT factorial representation of plane 1-2 for the countries (2010–2014)

with the spatial positioning, we can see a downward trend in EL and a stable one in LU and FI. Similarly, a downward trend is observed in the full path of DE and a stable trend in IE which, together with incomplete trajectories of PT, ES and AT, contribute 74% to the explicability of the second axis. These detected behaviours can be seen in Figure 2.

On the other hand, Table 8 describes the relative contributions of the 10 indicators, distributed in three dimensions where the most significant contributions to the construction of the factorial axes can be distinguished. Table 8 also shows the factorial coordinates of the variables (vectors) that allow a projection in the same Euclidean space (Figure 3) of the 10 indicators also spread over the four quadrants of the HJ-BIPLOT structure.



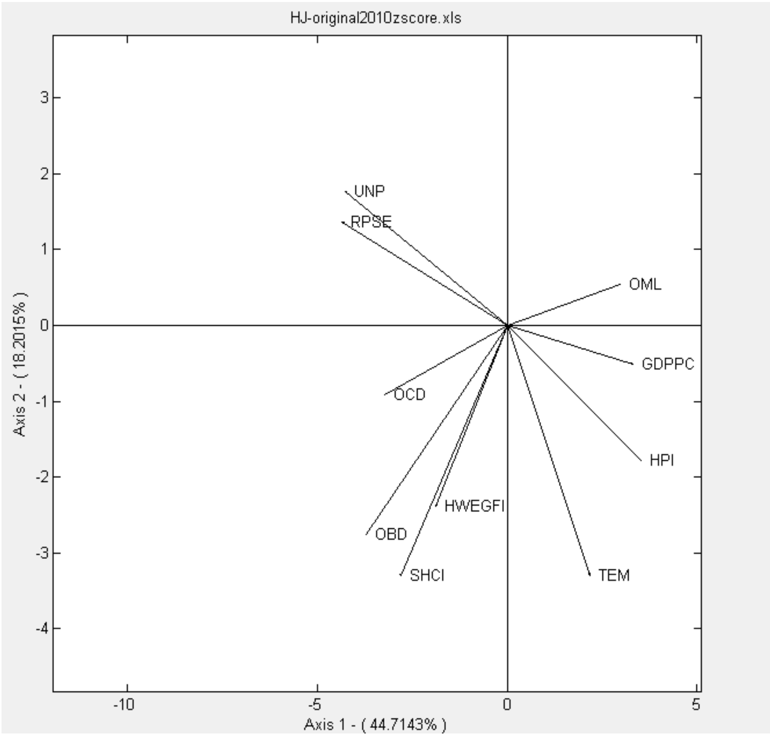
Source: MultBiplot (2015) output

Figure 2. Interpretation of detected trajectories

Table 8. HJ-BIPLOT columns relative contributions and coordinates

	Relative Contributions (Columns)			Coordinates (Columns)		
	Axis1	Axis2	Axis3	Axis1	Axis2	Axis3
OML	362	12	569	4.66	0.84	5.842
TEM	192	443	72	3.392	-5.153	-2.081
UNP	738	127	34	-6.655	2.765	1.434
OCD	422	34	356	-5.033	-1.428	-4.62
OBD	559	312	75	-5.794	-4.326	2.12
SHCI	323	445	129	-4.405	-5.167	2.78
GDPPC	450	11	14	5.198	-0.804	0.926
HWEGFI	144	232	71	-2.943	-3.732	2.059
RPSE	777	76	27	-6.827	2.135	-1.271
HPI	503	129	155	5.494	-2.779	-3.054

Source: MultBiplot (2015) output



Source: MultBiplot (2015) output

Figure 3. HJ-BIPLOT factorial representation of plane 1-2 for the indicators (2010–2014)

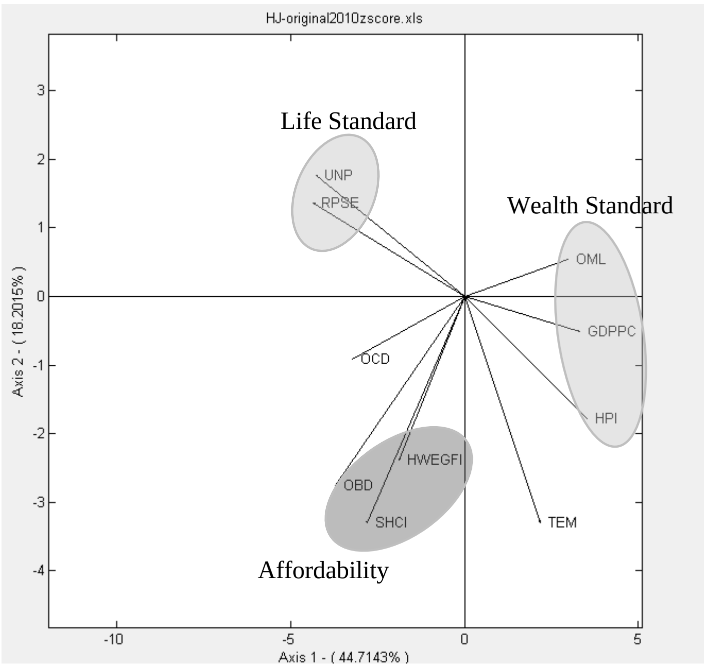
In Figure 3, the higher the norm of the vector, the greater the variability associated with the represented variable. For example, the SHCI and TEN variables show greater variability between the countries for the different years under review. Also from Figure 3 and according to the most relevant contributions, it becomes possible in Table 9 to interpret the correlations of the indicators between each other and associated with the two axes (by means of the angles which they form between themselves and with the two axes). Thus, the proximity (the smaller the angle, the higher the correlation) of RPSE, UNP and OCD, which we interpret as Life Standard, together with the proximity of HPI and GDPPC, which we interpret as Wealth Standard, contribute 65% to the total explicability of the first axis, which we globally designate LIFE & WEALTH STANDARDS. In turn, the proximity of SHCI, OBD and HWEGFI, which we interpret as Affordability, together with TEN, contribute 79% to the explicability of the second axis, which we globally call AFFORDABILITY.

Table 9. Contributions interpretation (columns)

Axis1 (65%)	RPSE	Population at risk of poverty (%)	Life Standard	LIFE & WEALTH STANDARDS
	UNP	Unemployment rate - annual average (%)		
	OCD	Housing overcrowding rate		
	HPI	House prices index	Wealth Standard	
	GDPPC	GDP per capita		
Axis2 (79%)	SHCI	Share of housing cost in disposable income (%)	Affordability	AFFORDA-BILITY
	OBD	Housing cost overburden rate (as % of population)		
	HWEGFI	Annual average index-housing, water, electricity, gas and other fuels		
	TEN	Tennant	Tennant	

Source: own elaboration

These detected patterns can be seen in Figure 4.

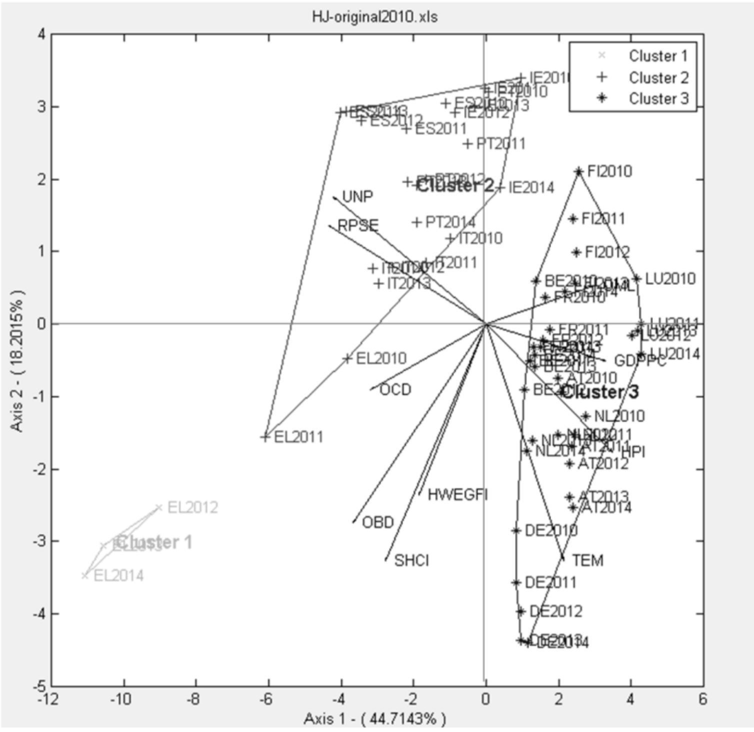


Source: MultBiplot (2015) output

Figure 4. Interpretation of detected patterns

Nevertheless, it is interesting to note that Life Standard is, on the one hand, negatively correlated with Wealth Standard (except OML, which has no significate correlation) but, on the other hand, shows almost no correlation with Affordability. It is also interesting to note that Wealth Standard is negatively correlated with Affordability (except HPI, which has a slightly positive correlation).

Figure 5 is an HJ-BIPLOT simultaneous representation of the observations and the variables, where three clusters of countries can be detected by a hierarchical segmentation process using Ward's method on the HJ-BIPLOT coordinates.



Source: MultBiplot (2015) output

Figure 5. HJ-BIPLOT simultaneous factorial representation of plane 1-2 and 3 clusters of countries (2010–2014)

Independently of the clusters found, the countries closest to the vectors are more related to the variables that these same vectors represent. Through the projection of the countries on the vectors (variables) we can identify which countries/years contributed most to the value of the variable. For example, Luxembourg (LU), for any of the years in question, was the greatest contributor to GDPPC. This finding is consistent with what we know about Luxembourg, which is the country with the highest GDP per capita in the Eurozone. Table 10 shows the formation of three clusters of countries associated with the period 2010–2014.

Table 10. Composition of clusters according to Ward's method

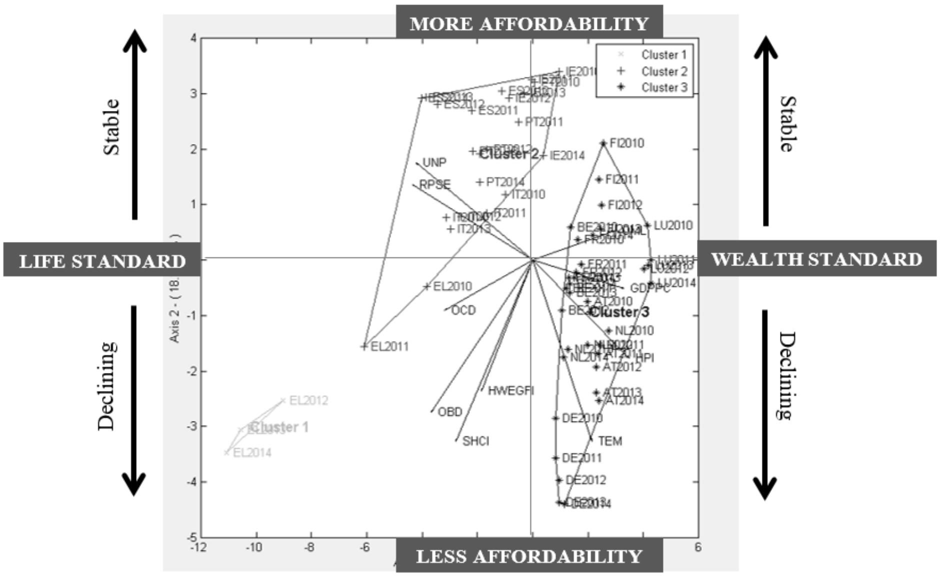
Cluster 1	Cluster 2		Cluster 3		
EL2012	EL2010	IE2014	AT2010	DE2012	FR2014
EL2013	EL2011	IT2010	AT2011	DE2013	LU2010
EL2014	ES2010	IT2011	AT2012	DE2014	LU2011
	ES2011	IT2012	AT2013	FI2010	LU2012
	ES2012	IT2013	AT2014	FI2011	LU2013
	ES2013	IT2014	BE2010	FI2012	LU2014
	ES2014	PT2010	BE2011	FI2013	NL2010
	IE2010	PT2011	BE2012	FI2014	NL2011
	IE2011	PT2012	BE2013	FR2010	NL2012
	IE2012	PT2013	BE2014	FR2011	NL2013
	IE2013	PT2014	DE2010	FR2012	NL2014
			DE2011	FR2013	

Source: own elaboration

It can be observed that countries in Clusters 2 or 3 generally maintain their affiliation throughout the study period. However, it is interesting to note that Greece (EL) belonged to Cluster 2 in 2010 and 2011 and joined Cluster 1 in 2012, 2013 and 2014. There was certainly a change in Greece's performance at the end of the period.

4. Discussion

In short, Figure 6 shows three behavioural typologies related to the performance of 12 Eurozone countries with regard to the effects of housing policy options, for the period 2010–2014.



Source: own compilation

Figure 6. Behavioural typologies

In Cluster 1 (third quadrant), it is observed that Greece revealed a decreasing performance in 2012, 2013 and 2014 concerning LIFE STANDARD associated with LESS AFFORDABILITY. In this period, Greece was subjected to measures related to the BCE/IMF/EU intervention that resulted in a negative outcome in these areas.

In Cluster 2 (second quadrant), a stable performance can be detected, except for Greece in 2010 and 2011, mostly concerning LIFE STANDARD associated with MORE AFFORDABILITY. Therefore, the countries characterized by this cluster in this time period were relatively unaffected and maintained their positioning.

In Cluster 3 (first and fourth quadrants), a stable performance can be perceived concerning WEALTH STANDARD, mostly for Finland and Luxembourg, associated with MORE AFFORDABILITY. On the other hand, for all of the other countries, there was a decreasing performance concerning

WEALTH STANDARD related to LESS AFFORDABILITY. A specificity of behaviour can be observed in the case of Finland and Luxembourg, which were able to maintain their levels of wealth and increase affordability; nonetheless, the other countries show a downward trend in the same aspects.

5. Conclusions

Thus, we conclude:

1. The ten selected socio-economic indicators highlighted relationships between wealth, living standards and affordability in the housing situation.
2. There are two main housing problem realities in the Eurozone linked to Wealth and Living Standards associated with Housing Affordability.
3. There are three behavioural typologies of countries, although some particularities are associated with some cluster members.
4. Greece has an untypical performance compared with the other countries.
5. The methodological approach with the use of the HJ-BIPLOT method produced a richer diagnosis, for the 2010–2014 period, of the effects of political, economic and social decisions on the twelve Eurozone countries, by identifying their similarities and dissimilarities.

This study can be seen as a contribution to the future application of multivariate data methods in housing research. Even from an exploratory perspective, it is a potential tool for producing richer information not only for academia but also for policy makers.

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APPENDIX

Table 4. EUROSTAT database for the period 2010–2014

	OML	TEN	UNP	OCD	OBD	SHCI	GDPPC	HWEGFI	RPSE	HPI
AT2010	25	42.6	4.8	12	6.5	18.6	35200	88.26	18.9	100
BE2010	41.7	28.4	8.3	4.2	8.9	20.5	33500	92.62	20.8	100
FI2010	42	25.7	8.4	6.1	4.2	17.6	34900	83.86	16.9	100
FR2010	29	38	9.3	9.2	5.1	17.8	30800	88.46	19.2	100
DE2010	27.8	46.8	7	7.1	14.5	27.5	32100	91.7	19.7	100
EL2010	17.5	22.8	12.7	25.5	18.1	29	20300	90.33	27.7	100
IE2010	34.5	26.7	13.9	3.4	4.9	16.2	36400	80	27.3	100
IT2010	15.8	27.4	8.4	24.3	7.7	16.7	26800	87.7	25	100
LU2010	39.4	31.9	4.6	7.8	4.7	13.8	77900	91.28	17.1	100
NL2010	59.5	32.8	5	2	14	28.6	38000	89.21	15.1	100
PT2010	32.5	25.1	12	14.6	4.2	14.3	17000	82.4	25.3	100
ES2010	34.4	20.2	19.9	5	9.7	17.7	23200	88.94	26.1	100
AT2011	23	47.6	4.6	12.2	5.5	18.6	36800	91.45	19.2	106.3
BE2011	41.9	28.2	7.2	2.2	10.6	21.3	34500	101.03	21	104
FI2011	41.9	25.9	7.8	6.5	4.4	17.5	36500	89.85	17.9	103.2
FR2011	29.4	36.9	9.2	8	5.2	18.1	31500	92.4	19.3	105.8
DE2011	28.1	46.6	5.8	6.7	16.1	28.3	33700	95.4	19.9	103.5
EL2011	15.7	24.1	17.9	25.9	24.2	32.3	18600	98.83	31	94.5
IE2011	34.6	29.8	14.7	2.6	6.1	17.3	38000	82.9	29.4	86.1
IT2011	15.6	26.8	8.4	24.5	8.7	17.2	27300	92.2	28.1	100.7
LU2011	40	31.8	4.8	6.8	4.2	13.8	81300	97.59	16.8	103.7
NL2011	59.6	32.9	5	1.7	14.5	29.1	38500	92.02	15.7	98
PT2011	34	25	12.9	11	7.2	16.7	16700	87.88	24.4	95.1
ES2011	32	20.3	21.4	6.6	10	18.4	22900	95.31	26.7	92.4
AT2012	26.4	42.5	4.9	13.9	7	18.9	37600	94.66	18.5	114
BE2012	43.2	27.6	7.6	1.6	11	22	35000	105.05	21.6	106.4
FI2012	42.2	26.1	7.7	6	4.5	17.9	36900	92.74	17.2	105.7
FR2012	29.9	36.3	9.8	8.1	5.2	17.9	31800	95.54	19.1	105.2
DE2012	28	46.7	5.4	6.6	16.6	27.9	34300	98.1	19.6	107.1
EL2012	15.2	24.1	24.5	26.5	33.1	37	17300	106.12	34.6	83.5
IE2012	34.9	30.4	14.7	3.2	6.6	19	38100	87.2	30	76.3
IT2012	16.1	25.8	10.7	26.1	8.1	16.8	26700	98.8	29.9	97.9
LU2012	42.6	29.2	5.1	7	4.9	14	82000	101.25	18.4	108
NL2012	59.9	32.5	5.8	2.5	14.4	29.2	38500	95.03	15	91.5
PT2012	33.8	25.5	15.8	10.1	8.3	18.2	16000	95.55	25.3	88.4
ES2012	31.8	21.1	24.8	5.6	10.7	19.1	22300	100.07	27.2	78.7
AT2013	26.4	42.7	5.4	14.7	7.2	19.2	38100	97.17	18.8	119.9
BE2013	42.9	27.7	8.4	2	9.6	20.8	35400	103.65	20.8	107.6
FI2013	42.6	26.4	8.2	6.9	4.9	18.2	37400	95.44	16	106.9
FR2013	31.8	35.7	10.3	7.4	5.2	18.2	32100	97.88	18.1	103.2
DE2013	27.6	47.4	5.2	6.7	16.4	28.2	35000	100.5	20.3	110.4
EL2013	15.6	24.2	27.5	27.3	36.9	39.9	16500	110.74	35.7	74.5
IE2013	35.5	30.1	13.1	2.8	4.9	15.7	39000	90.7	29.5	77.8
IT2013	17.2	26.7	12.1	27.1	8.9	17.4	26500	100.8	28.5	92.3
LU2013	45.6	27	5.9	6.2	5.6	13.8	85300	101.87	19	113.4
NL2013	60	32.9	7.3	2.6	15.7	29.5	38700	97.5	15.9	86
PT2013	34.6	25.8	16.4	11.4	8.3	18.3	16300	97.6	27.5	86.7
ES2013	32	22.3	26.1	5.2	10.3	19.5	22100	101	27.3	71.5
AT2014	25.3	42.8	5.6	15.3	6.6	18.3	38500	98.83	19.2	124.1
BE2014	42.9	28	8.5	2	10.4	20.8	35900	101.23	21.2	107.1
FI2014	43	26.8	8.7	7	5.1	18	37600	97.77	17.3	106.5
FR2014	31.3	35	10.3	7.1	5.1	18.3	32200	99.59	18.5	101.6
DE2014	26.6	47.5	5	6.6	15.9	27.3	36000	101.1	20.6	113.2
EL2014	13.3	26	26.5	27.4	40.7	42.5	16200	107.54	36	68.9
IE2014	34.8	31.4	11.3	3.6	5.5	15.4	41000	94.8	27.4	87.9
IT2014	17.3	26.9	12.7	27.2	8.5	17.1	26500	100.8	28.3	88.3
LU2014	42.5	27.5	6	6.7	6.8	14	87600	100.89	19	118.4
NL2014	59.2	33	7.4	3.5	15.4	29.4	39300	99.29	16.5	86.7
PT2014	35.5	25.1	14.1	10.3	9.2	19.3	16700	99.77	27.5	90.4
ES2014	32.1	21.2	24.5	5.3	10.9	19.1	22400	102.34	29.2	71.8

Table 6. HJ-BIPLOT rows relative contributions and coordinates

	Relative Contributions (Rows)			Coordinates (Rows)		
	Axis1	Axis2	Axis3	Axis1	Axis2	Axis3
AT2010	264	37	363	1 283	-0.482	-1 505
BE2010	452	87	201	0.88	0.387	0.588
FI2010	389	265	1	1 649	1 361	0.098
FR2010	305	16	267	1 057	0.24	-0.989
DE2010	41	467	23	0.543	-1 834	-0.405
EL2010	514	8	159	-2 464	-0.307	-1 372
IE2010	42	522	22	0.619	2 189	-0.445
IT2010	49	68	722	-0.646	0.758	-2 478
LU2010	614	14	0	2 678	0.402	-0.063
NL2010	273	59	355	1 766	-0.821	2 014
PT2010	0	501	204	0.039	2 073	-1 323
ES2010	77	577	10	-0.719	1 967	0.253
AT2011	265	137	397	1 516	-1 092	-1 856
BE2011	209	36	314	0.79	-0.327	0.969
FI2011	577	211	6	1 544	0.933	0.156
FR2011	469	1	277	1 127	-0.048	-0.867
DE2011	38	690	9	0.537	-2 298	-0.266
EL2011	841	56	29	-3 927	-1.01	-0.723
IE2011	0	522	0	-0.014	2 098	0.053
IT2011	144	37	697	-1 076	0.542	-2 368
LU2011	586	0	2	2 751	0.001	0.168
NL2011	228	90	453	1 567	-0.983	2 211
PT2011	24	607	51	-0.319	1 606	-0.464
ES2011	319	479	41	-1.42	1 741	0.508
AT2012	331	232	407	1 482	-1 241	-1 643
BE2012	90	69	292	0.671	-0.588	1 207
FI2012	654	105	18	1 609	0.644	0.267
FR2012	447	9	214	1 003	-0.14	-0.694
DE2012	46	784	9	0.618	-2 564	-0.273
EL2012	903	71	2	-5 817	-1 628	0.3
IE2012	36	434	31	-0.546	1 888	0.501
IT2012	294	27	482	-1.67	0.502	-2 137
LU2012	484	1	10	2 582	-0.103	0.38
NL2012	149	91	582	1 268	-0.99	2 503
PT2012	321	468	7	-1 064	1 285	0.152
ES2012	438	293	125	-2 212	1.81	1 182
AT2013	270	293	373	1 482	-1 544	-1 741
BE2013	170	33	245	0.857	-0.379	1 029
FI2013	616	32	31	1 586	0.362	0.355
FR2013	420	19	54	0.975	-0.205	-0.349
DE2013	39	819	12	0.617	-2 819	-0.336
EL2013	890	74	17	-6.81	-1.97	0.953

Source: MultBiplot (2015) output