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MODELING OF RESIDENTIAL PROPERTY PRICES INDEX USING COMMITTEES OF ARTIFICIAL NEURAL NETWORKS FOR PIGS[1], THE EUROPEAN-G8[2], AND POLAND

This paper develops models of residential property prices indices for PIGS, the European-G8 and Poland using a committee of artificial neural networks approach. Quarterly time series data are applied for testing and the empirical results suggest that population growth, unemployment rate, final consumption expenditure, net national income (ANNI), household final consumption expenditure, long-term interest rates, HICP rate of change of housing, water, electricity, gas and other fuels, HICP housing services, HICP actual rentals for housing, and HICP maintenance and repair of the dwelling are the major determinants of the residential property price index in PIGS, the European-G8 and Poland.

The developed models show that the economic and financial situation in a given country affects the residential property markets. Residential property markets are connected, despite the fact that they are situated in different parts of Europe. The economic and financial crisis in the countries of the PIGS group affects not only the PIGS markets but also the real estate markets of the European-G8 and Poland.

The results also suggest that a methodology based on a committee of artificial neural networks has the ability to learn, generalize, and converge the residential property prices index[3].

Keywords: residential property prices index, committee of artificial neural networks, PIGS, G8, Poland.

JEL codes: C45, E37, C52, R31

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[1] PIGS is a grouping acronym used by international bond analysts, academics, and by the international economic press that refers to the faltering and often indebted economies of Portugal, Ireland, Greece, and Spain (Kotlowski, 2000; Arestis et al., 2006), often in regard to matters relating to sovereign debt markets. Some news and economic organizations have limited or banned the use of these acronyms due to perceived offensive connotations (Mackintosh, 2010).

[2] Only Germany, France, Italy and the United Kingdom.

[3] The work makes use of the OLS, MLP, RBF and CANN models. The subject of the analyses was the not comparative analysis of the indicated methods but an attempt to find an answer to the posed research problems. The use of various methods was dictated by the premise of reducing requirements in terms of the comparability of the research methods in an effort to find the answer to the posed research problems. In this context, an *a priori* advantage of any of the methods was not assumed.

1. INTRODUCTION

The elite club of the world's most developed countries (G8) consists of eight countries, including four countries from the European Union (the European-G8: Germany, France, Italy, the United Kingdom). In addition, the EU members also include countries such as: Portugal, Ireland, Greece, and Spain. These countries have recently faced severe economic and financial problems. Poland, the economy of which, according to many analysts, has resisted the wave of crisis, is also a member of the European Union. The economies of the above mentioned countries are developing at different rates, as demonstrated by GDP values (Figure 1). One of the economic sectors in each of these countries is the real estate sector. In many cases, the financial and economic problems in recent years have been and continue to be connected with the real estate market.

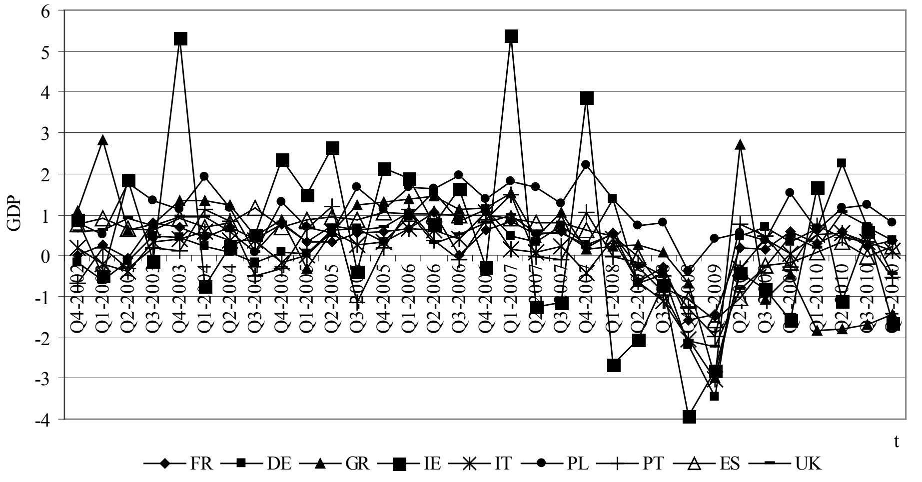

Fig. 1. GDP (expenditure approach) of PIGS, the European-G8, and Poland.

Source: OECD (1 May 2011).

The paper presents models of the residential property prices index for three groups of countries. PIGS (Portugal, Ireland, Greece and Spain) constitute the first group. *Portugal* was hit by the desire to have high wages and the inability to operate its national fiscal/currency policy to restart a failing economy (The Economist, 2010a). *Ireland* experienced a serious property bubble, which burst in 2008. This in turn led to a collapse in the construction sector which resulted in a steep, sudden decline in government revenue, simultaneously leading to the collapse of the banking system and nationalization of all the major banks following a series of attempted bailouts. This left the country with an explosive increase in national debt between 2008 and 2011 (The Economist, 2010a and 2010b). *Greece* experienced the most severe out of the above mentioned crises since 2000 and took out excessive overseas loans in the hope of restarting its national economy, especially after the slump in air travel related tourism that directly followed September 11th. *Spain* had a wage bill and economy like Ireland as well as sucking in lots of cheap imports at the expense of its own industrial base. It too, had a housing bubble that eventually burst (The Economist, 2010a).

The second group is the European-G8 (Germany, France, Italy, and the United Kingdom) which is comprised of well-developed countries with a developed real estate market. These countries have also been affected by economic and financial problems over recent years (experienced a negative GDP). At present they have resumed the path to economic growth and can serve as a reference base for the analysis of residential property prices.

The third group contains one country – Poland. Financial and economic problems in this country have led to stagnation but the economy has not noted a negative GDP in recent years. What is more, fluctuations in the real estate market have been moderate. Rapid falls in residential property prices were not noted during the time of stagnation. This may indicate a healthy real estate market as well as the good financial and business condition of the country. In light of the economic situation and state of the real estate market, Poland serves as a good example for the analysis of residential property prices and can be applied in the analysis as a reference object for countries in the PIGS and European-G8 groups.

In each of the designated groups, the processes occurring in real estate are subject to different impulses, depending on the financial and economic situation of a given country over the recent years. Thus, a group of these countries constitutes a good example for the analysis of relationships that occur between economic processes and the processes of the real estate market.

The purpose of the models presented in the study is to indicate whether the economic and financial situation in a given group and country is reflected in the overall economic situation of the real estate market. If an influence can be observed, a further purpose is to determine whether it is possible to indicate in which cases the effect is large, in which average, and in which only slight, or whether the (observed) relationships of the economic and financial situation of a country and the overall economic situation of its real estate market are correlated with the intensity of the crisis in a given group of countries or given country. These questions are extremely important from the perspective of predicting the impact of a crisis in the economy of a given country on the overall economic situation of its real estate market.

The remainder of the paper is organized as follows. The following section contains a brief description of the role of and relationships between the residential property market and macroeconomics, and the links between the real estate market and the world economic crisis. Applications of artificial neural networks and their committee in the analysis of the real estate market are presented in Section 3. Section 4 outlines the techniques used to solve the problems. The results of the experimental tests are presented in Section 5, with the conclusions of the study provided in Section 6.

2. THE RESIDENTIAL PROPERTY MARKET, MACROECONOMICS AND ECONOMIC CRISIS

2.1. Property market and macroeconomics

Property price volatility can have a significant impact on the economy as a whole (Ge and Runeson, 2004). The volatile economy indicators and property prices generated social costs in terms of increased repossessions (Wilson et al., 2002), created unemployment and stimulated unsound banking practices (Chan et al., 2001), impaired consumer confidence in the government, and led to an unstable economy. Accurate measures of the price trend are crucial for understanding the behaviour of the real estate market (Berg, 2005). Consumers would then be able to make informed property purchasing and selling decisions, and the government and banks would benefit in their housing policy formulation (Ge and Runeson, 2004).

The interlinkage between housing markets and the macroeconomy has been documented for countries that offer the availability of long-time series of housing prices (Agnello and Schuknecht, 2011). Single and cross-country studies generally find that housing markets and the macroeconomy are strongly interrelated at a country-level and internationally correlated. Such studies show that at national and regional levels, housing prices are strongly influenced by business cycles and therefore driven by fundamentals like income growth, industrial production and employment rate (see Ceron and Suarez, 2006; Hwang and Quigley, 2006). Moreover, financial variables such as interest rates, money, and credit supply have been found to be related to house prices developments (see e.g. Englund and Ioannides, 1997; Kasparova and White, 2001; Kennedy and Andersen, 1994), on the grounds that there may be credit rationing (e.g. IMF, 2004; Lecat and Mesonnier, 2005; Tsatsaronis and Zhu, 2004). Differences in the dynamics of real estate prices across countries can also be traced back to differences in regulatory setting and features of the mortgage market (see Adams and Füss, 2010). With regard to non-economic domestic indicators, Parker (2000) and Jud and Winkler (2002) conclude that, for example, real estate appreciation is strongly influenced by the growth of population (Agnello and Schuknecht, 2011).

The price of residential real estate, which can be characterized as both a consumption good and as an asset (or investment good), should bear a close long-term resemblance to rental yields. In the role of housing as a consumption good, the rental yield provides a proxy of the flow of housing services accruing to a homeowner, and in this way has a key influence on the decision to acquire housing services on a month-by-month basis or as a flow through outright purchase. In the role of housing as an asset, house prices not only embed information about dividends in the form of the flow of future housing services, but also regarding expected returns. In this way, understanding the drivers of house price movements can be intrinsically related to movements in both rents and expected returns (Hiebert and Sydow, 2011).

The return on real estate investment is closely related to housing prices. It has been pointed out by many researchers that housing prices are affected by many factors such as interest rates, land supply, and inflation rate. A major part of the research concentrates on devising regression models of the price and testing the correlation between the price and related factors. However, regression models usually disregard jumps. When looking at the market it is observable that jumps may appear in a time series of historical data regarding the housing price index (Huia et al., 2010). In general, structural changes can signify important events. For example, the introduction of financial innovations to a financial market will induce a structural change in the stock price series. The restructuring of the composition of constituent shares in a market index will bring about structural changes in the share price index. Therefore, identifying structural changes reveals important findings that enable policy-makers to look ahead. Very often, structural changes are revealed by abrupt changes, cusps or jump points.

Residential real estate is an important aspect of the quality of life in any community. Therefore the appropriate valuation of specific characteristics of a residential house is essential. To achieve this objective, empirical researchers often specify hedonic price functions or hedonic models (Adair et al., 2000; Bao and Wan, 2004; Bin, 2004; Fan et al., 2006; Filho and Bin, 2005; Fletcher et al., 2004; Janssen et al., 2001; Kestens et al., 2006; Kim and Park, 2005; Meese and Wallace, 2003; Ogwang and Wang, 2003; Stevenson, 2004).

So far empirical evidence on the importance of international factors affecting national housing markets is scarce and still lacking, especially concerning the role of global liquidity. Moreover, only a few papers have attempted to analyze the impact of the international regulatory framework of housing finance on housing prices. Exceptions include Muellbauer and Murphy (1997) and Iacovello and Minetti (2003), who argue that the financial liberalization of mortgage markets has led to a significant increase of the sensitivity of house prices to short term interest rates.

2.2. The economic crisis and real estate markets

The globalization of financial markets is affecting real estate markets. From 1985 to 1994, a great many countries experienced strong real estate booms that peaked around 1989 followed by severe asset price deflation and output contraction that usually lasted until 1994 (Renaud 1997).

The global nature of the financial crisis, in the context of a sharp weakening of the housing sector in many countries, has increased calls for monetary and regulatory policymakers to take into account emerging housing/asset price booms in their policy assessment and to develop early-warning devices for their identification (Agnello and Schuknecht, 2011).

Real estate prices can deviate from their fundamental value due to rigid supply, heterogeneity in quality, and various market imperfections, which have two contrasting effects on banks' stability. Higher prices increase the value of collateral and net wealth of borrowers and thus reduce the likelihood of credit defaults. In contrast, persistent deviations from fundamentals may foster the adverse selection of increasingly risky creditors by banks seeking to expand their loan portfolios, which increases bank distress probabilities (Koetter and Poghosyan, 2010). Quigley (2001) argues that a crisis can partly be attributed to a combination of outmoded banking practices and an immature real estate market.

The financial liberalization wave in emerging markets during the 1990s frequently led to boom–bust cycles, particularly when the initial boom was followed by a financial crisis. A significant amount of literature has focused on the dynamics of financial liberalization in emerging markets, where financial liberalization has led to large inflows of capital which bankroll growing current account deficits and magnify economic booms. Frequently these booms were manifested in sizable real estate and real exchange rate appreciations, and in the build-up of balance sheet vulnerabilities, leading ultimately to financial crises. Observers noted that the real estate market played a key role in the propagation of the boom and bust cycle, magnifying the welfare costs of pre-existing distortions (like moral hazard).

Many of the financial innovations of the last decade fuelled not only a financial sector boom, but in the context of low interest rates, also a house price and consumption boom in the UK and US, both of which also suffered substantial damages to their financial systems. Clearly, housing developments are intertwined with – and integral to – the crisis that has gripped financial markets since August 2007 and then resulted in a nearly complete standstill of credit flows in late 2008. Although private financial flows have resumed, the recovery in credit markets is still in train and far from complete (Duca et al., 2009).

Although the recent financial crisis has had a global impact, the channels of these effects vary across countries, reflecting not only the differences in the structure of housing and mortgage markets, but also the heterogeneity in the macroeconomic structures and linkages between macroeconomies. In part reflecting the adoption of similar monetary policies, there has been an increase in the correlation of national house price movements from the mid-1990s to the mid-2000s. Nevertheless, there are substantial cross-country differences in house price trends (Ahearn et al., 2005; Girouard et al., 2006).

3. ARTIFICIAL NEURAL NETWORKS (ANN) AND COMMITTEE OF ARTIFICIAL NEURAL NETWORKS (CANNS)

3.1. Artificial neural networks (ANN)

The opportunity for the use of artificial neural networks (ANN) to estimate price indices has been investigated (Kershaw and Rossini, 1999). Do and Grudnitski (1992) used data from a multiple listing service in California while Evans (1993) worked with residential housing in the United Kingdom. Important works have been published by Borst (1995), Borst and

McCluskey (1996), McCluskey (1996), McCluskey et al. (1996), Rossini (1997a, 1997b, 1997c) and Worzala (1995). Rossini's research was based on data from South Australia and demonstrated that the results from artificial neural networks approach could, under certain circumstances, potentially produce results superior to more traditional econometric models.

ANNs have been used extensively as robust tools for estimation and prediction in several research fields including real estate valuation (Khalafallah 2008). For example, Do and Grudnitski (1992) used an ANN to examine the effect of age on home value. The study showed that home value declines significantly with its age during the first sixteen to twenty years as a result of physical deterioration. Shaaf and Erfani (1996) used an ANN to explore the impact of air pollutants and air pollution controls on the median price of houses in Jacksonville, Florida. The findings of the study showed that property owners and buyers take air pollution and pollution controls into account when buying a house.

Kershaw and Rossini (1999) used a series of housing data sets to develop constant quality house price indices using neural networks and econometric techniques (Kershaw, Rossini 1999). Their analysis indicated that neural networks could be a real alternative to econometric methods. A broad overview of the work on neural network applications is in operation (Wong and Selvi 1998).

Among their various application areas, ANN models have been applied in real estate valuation (see e.g., Adair et al. 1998; Lenket et al. 1997; McGreal et al., Pagourtzi et al., 2003; Worzala et al. 1995).

Kauko et al. (2002) examined neural network modelling with an application to the housing market of Helsinki, Finland. The study shows how to identify various dimensions of housing sub-market formation by uncovering patterns in the data set, and also shows the classification abilities of two neural network techniques: the self-organizing map and the learning vector quantization. Kauko (2003) evaluated the pros and cons of neural network models of property valuation in comparison with hedonic models, and provided some examples. Liu et al. (2006) proposed a fuzzy neural network prediction model based on hedonic price theory to estimate the appropriate price level for new real estate.

Solutions such as ANNs indicate increased reliability and accuracy measured in relation to the solutions which are provided by individual (monolithic) structures (e.g. linear regression). The concept of increasing reliability by redundancy is a technique that has been known for a long time (Cho. B., Kim J.H. 1995). ANNs however, using this dependency, are characterized by exceptional achievements. ANN-type solutions are supported, above all, by research on generalization abilities. These abilities are significantly greater than the generalization abilities of regression methods. ANNs have also shown increased flexibility as compared to classical solutions. This flexibility ought to be connected with the possibility of choosing the best solutions among many (there may be a very large quantity of those) created in the calculation process. The solutions obtained by the use of this method bring the final solution closer to the optimal one. Thanks to a combination of individual networks, ANN structures provide excellent results in the case of neural network systems processing information which, in principle, leads to unstable solutions.

The conclusion, therefore, was that neural networks must be used very carefully for real estate valuation. Many studies have been carried out by other authors, e.g. Amabile and Rosato (1998), Rossini (1997a, 1997b, 1997c and 1998), Kershaw and Rossini (1999), Nguyen and Cripps (2001), Ge et al. (2003), and Wilson et al. (2002). Their results show a slight advantage of neural networks over classic (monolithic) models, e.g. linear regression. It is obvious that both techniques may show an advantage over one another depending on the quality and amount of data as well as the dependencies between the variables.

3.2. Committee of artificial neural networks (CANNs)

It is well known that a committee of predictors can improve prediction accuracy (Kontrimas and Verikas, 2011). A variety of schemes have been proposed for combining predictors. The most commonly used approaches include averaging, weighted averaging (Heskes, 2001; Krogh and Vedelsby, 1995; Merz and Pazzani, 1997; Sollich and Krogh, 1996; Wisniewski, 2008), the fuzzy integral (Cho and Kim, 1995; Kim et al., 2003; Verikas and Lipnickas, 2002), probabilistic aggregation (Kittler et al. 1998), and aggregation by a neural network or SVM (Kim et al., 2003; Verikas et al., 2002). The aggregation weights assigned to committee members can be the same in the entire data space or different – data dependent – in various regions of the space (Krogh and Vedelsby, 1995; Sollich and Krogh, 1996; Tresp and Taniguchi, 1995; Wisniewski, 2008; Verikas et al., 1999). The use of data-dependent weights, when properly estimated, provides higher estimation accuracy (Verikas et al., 1999). See Verikas et al. (1999) for a comparative study of different combination schemes.

The process of creating a committee of neural networks is a difficult matter. A reduction of error in the network committees should be combined, in particular, with the reduction of variance obtained by averaging a number of partial solutions. This suggests that a network meant to constitute a part of a committee cannot be selected in such a way as to optimize the ratio of variance and bias (Jacobs 1997; Geman et al., 1992). The choice should rely on selecting a network with a relatively low value of bias, because the variance itself can be reduced by averaging the results of individual networks within the committee (Bishop 1995). In certain practical situations a phenomenon based on the fact that certain networks which make up a committee have better predictive ability than others is observed. In this situation one can adopt a strategy which involves the creation of a committee using networks, but with assigned weights corresponding to their predictive ability.

The predictive ability of a network committee, which consists of networks, each of which is to have a determined significance, can be considered. In this situation, the weighted output of the network committee can be written as:

$$y_{GEN}\left(\mathbf{x}\right)=\sum_{i=1}^{L}\alpha_i y_i\left(\mathbf{x}\right)= \tag{1}$$

$$=h\left(\mathbf{x}\right)+\sum_{i=1}^{L}\alpha_i \varepsilon_i\left(\mathbf{x}\right) \tag{2}$$

with the α_i parameter defined below. Introducing the correlation matrix of errors $\mathbf{C}$ with elements of the matrix given as:

$$C_{ij}=\mathrm{E}\left[\varepsilon_i\left(\mathbf{x}\right)\varepsilon_j\left(\mathbf{x}\right)\right] \tag{3}$$

the generalization error of such a network committee can be written as:

$$E_{GEN}=\mathrm{E}\left[\left\{y_{GEN}\left(\mathbf{x}\right)-h\left(\mathbf{x}\right)\right\}^2\right]=\mathrm{E}\left[\left(\sum_{i=1}^{L}\alpha_i\varepsilon_i\right)\left(\sum_{j=1}^{L}\alpha_j\varepsilon_j\right)\right]= \tag{4}$$

$$=\sum_{i=1}^{L}\sum_{j=1}^{L}\alpha_i\alpha_j C_{ij} \tag{5}$$

The optimal value of α_i significance can be obtained by minimizing E_{GEN}. In order to obtain nontrivial solutions (i.e. for example, other than

$\alpha_i = 0$ for all *i*) some limitations to this parameter should be established. Bishop (1995) assumes, for instance, that:

$$\sum_{i=1}^{L} \alpha_i = 1. \tag{6}$$

Using the Lagrange multiplier λ (see Bishop 1995, p. 448):

$$2\sum_{j=1}^{L} \alpha_j \mathbf{C}_{ij} + \lambda = 0. \tag{7}$$

The solution of this equation is the relationship:

$$\alpha_i = -\frac{\lambda}{2}\sum_{j=1}^{L}\left(\mathbf{C}^{-1}\right)_{ij}. \tag{8}$$

The value of λ can be found by substituting equation (8) into equation (6). In such a way, the solution to α_i is obtained in the form of:

$$\alpha_i = \frac{\sum_{j=1}^{L}\left(\mathbf{C}^{-1}\right)_{ij}}{\sum_{k=1}^{L}\sum_{j=1}^{L}\left(\mathbf{C}^{-1}\right)_{kj}}. \tag{9}$$

By substituting (9) into (5), the minimum value of error can be established:

$$E_{GEN} = \left(\sum_{i=1}^{L}\sum_{j=1}^{L}\left(\mathbf{C}^{-1}\right)_{ij}\right)^{-1}. \tag{10}$$

In order to apply the presented deliberations, *L* ANNs must be trained and the **C** correlation matrix compiled using the approximation (3) given by the formula:

$$C_{ij} \cong \frac{1}{N}\sum_{n=1}^{N}\left(y_i\left(\mathbf{x}^n\right) - t^n\right)\left(y_j\left(\mathbf{x}^n\right) - t^n\right). \tag{11}$$

where t^n is the value corresponding to the $\mathbf{x}^n$ input vector. $\mathbf{C}^{-1}$ should then be determined, α_i calculated using equation (2) and afterwards, using equation (1), a new predictor should be drawn up.

Since network committee formed in accordance with $E = \sum_{i=1}^{n} \left(y_i - c_i \right)^2$ is a distinctive example of a committee which, defined as $y_{COM}\left(\mathbf{x}\right) = \frac{1}{L}\sum_{i=1}^{L} y_i\left(\mathbf{x}\right)$, it yields the following inequality:

$$E_{GEN} \le E_{COM} \tag{12}$$

The inequality (12) provides the theoretical basis for searching for modules, intended to constitute the components (ANNs) of network committees (CANNs), that will create better solutions as compared to monolithic models of neural networks.

CANNs, thanks to their architecture, way of operating and possibilities for application, are among the best models reflecting the complicated structure of properties and relations occurring in the real estate market system (including the observed modularity). Their natural predispositions concern, above all:

- the possibilities to imitate the real estate market system in the plane in which it functions,
- the abilities to generalize highly variable, complicated and uncertain results,
- the possibility of modelling individual as well as group behaviours of real estate market participants, even under conditions of delayed reactions occurring in the information structure by variation grouping processes,
- the ability to find hidden market information patterns by the analysis of many solutions at the same time.

The advantages of CANNs include:

- using a scheme of processing complex problems that is commonly encountered in nature,
- the elimination of the outside factor creating the artificial division of problems during the course of carrying out calculation procedures,
- increasing the abilities to generalize by the division and redundancy of the solution space,
- decreasing expectations connected with the size of sets of learning, testing and verifying cases (network systems),
- the possibility of processing split sets of variables with a high level of redundancy,
- increasing the precision of the obtained solutions thanks to algorithms of combining the answers from the solutions of a few local experts (modules),

– decreasing the rigours connected with the choice of the optimal architecture of networks constituting the modules,
– unrestricted possibilities of structuring tasks and introducing functional connections between modules,
– the possibility of specializing modules in processing only a select group of cases, e.g. outliers,
– extended possibilities of applying sensitivity analysis,

The shortcomings of CANNs are:

– problems with the choice of the architecture for the entire structure (many possibilities),
– choosing the type of modules (networks in modules) as well as their numbers,
– increasing the time of calculations and requirements regarding the computing power of computers,
– problems with overtraining networks in modules,
– increased level of difficulty in interpreting the structural analysis of the created result,
– the so-called MBB (multi-black-box) problem.

The indicated shortcomings of artificial neural networks, according to the author, do not necessarily discredit the ANN-type or CANN-type methods. They are the basis for determining that the ANN-type methods can be commonly applied for the analysis of trends and general trends analyzed within the present work (residential property market, macroeconomics and economic crisis). In the event of detailed analyses, the application of such type of methods depends on the aim of the conducted analyses.

4. METHODS

4.1. Ordinary least squares (OLS) – linear regression

The standard regression model is given by:

$$\mathbf{y} = \boldsymbol{\alpha}\mathbf{X} + \boldsymbol{\varepsilon}, \tag{13}$$

where $\mathbf{y}$ is a $n\times 1$ vector of dependent variable values (residential property prices index) with n being the number of observations, $\mathbf{X}$ is a $n\times m$ matrix containing values of independent variables, $\boldsymbol{\alpha}$ is a $m\times 1$ vector of regression coefficients, $\boldsymbol{\varepsilon}$ is a $n\times 1$ vector of true errors with the standard deviation σ, and m is the number of independent variables. The meaning of $\mathbf{X}$ and $\mathbf{y}$

stated here is maintained throughout the entire work. The estimate $\mathbf{b}$ of $\boldsymbol{\alpha}$ is obtained as a solution to:

$$\min_{b} Q_{OLS}(\mathbf{b}), \tag{14}$$

where $Q_{OLS} = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 = \sum_{i=1}^{n} e_i^2$, where e_i is the estimation of the true error, and $\hat{y}_i$ is an estimate of y_i.

4.2. Multilayer perceptron (MLP)

A multilayer perceptron (MLP) is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate output. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function (Bishop 1995). A feedforward MLP with one hidden layer was employed in the study.

The input neurons have no activation functions whatsoever (they have the function of identity, not making any changes to the signal). The signals from the input layer are combined using weights (weights in the hidden layer) and propagated forward to the next layer (hidden). The hidden layer is most often used following activation functions: linear, logistic, hyperbolic tangent, and exponential function (negatively). In the case of output layer neurons an activation function similar to that of the hidden layer is used.

A cross-validation data set based on early stopping is the usual way to control overfitting. Due to the small data sets available, the use of cross-validation data sets was avoided. Instead, Bayesian regularization (Bishop 1995; Foresee and Hagan, 1997), which is implemented by minimizing the following objective function (Kontrimas and Verikas, 2011) was used to prevent overfitting:

$$E = \beta E_D + \alpha E_w = \frac{\beta}{2}\sum_{i=1}^{n}\sum_{j=1}^{Q}\left\{y_k(\mathbf{x}_i,\mathbf{w}) - t_j^i\right\}^2 + \frac{\alpha}{2}\sum_{s=1}^{n_w}(w_s)^2, \tag{15}$$

where $\mathbf{x}_i$ is the input data point, n is the number of the observations, Q is the number of outputs in the network, $\mathbf{w}$ is the weights vector, n_w is the number of weights, and α, β are hyperparameters. The second part of the objective function performs regularization.

Neural networks (MLP) are tools of non-linear analysis which usually use iterative algorithms. The most recommended MLP learning algorithms are the BFGS (Broyden-Fletcher-Goldfarb-Shanno) and the SCG (scaled conjugate gradient); see Bishop 1995. Although these algorithms are much better than the previously used algorithms, such as the backpropagation method, they have high demands for computer memory and speed of calculations. Overall, however, they require less iterations in the learning process because they are rapidly converging, with a more advanced exploration mechanism.

4.3. Radial basis function network

Radial basis function network (RBF) was used in the work in order to introduce solutions other than those obtained by applying MLP models to the neural networks.

A radial basis function network is an artificial neural network that uses radial basis functions as activation functions. It is a linear combination of radial basis functions. Radial basis function networks typically have three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer. The output, $y:\mathbb{R}^n \to \mathbb{R}$, of the network is thus:

$$\varphi(\mathbf{x}) = \sum_{i=1}^{n} \alpha_i \rho\left(\left\|\mathbf{x} - \mathbf{c}_i\right\|\right), \tag{16}$$

where n is the number of neurons in the hidden layer, $\mathbf{c}_i$ is the central vector for neuron i, and α_i are the weights of the linear output neuron. The norm is typically taken to be the Euclidean distance and the basis function is taken to be Gaussian:

$$\rho\left(\left\|\mathbf{x} - \mathbf{c}_i\right\|\right) = \exp\left[-\beta\left\|\mathbf{x} - \mathbf{c}_i\right\|^2\right]. \tag{17}$$

The Gaussian basis functions are local in the sense that:

$$\lim_{\|x\|\to\infty} \rho\left(\left\|\mathbf{x} - \mathbf{c}_i\right\|\right) = 0\,, \tag{18}$$

i.e. changing the parameters of one neuron has only a small effect for input values that are far away from the centre of that neuron. RBF networks are universal approximators on a compact subset of $\mathbb{R}^n$. This means that a RBF network with enough hidden neurons can approximate any continuous function with arbitrary precision. The weights α_i, c_i, and β are determined in a manner that optimizes the fit between φ and the data.

In a RBF network there are three types of parameters that need to be chosen to adapt the network for a particular task: the central vectors c_i, the output weights $w_{i\,i}$, and the RBF width parameters β_i. In the sequential training, the weights are updated at each time step as data stream in. For some tasks it makes sense to define an objective function and select the parameter values that minimize its value. The most common objective function is the least squares function (Haykin 1994; Bishop 1995):

$$K\left(\mathbf{w}\right) \overset{def}{=} \sum_{t=1}^{\infty} K_t\left(\mathbf{w}\right), \tag{19}$$

where:

$$K_i\left(\mathbf{w}\right) \overset{def}{=} \left[y\left(t\right) - \varphi\left(\mathbf{x}\left(t\right), \mathbf{w}\right)\right]^2. \tag{20}$$

We have explicitly included the dependence on the weights. Minimization of the least squares objective function by optimal choice of weights optimizes the accuracy of fit.

RBF networks with linear activation functions are learnt in two stages. In the first, radial functions are to be arranged using only input variables from the data. In the second stage the network is fixed with the weights connecting the radial functions of the output neurons. In the case of a linear activation function, it is only necessary to simply reverse the matrix at the output, which is more accurate and does not require iteration.

The linear learning process, however, applies only if the error function constitutes a sum of squares and the activation function of output neurons is linear. If these conditions are not met, the activation function is more complicated; one must return to the iterative algorithms, such as RBFT (red baron flight training), in order to determine the weights of the hidden layer and finish the process of neural network learning of the RBF type.

4.4. CANN – a committee of predictors

In recent years, the committee of artificial neural networks (CANN) modelling technique has become a serious alternative to conventional methods of modelling property value. Some research has been conducted and can be found in literature (see e.g. Wisniewski 2008).

Committees of artificial neural networks have been applied to the real estate market by Wisniewski (2003, 2004, 2008). In these works, it was proven that the application of committees of neural networks significantly contributes to lowering property value modelling errors in comparison to the MRA, ADL, and ARIMA models. The study was conducted for various property markets including the residential market.

In this study, committees of artificial neural networks consisting of single networks of MLP and RBF type were used.

The process of creating responses in the interpreter module of a committee of neural networks, that is the means of determining a result for a whole committee of neural networks, can be carried out using different methods. The property value for a given observation ($i = 1, \ldots, N$, where N is the number of observations used in network processes) can be obtained by using the following methods (Wisniewski, 2008):

a) arithmetic mean of the outputs of individual networks in the committee – SRA:

$$SRA_i = \frac{1}{M} \sum_{k=1}^{M} y_k \,, \tag{21}$$

where: y_k is the value calculated by the k-th network for the i-th observation (Residential Property Prices Indices), $k = 1, \ldots, M$, where M is the number of networks in the band,

b) weighted average – OS:

$$OS_i = y_k Wos_k \,, \tag{22}$$

weight Wos_k determined by applying the formula proposed by Opitz and Shavlik (1996):

$$Wos_k = \frac{1 - SSE_k}{\sum_{k=1}^{M} \left(1 - SSE_k\right)} \,, \tag{23}$$

where: $SSE_k = \sum_{i=1}^{N} \left(x_i - y_i\right)^2$,

c) weights of linear neural networks:

$$SSNL_i = y_k Wssnl_k \,, \tag{24}$$

a standardized set of neural network weights of a linear structure was used as the $Wssnl_k$ weight. The SNN (Artificial Neural Network) linear model is represented by a network having no hidden layers, with neurons contained in the output layer being fully linear, i.e., these are the neurons in which the total excitation is determined as a linear combination of input values and which possess a linear activation function. Linear SSN are usually learnt by using a standard linear optimization algorithm, based on a so called pseudo-inversion technique (SVD) (Wisniewski, 2008). Standardization was carried out based on the following relationship:

$$Wos_k = \frac{Wssnl_k}{\sum_{k=1}^{M}\left(Wssnl_k\right)}, \tag{25}$$

d) weighted average – SRW:

$$SRW_i = y_k Wsrw_k, \tag{26}$$

$Wsrw_k$ weight was calculated using the formula (Wisniewski 2008):

$$Wsrw_k = \frac{\dfrac{1}{\ln\left(MSE_k\right)}}{\sum_{k=1}^{M}\left(\dfrac{1}{\ln\left(MSE_k\right)}\right)}, \tag{27}$$

where: $MSE_k = \dfrac{SSE_k}{N}$.

Within the preliminary works, the SRA (21) method was selected for further analysis, assuming that averaging the results will constitute an appropriate compromise between matching the solutions obtained by the individual networks and their abilities to generalize.

4.5. Feature selection

It is well known that not all features are useful for solving the task at hand. There are many feature selection techniques ranging from the sequential forward selection or backward elimination, to the genetic or taboo search (Kontrimas and Verikas, 2011). Usually feature selection methods are categorized as being based on filter or wrapper approaches.

In the case of limited data sets, some features may even weaken prediction accuracy. The accuracy of a prediction may increase after elimination, it can, however, decrease if the method of selection eliminates an important part of the data space. In such a case, the models will get good results, but their applicability will prove to be low.

For these reasons, feature selection was not applied to ANNs and CANNs in this study.

4.6. Error function in ANN

The error prediction function is a measure of compliance between the artificial network prediction and the set value. It is used to establish the amount of the necessary changes to weights of neurons in each iteration. Error functions used in neural network learning should give some measure of difference between the prediction and actual value, at a given point of the input variable space. It is, therefore, natural to use the sum of squares of differences (SOS – sum of squares) as a function of error:

$$E_{SOS} = \sum_{i=1}^{n} \left(x_i - y_i\right)^2 \tag{28}$$

n is the number of cases (input-output pairs) used for learning, y_i is the prediction of a network (network output), and x_i is an “actual” value (output according to data) for the i-th case. The bigger the differences the greater the error and the more corrections required by a network.

4.7. Assessment of models

Correlation coefficient, the Durbin–Watson coefficient, MAPD, MAE, RMSE, and R^2 are the parameters which are usually used to assess ordinary least squares linear regression models. The correlation coefficient R_{xy} indicates the strength and direction of a linear relationship between the variables x and y (Kontrimas and Verikas, 2011):

$$R_{xy} = \frac{\sum x_i y_i - n\overline{xy}}{\left(n-1\right) s_x s_y} \tag{29}$$

where $\overline{x}$ and $\overline{y}$ are means of the variables, s_x and s_y are the standard deviations, and n is the number of observations.

The Durbin–Watson coefficient is used to investigate autocorrelation (Bishop 1995). The coefficient is computed as:

$$d = \frac{\sum_{i=1}^{n}\left(e_i - e_{i-1}\right)^2}{\sum_{i=1}^{n} e_i^2}, \tag{30}$$

where e is the residual. The parameter d is compared with the upper and lower limits of autocorrelation. Values of the limits depend on the significance level, the number of observations, and the number of independent variables. These values are usually taken from special tables.

A measure of the performance quality of a neural network is the degree of generalizing knowledge which is contained in the training data, that is the ability to predict the values of output variables for new data, not used in the learning process. The problem of generalizing knowledge is one of the most important issues of learning networks. It is fairly easy to "teach" a (sufficiently large) network to precisely map training data, but the network would then contain, in addition to true knowledge, of all the noise contained in the training data, which can severely spoil the results for new data. This is the problem of overfitting which must be prevented.

The quality of non-linear models, such as MLP, RGB, and CANN, is usually assessed by estimating the generalization performance (the prediction error for unseen data) of the models. The analysis of ANNs and CANNs also used: the mean absolute percentage difference between the real x and predicted $\hat{y}$ (MAPD), the mean absolute error between the real and predicted $\hat{y}$ (MAE), the root mean square error (RMSE), and the correlation coefficient ($R_{xy} = R_{cy}$); StatSoft 2009. Measures such as MAPD, MAE, RMSE, R^2 and R_{cy} were used to determine the quality of the training set, testing and validation.

The methods of assessment indicated above have been used in the case of all the models. According to the accepted assumptions, the models used for the studies were not assessed in terms of effectiveness – the construction, the size of networks, statistic properties, the speed of learning and testing, the number of iterations and time of learning were not taken into account. The aim of the work was not the comparative analysis of research methods but identifying the relationships between an economic crisis and its influence on the real estate market in the individual countries. The question of whether accounting for the indicated elements (construction and size of network, statistical properties, etc.) would have an influence on the obtained results remains open. This is a very interesting problem which ought to be the topic of further, additional research.

5. EXPERIMENTAL INVESTIGATIONS

5.1. Data

The data set used in the presented study includes quarterly time series for nine European countries (PIGS, the European-G8 and Poland). Data are from the Q4-2002 – Q4-2010 period. Residential Property Prices Indices (RPPI) for all dwellings in the country per square m (Q4-2000 index = 100) and 14 variables describing the economic situation of a given country were

Table 1

Definition of variables

Variable	Name	Definition	Source
Dependent	**RPPI**	Residential Property Prices Index for all dwellings in country, per square m (index Q4-2002=100).	BIS (www.bis.org)
Independent	**GDP**	Gross Domestic Product, expenditure approach. Growth rate compared to previous quarter, seasonally adjusted.	OECD (stats.oecd.org)
	UE	Harmonized unemployment rate: all persons. Level.	OECD (stats.oecd.org)
	MEI	Long-term interest rates, per cent per annum quarterly.	OECD (stats.oecd.org)
	CPI	Consumer Prices Index, all items. Percentage change from previous period quarterly.	OECD (stats.oecd.org)
	HICP_H	Harmonized Index of Consumer Prices; housing, water, electricity, gas and other fuels. Quarterly rate of change. Neither seasonally nor working day adjusted.	European Commission (Eurostat) and European Central Bank calculations based on Eurostat data (ec.europa. eu/eurostat)
	HICP_AR	Actual rentals for housing. Quarterly rate of change. Neither seasonally nor working day adjusted.	
	HICP_M	Maintenance and repair of the dwelling. Quarterly rate of change. Neither seasonally nor working day adjusted.	
	HICP_HS	Housing services. Quarterly rate of change. Neither seasonally nor working day adjusted.	
	ANNI*	Adjusted net national income (annual % growth)	IMF (www.imfstatistics. org)
	FCE*	Final consumption expenditure (annual % growth)	
	HFCE*	Household final consumption expenditure (annual % growth)	
	PG*	Population growth (annual %)	
	GGD	General government debt. Quarterly rate of change (index Q4-2002=1).	
	LTL	Long term loans. Quarterly rate of change (index Q4-2002=1).	

Note: * annual data adopted in each quarter at an annual level, no data available for 2010.

Source: own calculations

collected for each of the countries. In some cases, appropriate changes and transformations of variables were made in order to achieve the uniformity of data. Table 1 summarizes the variables applied in this study. Each variable in the study described in Table 1 includes a suffix denoting the country (FR-*France*; DE-*Germany*; GR-*Greece*; IE-*Ireland*; IT-*Italy*; PL-*Poland*; PT-*Portugal*; ES-*Spain*; UK-*United Kingdom*). The basic descriptive statistics for RPPI have been compiled in Table 2. Descriptive statistics for independent variables are shown in Annex 1.

Table 2

Descriptive statistics for all RPPI

Variable	No. of cases	Average	St. dev.	Min.	Max.	Skewness	Kurtosis
RPPI–FR	32	133.78	18.76	100.00	160.67	–0.44	–1.20
RPPI–DE	33	96.00	1.58	94.34	100.00	0.83	–0.42
RPPI–IT	33	124.67	12.44	100.00	136.56	–0.66	–1.08
RPPI–GB	31	119.69	10.99	100.00	135.87	–0.20	–1.38
RPPI–PL	28	193.63	62.20	97.27	257.73	–0.46	–1.70
RPPI–PT	33	107.41	5.03	100.00	115.30	0.07	–1.45
RPPI–IE	33	123.52	17.57	93.16	150.99	–0.05	–1.12
RPPI–GR	33	124.06	15.08	100.00	141.39	–0.45	–1.45
RPPI–ES	33	153.43	23.27	100.00	180.34	–0.91	–0.25

Source: own calculation

The skewness of only two RPPI distributions is asymmetric to the right (RPPI–DE, RPPI–PT), the remaining distributions are skewed left (the left tail of the distribution is extended). The calculated kurtosis coefficient of the distributions indicates that the distributions are platykurtic – RPPI values are less concentrated than when dealing with a normal distribution. The highest average RPPI was observed for Poland (193), the lowest for Germany (less than 100). The largest standard deviation (largest variation) was observed for the RPPI–PL variable, the smallest for the RPPI–DE variable.

5.2. Results

All experiments were carried out using STATISTICA (ver. 9). The OLS, ANN and CANN models were built for all independent variables. The training, testing and validation of ANNs was carried out under the following assumptions:

a) Dependent variable: RPPI–*x* (suffix *x* equal to the given country).

b) Independent variables: 14 – as shown in Table 1 (with suffix *x* equal to the given country).

c) Number of ANNs tested in each CANN: 500 – the analysis covered a few hundred various structural solutions.

d) Number of retained networks: 50 – this number indicates how many neural networks were selected for creating the final effect.

e) Types of networks/learning method: RBF/RBFT, MLP3/BFGS.

f) Activation function: linear, logistic, hyperbolic tangent, exponential function (negatively), and gauss (RGB).

g) Number of hidden neurons: MLP – minimum 5 (⅓ inputs), maximum – 15 (½ (inputs + outputs) + square root of the number of patterns in the training file); RBF – minimum 7 (½ inputs), maximum – 15 (number of inputs).

h) Number of cases used in network processes: 33. Missing cases were replaced with the average at input.

i) Weight reduction was applied for the hidden and output layers.

j) Criterion for selecting the retained networks: the correlation coefficient (R_{cy}).

k) Division of the data set into trials: learning (L), testing (T), and validation (V); shares of individual tests: L – 70%, T – 15%, V – 15%. Number of samples: 500.

l) Subsampling method: bootstrap – generate multiple subsamples of the original dataset based upon sampling with replacement.

m) Operationalization of variables – minimax (0.1).

n) Error function for learning, validation and testing of networks: E_{SOS}.

o) Quality of learning, validation, and testing of networks: the correlation coefficient (R_{cy}).

p) Formation of a committee: SRA – arithmetic mean of the outputs from individual networks.

q) The quality of CANN: MAPD, MAE, RMSE, R^2, the correlation coefficient (R_{cy}) for learning (L), testing (T) and validation (V) set.

The calculation process, using the STATISTICA package, was prepared and implemented for the needs of the present work. The choice of parameters is not coincidental. The presented study assumptions are the result of many years of work with ANN and CANN type methods.

Over the course of preliminary analyses, other programs, including Matlab Neural Network Toolbox, were used. During analyses, the learning process was observed – the aim was to avoid reaching the local centre by the network (such a model of the network was eliminated) and the elimination of cases of overlearning (the learning process was stopped).

The work used 14 independent variables for 32 quarterly RPPI coefficients in the analyzed countries. The number of 32 cases was determined by the restrictions connected with the availability of statistical data – such data had not been published earlier. The question of whether carrying out such analyses for 32 cases is valid remains open. The author, being aware of the needs of CANNs for a specific amount of input data, believes the number to be at the minimum acceptable level. Based on analyses carried out for many years, CANNs have been found to obtain good results also in cases of small sets of input data.

The work uses a method which enables the bootstrapping method to be used each time when creating the network. Therefore, in each case, the analyses could be carried out using all of the 32 cases. The redundancy of input data causing correlation is not a problem here as CANNs models are resistant to such types of dependencies. Creating redundant sets of input data can increase the quality of the obtained results. Creating the result by CANNs in the multidimensional space of input data (often redundant) is their advantage.

The indicated analysis allows to state that using CANNs in the present study makes it possible to draw conclusions concerning economic aspects.

5.2.1. Linear regression – OLS models

Values of the linear regression equation parameters, *t*-values and *p*-value, estimated by ordinary least squares using all the data (Annex 2).

Most of the variables were not found to be statistically significant at significance level of 0.05. The significance of variables increases only slightly at 0.1. In the case of France, the following variables were shown to be significant (at a level of 0.1): GDP, MEI, HICP_M, HICP_HS and ANNI; in Germany: UE, FCE, HFCE and PG; in Italy: UE, HICP_H, HICP_AR, HICP_HS, ANNI, FCE, HFCE and PG; in the United Kingdom: UE, MEI, HICP_HS, ANNI, FCE, PG, GGD, LTL; in Poland: GDP, UE, HICP_H, FCE and HFCE; in Portugal: UE, MEI, HICP_H, HICP_AR, HICP_M, ANNI, PG; in Ireland: UE, HICP_AR, HICP_M, HICP_HS, ANNI, FCE, HFCE, PG; in Greece: UE, MEI, ANNI, HFCE, PG; in Spain: HICP_H.

The analysis of a set of significant variables in individual OLS models reveals, in the analyzed countries, RPPI most often depends on: unemployment rate (EU) – 7 countries, net national income (ANNI) – 6 countries, population growth (PG) – 6 countries, final consumption expenditure (FCE) – 5 countries, household final consumption expenditure (HFCE) – 5 countries, long-term interest rates (MEI) – 4 countries, quarterly rate of change of price index for housing, water, electricity, gas and other fuels (HICP_H) – 4 countries, housing services (HICP_HS) – 4 countries, actual rentals for housing (HICP_AR) – 3 countries, maintenance and repair of the dwelling (HICP_M) – 3 countries. The variables GDP, CPI, GGD_FR and LTL proved to be statistically insignificant at a level of 0.1 in nearly all of the analyzed countries.

The values of the Durbin–Watson coefficients (d) are given in Table 3. The bounds at a 95% level of significance are $d_{L,0.025} = 0.43$, $d_{U,0.025} = 2.72$. Thus there is no negative autocorrelation between observations and no evidence to suggest that there is positive autocorrelation.

The mean absolute percentage differences (MAPD) between the real and predicted $\hat{y}$ values range from 0.3 % (OLS–DE) to 7.8 % (OLS–ES), with mean absolute error (MAE) values ranging from 0.267 (OLS–DE) to 11.297 (OLS–ES), root mean square error (RMSE) from 0.316 (OLS–DE) to 15.007 (OLS–ES), and R^2 from 0.571 (minimum) for OLS–ES to 0.995 (maximum) for OLS–PL. The test results are summarized in Table 3 (OLS models).

Table 3

Results of modelling RPPI for OLS and CANN models

Predictor	MAPD	MAE	RMSE	R^2	R_{cy} (U)	R_{cy} (T)	R_{cy} (V)	d*
CANN–FR	0.056	7.196	8.964	0.816	0.785	0.716	0.952	-
OLS–FR	0.070	8.881	10.144	0.689	-	-	-	1.398
CANN–DE	0.003	0.245	0.295	0.974	0.940	0.976	0.984	-
OLS–DE	0.003	0.267	0.316	0.959	-	-	-	1.826
CANN–IT	0.013	1.537	2.219	0.975	0.949	0.993	0.980	-
OLS–IT	0.014	1.755	2.228	0.967	-	-	-	2.521
CANN–GB	0.019	2.274	2.763	0.947	0.931	0.967	0.974	-
OLS–GB	0.015	1.830	2.290	0.952	-	-	-	2.148
CANN–PL	0.016	2.614	3.628	0.997	0.994	0.992	0.999	-
OLS–PL	0.024	3.705	4.764	0.995	-	-	-	1.483
CANN–PT	0.006	0.626	0.859	0.972	0.982	0.991	0.998	-
OLS–PT	0.006	0.648	0.774	0.976	-	-	-	1.735
CANN–IE	0.020	2.468	3.241	0.970	0.977	0.986	0.994	-
OLS–IE	0.022	2.680	3.241	0.965	-	-	-	1.685
CANN–GR	0.021	2.582	3.461	0.949	0.976	0.972	0.994	-
OLS–GR	0.018	2.170	2.861	0.963	-	-	-	1.668
CANN–ES	0.042	5.816	8.643	0.903	0.868	0.689	0.934	-
OLS–ES	0.078	11.297	15.007	0.571	-	-	-	0.642

Note: * Durbin–Watson (D–W) coefficient.

Source: own calculations

5.2.2. Committee of artificial neural network models

During the construction of CANN the auto designer of artificial neural networks function of the STATISTICA package was used. In the case of each data set (9 sets – 9 countries), the process of finding the top 50 ANNs was launched once. The guidelines assumed in section four were applied over the course of the study. The test results are summarized in Table 3 (CANN models). Figure 2 shows sample results for the CANN–PL model.

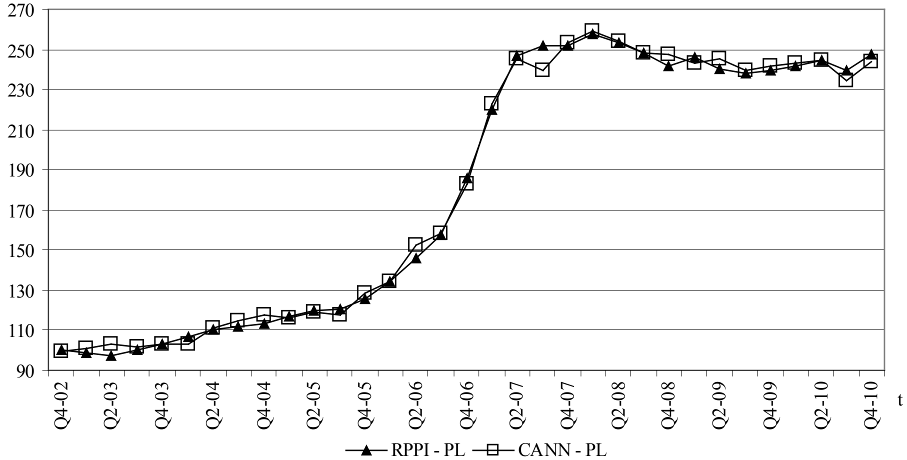

Fig. 2. RPPI–PL and CANN–PL.

Source: own calculations

When taking into account the values of R^2, R_{cy} (U), R_{cy} (T) and R_{cy} (V) indicators, the best results were obtained with CANN–PL.

The minimum mean absolute percentage difference (MAPD) between the real and predicted $\hat{y}$ values was 0.3% (CANN–DE), the minimum mean absolute error (MAE) was 0.245, and the minimum root mean square error (RMSE) was 0.316. The maximum MAPD, MAE and RMSE were 5.6% (CANN–FR), 7.196, and 8.964, respectively. The resulting coefficients indicate that the CANN models were well matched with the data.

Based on almost all the parameters, OLS performed worse than the CANN. The conducted analyses showed that CANN models enable better modeling of RPPI than the OLS models. The combination of 50 ANNs into one committee allows for the searching of a large variability space contained within the data, obtaining the necessary accuracy, and an appropriate level of generalization. All these factors make it possible for CANN to be applied in modelling RPPI. In further research, CANN models will be used to determine the influence of individual variables on RPPI and the relationships between the analyzed RPPI indicators for individual countries.

5.2.3. Relationship between the economic and financial situation and the residential property market

The economic and financial situation of the individual countries under study varies (Figure 1). It is different for the group of the European-G8 countries and for countries included under the acronym PIGS, and still different, in the case of Poland. Figures 1, 3, and 4 illustrate that the 2008 crisis affected the economies of all countries included in the research. Countries belonging to the European-G8 group (Figure 3) reached a positive GDP index relatively quickly (Q2-2009). On the other hand, countries in the PIGS group (Figure 4) are, as of today, still dealing with problems brought about by the financial crisis or have reached GDP values which only minimally exceed zero. Both figures also show the GDP for Poland, in both cases the GDP indicator is highest for this country. This means that the Polish GDP was maintained at values higher than those characteristic of the crisis zone.

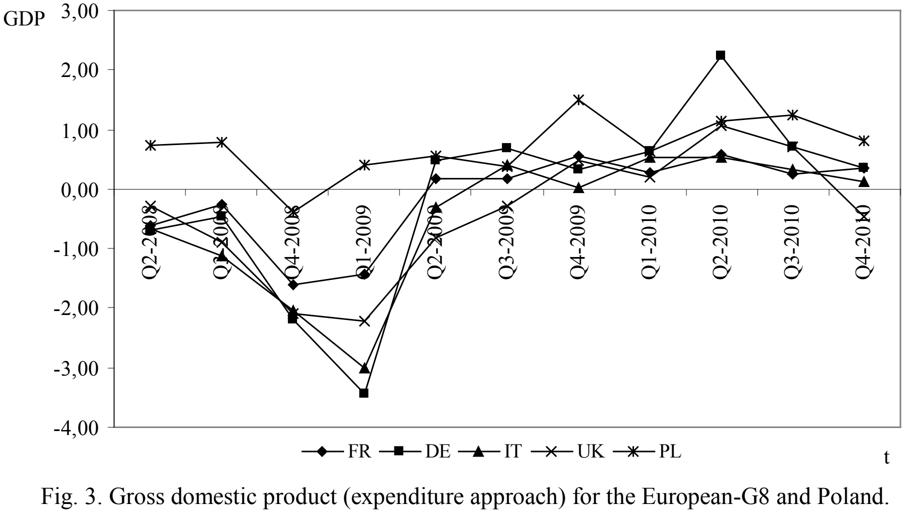

Fig. 3. Gross domestic product (expenditure approach) for the European-G8 and Poland.

Source: OECD (1 May 2011).

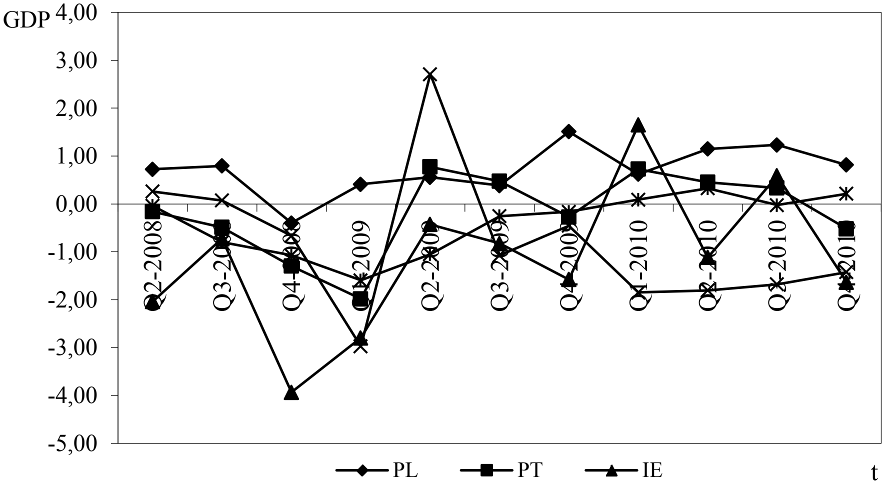

Fig. 4. Gross domestic product (expenditure approach) for PIGS and Poland.

Source: OECD (1 May 2011).

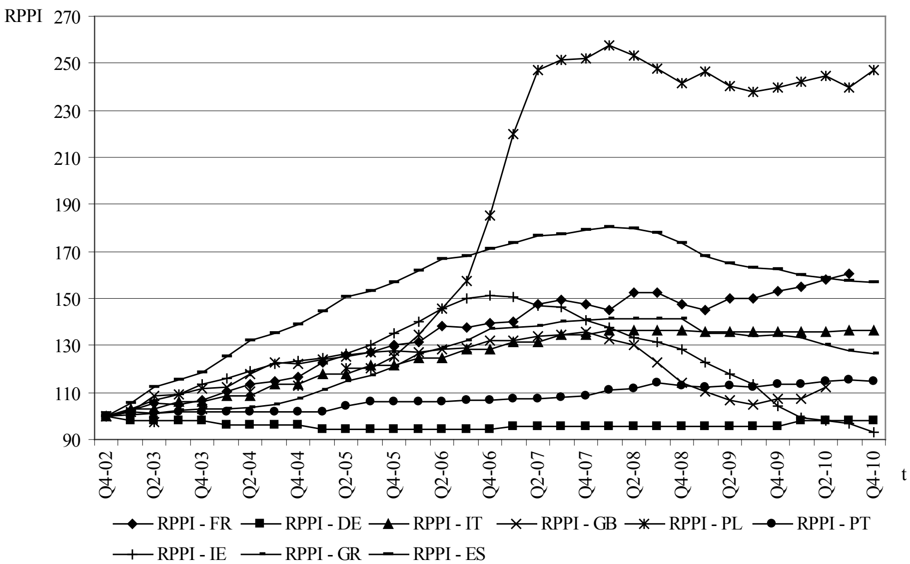

Fig. 5. Residential Property Prices Index for all dwellings in country (PIGS, the European-G8 and Poland), (per square m; index Q4-02=100).

Source: BIS.

Figure 5 illustrates the RPPI for PIGS, the European-G8 and Poland. Various effects of the 2008 financial crisis can be observed in the figure. For countries in the European-G8 group as well as Poland (Figure 6), the crisis had very little negative effect on residential property markets. The residential property market of Great Britain was the only exception, where a falling tendency could already be observed in Q1-2008. Similarly to the analysis of GDP, Q2-2009/Q3-2009 is a period where a change in the trend can be observed. During this period, RPPI indices (even for GB) once again began to increase.

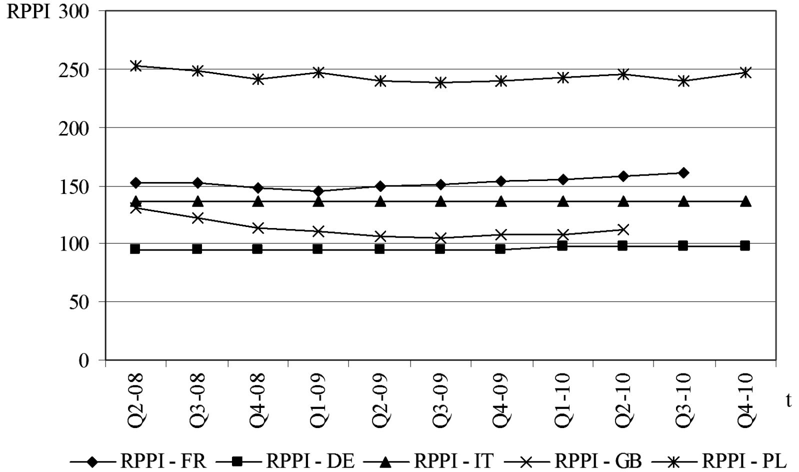

Fig. 6. Residential Property Prices Index for all dwellings in the European-G8 and Poland during the time of crisis (per square m; index Q4-02=100).

Source: BIS.

The reverse situation can be observed in the case of the PIGS group. The analysis of data presented in Figure 7 reveals that the residential property markets crashed as a result of the economic crisis and the situation is still current. Residential Property Prices Indices continue to fall. This signifies that the ongoing economic crisis (observed based on GDP) also applies to residential property markets. One additional conclusion can be drawn from the analysis of RPPI. When analyzing RPPI for Portugal, it can be observed that its value (with the exception of Q3-2009) is continuously increasing. This may imply that the situation of the residential property market in Portugal is not directly connected with the country's economic situation.

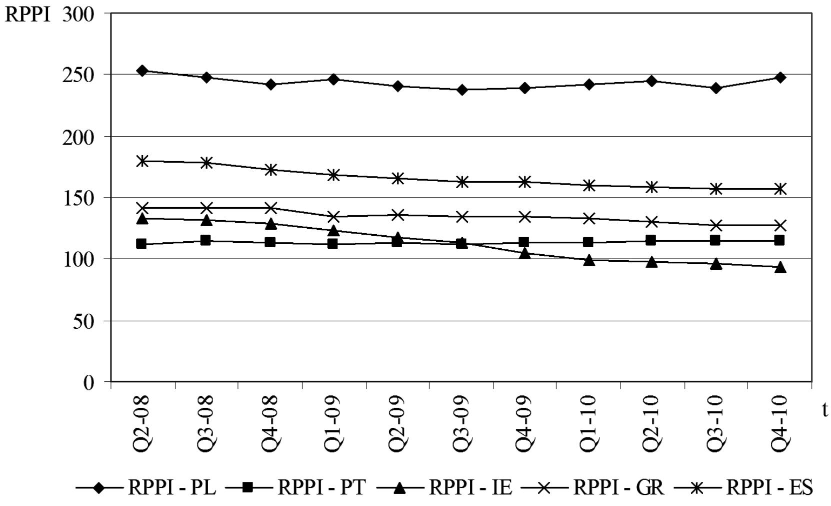

Fig. 7. Residential Property Prices Index for all dwellings in PIGS and Poland during the crisis (per square m; index Q4-02=100).

Source: BIS.

In an attempt to determine the variables which influence the relationship between the economic and financial situations and the residential property market, additional analyses were conducted. Correlation coefficients calculated for RPPI and all independent variables are presented in Annex 3. The analysis of correlation coefficients indicates that RPPI is correlated with the variables (countries belonging to the European-G8 group and Poland are indicated in bold):

– ANNI in the case of six countries (**FR**, **IT**, **GB**, **PL**, GR and ES) – in four cases the value of this coefficient is negative which indicates that the increase of net national income has a negative influence on RPPI;
– HICP_HS in the case of six countries (**FR**, IT, **GB**, **PL**, IE and GR) – in four cases the value of this coefficient is positive which indicates that an increase in HICP housing services has a positive influence on RPPI;
– FCE and HFCE in the case of five countries (**FR, DE**, **IT**, **PL** and IE) – the value of this coefficient varies;
– HICP_H in the case of five countries (**DE**, **PL**, PT, IE and GR) – the value of this coefficient varies;
– UE in the case of four countries (**IT**, **GB**, **PL** and GR) – in every case the correlation coefficient has a negative value which indicates that an increase in unemployment has a negative influence on RPPI;

- HICP_AR in the case of four countries (**GB**, **PL**, IE and GR) – in three cases the value of this coefficient is positive which indicates that an increase in HICP actual rentals for housing has a positive influence on RPPI;
- HICP_M in the case of four countries (**DE**, **IT**, PT and GR) – the value of this coefficient varies;
- PG in the case of four countries (**DE**, **PL**, IE and GR) – in every case the correlation coefficient has a positive value which indicates that population growth has a positive influence on RPPI;
- MEI in the case of three countries (**DE**, **GB** and GR) – a positive value of the correlation coefficient indicates that an increase in the value of long-term interest rate has a positive influence on RPPI.

In many cases, this analysis confirms the results of variable significance analysis conducted for OLS models. It should, however, be noted that the analysis of correlation coefficients can be burdened with many errors resulting from statistical conditions which must be met in such a case. Moreover, based on the conclusions in Section 4.2.2, the CANN models were shown to be better at modelling RPPI. This is the reason behind applying the results obtained for the CANN models when carrying out the analysis of variable sensitivity in these models.

Variable sensitivity analysis relies on calculating the residual sum of squares after the tested predictor has been removed from the network. Quotients (for the full model in relation to the model with the removed predictor) are given, with the actual predictors ordered according to their importance to a given neuron network.

Results of the sensitivity analysis of independent variables for CANN models are presented in Annex 4. The following independent variables (countries belonging to the European-G8 group and Poland are written in bold) were shown to be the most significant in the CANN models (the first five variables were subjected to analysis):

- PG in the case of seven countries (**FR**, **DE**, **GB**, **PL**, PT, IE and GR) – in two countries the increase in the unemployment variable was shown to have the most influence (first position in sensitivity analysis) on RPPI, and held second position in the next four countries,
- UE in the case of eight countries (**DE**, **IT**, **GB**, **PL**, PT, IE, GR and ES) – in two countries the population growth variable was shown to have the most influence (first position in sensitivity analysis) on RPPI,
- FCE in the case of five countries (**FR**, **DE**, **IT**, **PL** and GR) – in one country the final consumption expenditure variable was shown to have

the most influence (first position in sensitivity analysis) on RPPI and held second position in another,
- ANNI in the case of five countries (**FR**, **GB**, PT, IE and ES) – in two countries the net national income variable held second position for sensitivity analysis and either third or fourth in the remaining ones,
- HFCE in the case of five countries (**FR**, **DE**, **IT**, **PL** and IE) – in two countries the household final consumption expenditure variable was third in sensitivity analysis,
- HICP_AR in the case of four countries (**IT**, **GB**, IE and GR) – in one country the actual rentals for housing variable held second position in sensitivity analysis and was third in another,
- HICP_HS in the case of three countries (**GB**, **PL** and ES) – in one country the housing services variable held second position in sensitivity analysis,
- HICP_M in the case of three countries (**DE**, PT and ES) – in one country the maintenance and repair of the dwelling variable held third position in sensitivity analysis,
- MEI in the case of three countries (**GB**, PT and GR) – in one country the increase in the level of long-term interest rate variable held fourth position in sensitivity analysis,
- HICP_H in the case of two countries (**IT** and ES) – in one country the HICP_H variable held fourth position in sensitivity analysis.

The remaining variables, i.e. GDP, CPI, GGD and LTL, held the last positions in the sensitivity analysis. The results of the conducted sensitivity analysis of independent variables for CANN confirmed the results of the previously conducted correlation analysis and variable significance analysis in the OLS models.

In order to determine the amount of influence of the economic crisis on residential property markets further analyses were conducted. Variable 1, named the "crisis" variable, was added to the group of variables described in Table 1. This variable holds value zero (0) for the Q4-2002-2008 period (no crisis before the collapse of Lehman Brothers in September 2008), and value one (1) for the Q3-2008-Q4-2010 period (crisis situation). Analyses were conducted for all countries, utilizing the CANN models and applying the assumptions accepted in Section 4.2. For models labelled as CANNc – the "c" suffix indicates a model with the additional "crisis" variable.

The results of sensitivity analysis are presented in Annex 4. The conducted sensitivity analyses indicate that the "crisis" variable has the most influence on RPPI. In eight countries, Ireland constituted the exception (position 3), this variable was in first position. Based on the conducted analysis, it is difficult to explicitly determine whether this influence is stronger in the group of European-G8 countries, Poland, or countries in the PIGS group. The relative influence of the "crisis" variable ranges from 12.2.% (PT – a country from the PIGS group) to 81.3% (IT – a country from the European-G8 group). It can, however, be observed that (besides Italy which, as we know, is currently experiencing financial and economic problems) countries in the European-G8 group reached lower relative sensitivity coefficients in this analysis at an average level of 36%. In the case of countries in the PIGS group (with the exception of Portugal), this coefficient averaged 57%.

The influence of the remaining variables is much lower and at different levels. It should, however, be noted that besides the fact that the "crisis" variable took first position in the analysis, the introduction of a new variable did not significantly influence the further order of variables. Their positions were similar to those which they held in the sensitivity analysis of independent variables for the CANN models. Therefore, the additional "crisis" variable significantly reflects the influence of the ensuing crisis situation, without destroying the structure of the influence (model sensitivity) of the remaining variables. The test results for CANNc models are summarized in Table 4. The results indicate that the quality of CANNc models is slightly better than the CANN models. This implies that the additional variable improved the modeling results.

Table 4

The results of RPPI modelling for the CANNc models

Predictor	**MAPD**	**MAE**	**RMSE**	$\mathbf{R^2}$	R_{cy} **(U)**	R_{cy} **(T)**	R_{cy} **(V)**
CANNc–FR	0.040	5.168	6.504	0.889	0.888	0.832	0.987
CANNc–DE	0.005	0.450	0.540	0.954	0.915	0.921	0.992
CANNc–IT	0.008	0.917	1.383	0.988	0.991	0.990	0.999
CANNc–GB	0.017	1.972	2.369	0.953	0.968	0.985	0.978
CANNc–PL	0.017	2.761	3.577	0.997	0.995	0.993	0.999
CANNc–PT	0.007	0.774	0.957	0.967	0.941	0.940	0.998
CANNc–IE	0.018	2.174	2.631	0.977	0.982	0.959	0.994
CANNc–GR	0.020	2.547	2.941	0.963	0.971	0.986	0.996
CANNc–ES	0.022	3.059	5.375	0.951	0.991	0.893	0.982

Source: own calculation

The influence of the crisis situation is very strong. This means that the crisis situation which occurred in the third quarter of 2008 had and continues to have a significant effect on the shaping of relations in the residential property markets throughout Europe.

5.2.4. Relationship between the crisis and residential property markets

In Section 4.2.3, a connection between the economic and financial situation of a given country and the overall economic situation of residential property markets was observed. In an effort to establish common relationships of residential property markets in the analyzed countries and groups of countries, as well as to identify and establish the strength of these relationships, further studies were conducted. Correlation analysis, CANN models and sensitivity analysis were all applied in these analyses.

Table 5 presents the correlation coefficients calculated for all RPPIs as well as the additional "crisis" variable. These coefficients show common relationships between RPPIs for individual markets. In the European-G8 group of countries, the residential property markets of France and Great Britain are the only ones which do not show a correlation relationship. The remaining markets in this group are connected with each other. The strength of this relationship, as expressed by the correlation coefficient, varies and has different means of influence (positive and negative value). In this group, the strongest relationships were noted for the markets of GB and FR, whilst the lowest were for GB and IT. The relationships of this group with the variable representing the crisis indicate that such a relationship cannot be noted for the German market.

In the PIGS group, strong correlation relationships could be noted for the majority of residential property markets. An exception to this are the relationships between Ireland and Portugal. Significant correlation relationships of PIGS with the "crisis" variable did not occur only in the case of Spain. In this group, the strength and kind of relationship is uniform in character. Correlation coefficients have a positive value, so the strength of the relationship is directly proportional. An increase in RPPI in one of the markets results in an increase in the remaining markets. The strongest significant relationships can be noted for the GR and ES markets, with the weakest for GR and IE.

Table 5

Values of the correlation coefficient (RPPI and "crisis" in all countries)

Predictor	RPPI FR	RPPI DE	RPPI IT	RPPI GB	RPPI PL	Crisis	RPPI PT	RPPI IE	RPPI GR	RPPI ES
RPPI – FR	1.00	–0.47	0.99	**0.32**	0.93	0.60	0.94	**0.33**	0.95	0.92
RPPI – DE	–0.47	1.00	–0.53	–0.69	**–0.27**	**0.05**	**–0.29**	–0.77	–0.53	–0.72
RPPI – IT	0.99	–0.53	1.00	0.36	0.93	0.58	0.93	0.39	0.97	0.94
RPPI – GB	**0.32**	–0.69	0.36	1.00	**0.21**	–0.49	**0.06**	0.90	0.44	0.63
RPPI – PL	0.93	**–0.27**	0.93	**0.21**	1.00	0.61	0.91	**0.24**	0.92	0.82
Crisis	0.60	**0.05**	0.58	–0.49	0.61	1.00	0.78	–0.40	0.45	**0.32**
RPPI – PT	0.94	**–0.29**	0.93	**0.06**	0.91	0.78	1.00	**0.09**	0.87	0.79
RPPI – IE	**0.33**	–0.77	0.39	0.90	**0.24**	–0.40	**0.09**	1.00	0.52	0.66
RPPI – GR	0.95	–0.53	0.97	0.44	0.92	0.45	0.87	0.52	1.00	0.95
RPPI – ES	0.92	–0.72	0.94	0.63	0.82	**0.32**	0.79	0.66	0.95	1.00

Note: correlation coefficients in bold are not significant at $p < 0,05$.

Source: own calculations

When analysing the situation in Poland it should be noted that its RPPI is not correlated with the DE, GB, and IE markets. In the remaining cases, the correlations are significant and the positive value of nearly all the correlations coefficients shows that the state of the other real estate markets is positively reflected by the Polish real estate market.

The following analysis was conducted in an effort to identify and determine the strength of relationships between RPPI in individual countries and groups. CANN models were used for this purpose, applying the guidelines adopted in Section 4.2. In models labeled as CANNp - the "p" suffix indicates an RPPI model drawn up based on the remaining RPPIs as independent variables. Nine CANNp models were drawn up for individual countries, accepting the RPPIs of the remaining countries as independent variables. The results of the sensitivity analysis for the CANNp models are presented in Table 6.

The sensitivity analysis shows very interesting relationships regarding the crisis situation in a given country or group of countries and the situation in other countries or groups of countries. These relationships have different strengths, expressed by the relative share of a given variable in creating the result (RPPI). For example, for the CANNp–GB model, the first variable (RPPI–ES) influences the final result by 66%. The average share of the first four variables in creating the final result is, in each case, no lower than 75%. At the same time, it should be noted that in the group of the first four variables, each model contains, above all, the RPPI of countries in the PIGS group, with Poland and Italy present on occasions.

Analysis of data regarding countries of the European-G8 group indicates that the residential property markets of these countries are especially connected by relationships with the markets of Portugal, Greece, Italy and Poland. In a few of the cases, the indicated relationships can be explained by the direct proximity of the markets (CANNp–FR: PT, IT). The present relationships are spatially interdependent, which means that the markets are somewhat dependent on one another. In other cases, the existing relationships may be connected with the financial situation of these countries, especially in the banking sector. The common economic and financial policy of the European Union, which guarantees a free flow of capital and services, by some means connects the analyzed markets into one giant market mechanism. Relationships occurring within are spread from one country or part of Europe to another.

Table 6

Sensitivity analysis for variables in the CANNp models

Predictor	**Variables**							
CANNp - FR	RPPI - PT	RPPI - PL	RPPI - GR	RPPI - IT	RPPI - ES	RPPI – IE	RPPI - GB	RPPI - DE
% *	26.1%	17.5%	15.4%	13.7%	9.9%	6.3%	5.7%	5.4%
CANNp - DE	RPPI - IE	RPPI - ES	RPPI - PL	RPPI - GR	RPPI - PT	RPPI - IT	RPPI - GB	RPPI - FR
% *	17.6%	15.5%	15.2%	14.8%	11.4%	9.4%	8.4%	7.8%
CANNp - IT	RPPI - PL	RPPI - PT	RPPI - GR	RPPI - ES	RPPI - DE	RPPI - FR	RPPI - IE	RPPI - GB
% *	39.8%	21.5%	10.8%	9.5%	5.7%	5.1%	4.3%	3.2%
CANNp - GB	RPPI - ES	RPPI - GR	RPPI - PL	RPPI - IE	RPPI - IT	RPPI - PT	RPPI - DE	RPPI - FR
% *	66.0%	11.7%	10.0%	3.6%	3.4%	3.3%	1.1%	1.0%
CANNp - PL	RPPI - GR	RPPI - ES	RPPI - IE	RPPI - DE	RPPI - IT	RPPI - PT	RPPI - FR	RPPI - GB
% *	24.1%	19.9%	19.8%	10.9%	10.1%	5.3%	5.0%	4.8%
CANNp - PT	RPPI - IT	RPPI - ES	RPPI - IE	RPPI - PL	RPPI - GR	RPPI - FR	RPPI - DE	RPPI - GB
% *	30.5%	14.6%	14.5%	13.4%	11.4%	7.1%	5.0%	3.6%
CANNp - IE	RPPI - GR	RPPI - ES	RPPI - PT	RPPI - IT	RPPI - PL	RPPI - DE	RPPI - GB	RPPI - FR
% *	44.8%	20.1%	16.0%	4.4%	4.1%	3.7%	3.5%	3.3%
CANNp - GR	RPPI - PL	RPPI - ES	RPPI - IE	RPPI - PT	RPPI - IT	RPPI - GB	RPPI - DE	RPPI - FR
% *	35.4%	18.5%	13.4%	9.9%	8.7%	4.9%	4.6%	4.6%
CANNp - ES	RPPI - PL	RPPI - GR	RPPI - IT	RPPI - GB	RPPI - IE	RPPI - PT	RPPI - DE	RPPI - FR
% *	35.8%	28.0%	8.4%	8.2%	7.9%	4.4%	4.3%	3.0%

* – % relative contribution of the variable.

Source: own calculations

The situation is a bit more complicated within the PIGS group of countries. The most significant variables in sensitivity analysis turned out to be the RPPI of other countries in this group as well as Poland. The model shows that the markets of these countries are interconnected by cross-border relationships, the character of which probably results from the economic situation in these countries and, indirectly, from the situation of the real estate market. Capital transfers which had started the moment the crisis began are happening to this day. This signifies the outflow of capital from the real estate markets of the PIGS group to the markets of other countries, especially those of the analyzed European-G8 group and Poland.

The positive economic situation in Poland, tax exemptions and permits for material investments, including those in residential property markets, have influenced and continue to influence the transfer of capital into this country. The relationships shown in Table 6 indicate that the Polish market is strictly connected with numerous markets: IT, GR, ES. These relationships are of a different nature.

Analysis of the CANNp models allows one to state that the economic crisis influenced and to this day continues to influence residential property markets. The strength of this influence is significant. In the case of modelling all RPPIs based on the RPPIs of other countries, the influence of markets in the PIGS group of countries is far-reaching and goes beyond the spatial effect on their immediate neighbours, which is typical of real estate markets.

Table 7

The results of modelling for RPPI to RPPI in the models CANNp

Predictor	MAPD	MAE	RMSE	R^2	R_{cy} (U)	R_{cy} (T)	R_{cy} (V)
CANNp–FR	0.018	2.520	3.997	0.952	0.963	0.994	0.993
CANNp–DE	0.004	0.361	0.475	0.910	0.921	0.939	0.860
CANNp–IT	0.006	0.703	0.934	0.994	0.996	0.998	1.000
CANNp–GB	0.024	2.859	3.705	0.891	0.874	0.883	0.983
CANNp–PL	0.017	2.884	3.548	0.997	0.995	0.997	0.999
CANNp–PT	0.005	0.549	0.733	0.979	0.974	0.990	0.988
CANNp–IE	0.021	2.604	3.074	0.971	0.979	0.993	0.997
CANNp–GR	0.008	0.951	1.175	0.994	0.992	0.996	0.995
CANNp–ES	0.008	1.135	1.420	0.996	0.994	0.996	0.996

Source: own calculation

The test results for the CANNp models are summarized in Table 7. RPPI modelling with the incorporation of a committee of artificial neural networks has shown the accuracy of applying these methods. The applied quality indicators take on very low values of MAPD, MAE and RMSE, and high in case of R^2 and R_{cy} .

CONCLUSIONS

The conducted analyses lead to the conclusion that the CANN models presented in the study indicate that the economic situation in a given country or given group of countries (different for the European-G8, different for the PIGS group) is reflected by the overall economic situation of the residential property markets. Variables which have an influence on the situation observed in the residential property markets of individual countries were indicated in the study. The main variables influencing RPPI are: population growth (PG), unemployment rate (UE), final consumption expenditure (FCE), net national income (ANNI), household final consumption expenditure (HFCE), long-term interest rates (MEI), quarterly rate of change of price index for housing, water, electricity, gas and other fuels (HICP_H), housing services (HICP_HS), actual rental for housing (HICP_AR), and maintenance and repair of the dwelling (HICP_M). The first four variables are directly connected with the influence of the economic and financial situation in residential property markets. The remaining six variables describe a situation which occurs in a specific real estate market. In nearly every analyzed country and analysis, the variables: GDP, CPI, GGD_FR and LTL turned out to have low significance or to be insignificant. The conducted analyses showed that residential property markets are connected with the economy as a whole but, all the while, have their own features. This allows one to state that the residential property market constitutes an integral and relatively independent goods market in the economy of each country under analysis.

The influence of the economic and financial situation in a given country and group on residential property markets varies. A general conclusion can be formulated as follows: residential property markets in countries (the European-G8 and Poland), which quickly coped with the economic crisis (currently, some of them are experiencing a period of stagnation) are in a good shape – RPPI is slowly increasing. Countries in a state of crisis (PIGS, with the exception of Portugal) are experiencing a crisis in residential property markets – RPPIs are falling.

The results of analyses when applying the additional “crisis” variable confirm that the crisis situation in the analyzed countries and groups of countries is significantly reflected in residential property markets. The additional variable had the most influence on the results of modelling the CANNc models. Its relative influence in sensitivity analysis was very high in terms of the remaining variables, often four times higher than the next variable down. At the same time, it is difficult to determine the strength of the influence that the crisis situation had. The sensitivity analysis revealed that in the European-G8 group of countries as well as PIGS, the "crisis" variable reached various levels of relative sensitivity. For example, in Portugal (a country in the PIGS group), this sensitivity equalled 67.6% whilst for Italy (a country from the European-G8 group) the sensitivity was 81.3% (the highest of all the registered levels).

Modelling the RPPI of a given country incorporating the RPPIs of other countries leads to the conclusion that the economic crisis of individual countries in the PIGS group is reflected by the level of RPPIs in other countries belonging to the same group. Interestingly enough, although not surprising, is that this is also reflected by the RPPI level of countries in the European-G8 and Poland. European integration, a common currency, the free flow of capital, all these factors contribute to the formation of cross-border relations between residential property markets in various countries. The calculated correlation coefficients (RPPI to RPPI) confirm this fact.

Analyses of the CANN, CANNc and CANNp models carried out in the study show that correlations between the intensity of the crisis situation (economic and financial) of a given country or group of countries, and the state of residential property markets exist.

Modelling RPPI by incorporating CANNs indicates that these models can be applied for residential property markets. The obtained indicators which assess the quality of individual models are promising. These models are characterized by a strong resistance to a lack of data, allow for the analysis of correlated variables and, most importantly, enable the generalization of knowledge contained in data sets.

The economic crisis is directly reflected by residential property markets. This fact is confirmed by the conducted research. Hopefully the entities selected for analysis (the European-G8, PIGS, and Poland) constitute a representative sample of real estate markets in Europe and the obtained results can be generalized for the remaining markets.

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ANNEX 1

Descriptive statistics for all variables

Variable	No. of cases	Average	St. dev.	Min.	Max.	Skewness	Kurtosis
1	2	3	4	5	6	7	8
RPPI - FR	32	133.78	18.76	100.00	160.67	-0.44	-1.20
GDP-FR	33	0.28	0.57	-1.60	1.07	-1.99	4.56
UE-FR	33	9.01	0.63	7.60	9.93	-0.85	0.07
MEI-FR	33	3.86	0.45	2.78	4.49	-0.49	-0.42
CPI-FR	33	0.42	0.43	-0.51	1.39	0.06	-0.10
HICP_H-FR	33	3.21	1.67	-1.03	5.60	-0.85	0.67
HICP_AR-FR	33	2.78	0.71	1.20	3.80	-0.59	-0.56
HICP_M-FR	33	3.22	0.55	1.80	3.90	-1.11	0.45
HICP_HS-FR	33	3.08	0.73	1.73	4.23	-0.30	-1.06
ANNI-FR	29	1.01	1.88	-2.84	2.90	-1.13	0.09
FCE-FR	29	1.93	0.62	0.89	2.57	-0.84	-1.00
HFCE-FR	29	1.90	0.84	0.55	2.57	-0.93	-1.05
PG-FR	29	0.70	0.17	0.54	0.95	0.51	-1.53
GGD-FR	33	1.04	0.05	0.94	1.17	0.50	-0.31
LTL-FR	33	1.00	0.06	0.86	1.11	-0.47	-0.14
RPPI-GR	33	124.06	15.08	100.00	141.39	-0.45	-1.45
GDP-GR	33	0.39	1.31	-2.98	2.81	-0.67	0.37
UE-GR	33	9.65	1.47	7.50	14.10	1.09	1.87
MEI-GR	33	4.96	1.78	3.41	11.03	2.64	6.80
CPI-GR	33	0.86	1.29	-1.38	3.55	-0.08	-1.06
HICP_H-GR	33	5.47	5.00	-6.73	12.67	-0.81	0.24
HICP_AR-GR	33	4.24	0.94	1.83	5.50	-0.69	0.12
HICP_M-GR	33	3.79	1.13	1.67	5.93	-0.21	-0.75
HICP_HS-GR	33	4.12	0.90	1.90	5.37	-0.94	0.62
ANNI-GR	29	2.34	2.48	-2.45	4.60	-0.88	-0.52
FCE-GR	29	3.48	1.41	0.54	5.19	-1.17	0.29
HFCE-GR	29	3.15	2.14	-1.71	5.52	-1.54	1.69
PG-GR	29	0.38	0.03	0.33	0.41	-0.74	-1.07
GGD-GR	31	1.03	0.08	0.79	1.22	-0.38	1.98
LTL-GR	31	1.09	0.42	0.86	3.27	4.96	25.92
RPPI-ES	33	153.43	23.27	100.00	180.34	-0.91	-0.25
GDP-ES	33	0.43	0.70	-1.60	1.16	-1.47	1.43
UE-ES	33	12.11	4.23	7.97	20.50	1.03	-0.49
MEI-ES	33	4.05	0.37	3.18	4.70	-0.52	0.10
CPI-ES	33	0.69	1.08	-1.65	2.38	0.06	-1.05
HICP_H-ES	33	4.16	2.07	-0.43	8.07	-0.18	-0.22
HICP_AR-ES	33	3.88	1.02	0.90	5.27	-2.02	3.25
HICP_M-ES	33	3.92	1.72	-0.10	5.70	-1.25	0.25
HICP_HS-ES	33	4.03	0.90	1.80	5.03	-1.47	1.22
ANNI-ES	29	2.33	1.72	-1.29	3.69	-1.30	0.35
FCE-ES	29	2.77	2.84	-3.19	5.03	-1.32	0.35
HFCE-ES	29	2.03	2.99	-4.23	4.24	-1.33	0.30

Annex 1, cont.

1	2	3	4	5	6	7	8
PG-ES	29	1.52	0.27	0.88	1.71	-1.94	2.35
GGD-ES	33	1.02	0.06	0.85	1.16	0.07	1.36
LTL-ES	33	1.04	0.08	0.89	1.39	2.42	10.18
RPPI-IE	33	123.52	17.57	93.16	150.99	-0.05	-1.12
GDP-IE	33	0.33	2.16	-3.93	5.40	0.53	0.36
UE-IE	33	6.74	3.60	4.20	14.50	1.23	-0.25
MEI-IE	33	4.43	0.96	3.11	8.41	2.31	8.47
CPI-IE	33	0.47	1.01	-3.05	1.85	-1.53	3.45
HICP_H-IE	33	3.69	5.57	-11.13	10.57	-1.32	1.24
HICP_AR-IE	33	0.16	7.55	-16.13	11.20	-0.48	-0.19
HICP_M-IE	33	1.88	3.02	-4.63	5.87	-0.87	-0.27
HICP_HS-IE	33	1.63	4.20	-7.20	7.33	-0.69	-0.29
ANNI-IE	29	0.26	8.49	-18.40	6.58	-1.52	0.95
FCE-IE	29	2.94	4.54	-5.32	7.70	-0.67	-0.87
HFCE-IE	29	2.50	4.77	-7.11	6.68	-1.08	-0.07
PG-IE	29	1.77	0.58	0.56	2.42	-1.04	0.39
GGD-IE	33	1.05	0.10	0.85	1.33	0.72	0.88
LTL-IE	29	0.92	0.22	0.03	1.25	-2.81	9.33
RPPI-DE	33	96.00	1.58	94.34	100.00	0.83	-0.42
GDP-DE	33	0.24	1.00	-3.44	2.23	-1.77	5.88
UE-DE	33	8.69	1.32	6.57	10.70	-0.01	-1.37
MEI-DE	33	3.70	0.54	2.42	4.42	-0.65	-0.40
CPI-DE	33	0.38	0.34	-0.56	0.90	-0.50	0.30
HICP_H-DE	33	2.38	1.73	-1.27	5.40	-0.24	-0.27
HICP_AR-DE	33	1.06	0.12	0.77	1.40	0.18	1.24
HICP_M-DE	33	2.47	1.67	0.20	6.20	0.64	-0.87
HICP_HS-DE	33	1.20	0.14	0.97	1.57	0.72	0.16
ANNI-DE	29	1.17	1.99	-2.30	4.15	-0.18	-0.65
FCE-DE	29	0.52	0.52	-0.22	1.18	0.11	-1.74
HFCE-DE	29	0.27	0.57	-0.78	1.36	0.69	-0.08
PG-DE	29	-0.10	0.12	-0.28	0.21	0.36	0.57
GGD-DE	33	1.03	0.05	0.95	1.17	0.69	0.19
LTL-DE	33	1.03	0.10	0.88	1.42	2.00	7.48
RPPI-PL	28	193.63	62.20	97.27	257.73	-0.46	-1.70
GDP-PL	33	1.12	0.59	-0.40	2.21	-0.38	-0.12
UE-PL	33	13.34	4.98	6.97	20.17	0.15	-1.76
MEI-PL	33	5.83	0.60	4.72	7.25	0.53	0.35
CPI-PL	33	0.66	0.61	-0.52	2.01	0.43	-0.18
HICP_H-PL	33	4.72	1.79	2.70	9.23	1.23	0.80
HICP_AR-PL	33	4.11	1.31	2.53	6.47	0.45	-1.28
HICP_M-PL	33	3.20	3.83	-0.33	12.17	1.25	0.35
HICP_HS-PL	33	4.21	1.87	2.17	8.20	1.02	-0.09
ANNI-PL	29	4.55	1.92	1.22	7.10	-0.14	-1.66
FCE-PL	29	3.86	1.47	1.94	6.32	0.36	-1.11
HFCE-PL	29	3.74	1.52	1.89	5.92	0.01	-1.67
PG-PL	29	-0.03	0.05	-0.07	0.06	1.25	0.05

1	2	3	4	5	6	7	8
GGD-PL	33	1.04	0.09	0.89	1.36	1.50	4.70
LTL-PL	33	1.00	0.09	0.76	1.25	0.43	2.45
RPPI-PT	33	107.41	5.03	100.00	115.30	0.07	-1.45
GDP-PT	33	0.13	0.77	-1.98	1.48	-0.58	0.55
UE-PT	33	8.07	1.48	6.00	11.20	0.83	-0.10
MEI-PT	33	4.29	0.62	3.32	6.50	1.49	4.31
CPI-PT	33	0.52	0.72	-0.93	1.80	0.04	-0.68
HICP_H-PT	33	3.68	0.87	1.67	5.23	-0.57	-0.02
HICP_AR-PT	33	2.58	0.34	1.67	3.30	-0.24	0.75
HICP_M-PT	33	3.18	1.35	0.67	6.77	0.40	1.17
HICP_HS-PT	33	3.63	0.76	2.70	6.33	1.95	4.73
ANNI-PT	29	0.13	1.40	-1.55	2.59	0.72	-0.81
FCE-PT	29	1.40	1.02	-0.09	2.82	-0.33	-1.21
HFCE-PT	29	1.32	1.27	-0.93	2.67	-0.82	-0.81
PG-PT	29	0.37	0.22	0.09	0.73	0.24	-1.39
GGD-PT	30	1.03	0.08	0.81	1.18	-0.32	1.49
LTL-PT	30	1.07	0.30	0.25	2.18	1.47	7.61
RPPI-GB	31	119.69	10.99	100.00	135.87	-0.20	-1.38
GDP-GB	33	0.29	0.80	-2.23	1.07	-1.93	3.66
UE-GB	33	5.75	1.18	4.63	7.93	1.01	-0.64
MEI-GB	33	4.40	0.53	3.26	5.21	-0.60	-0.45
CPI-GB	33	0.59	0.52	-0.39	2.01	0.43	0.39
HICP_H-GB	33	4.88	3.96	-1.10	14.77	0.66	-0.28
HICP_AR-GB	33	2.49	0.90	0.97	3.90	-0.32	-1.36
HICP_M-GB	33	3.40	1.44	0.90	6.00	0.08	-1.14
HICP_HS-GB	33	3.03	0.92	1.23	4.43	-0.68	-0.66
ANNI-GB	29	1.06	3.49	-6.96	4.36	-1.68	1.76
FCE-GB	29	1.68	1.66	-2.05	3.57	-1.47	1.41
HFCE-GB	29	1.43	2.05	-3.14	3.55	-1.51	1.24
PG-GB	29	0.58	0.10	0.37	0.70	-0.72	-0.51
GGD-GB	30	1.06	0.06	0.86	1.15	-0.92	2.44
LTL-GB	30	1.03	0.11	0.86	1.48	2.58	10.15
RPPI-IT	33	124.67	12.44	100.00	136.56	-0.66	-1.08
GDP-IT	33	0.02	0.79	-3.01	1.05	-2.42	6.94
UE-IT	33	7.54	0.84	6.00	8.73	-0.43	-1.21
MEI-IT	33	4.22	0.37	3.39	4.90	-0.44	-0.13
CPI-IT	33	0.50	0.33	-0.44	1.14	-0.71	1.48
HICP_H-IT	33	3.27	2.49	-2.23	8.17	-0.34	-0.04
HICP_AR-IT	33	2.56	0.49	1.60	3.60	0.27	-0.25
HICP_M-IT	33	2.81	0.60	1.73	4.10	0.30	-0.33
HICP_HS-IT	33	3.01	0.53	2.10	4.37	1.03	1.06
ANNI-IT	29	0.04	1.67	-3.55	1.75	-1.25	0.72
FCE-IT	29	0.63	0.91	-1.16	1.39	-1.16	-0.30
HFCE-IT	29	0.39	1.08	-1.74	1.25	-1.14	-0.31
PG-IT	29	0.73	0.14	0.31	0.99	-0.35	1.87
GGD-IT	33	1.02	0.06	0.91	1.13	0.19	-0.44
LTL-IT	33	0.89	0.33	0.03	2.15	1.09	6.66

ANNEX 2

Values of the linear regression equation parameters for OLS models

Predictor	**Stat.***	**Inter-cept**	**GDP**	**UE**	**MEI**	**CPI**	**HICP_H**	**HICP_AR**	**HICP_M**	**HICP_HS**	**ANNI**	**FCE**	**HFCE**	**PG**	**GGD_FR**	**LTL**
OLS-FR	**alfa**	***474.91***	*15.14*	-1.61	***-39.22***	5.20	-5.89	24.05	*37.63*	*-51.63*	*12.18*	-56.81	22.09	-44.76	-52.78	-49.97
	***t*-stat.**	***3.21***	*1.94*	-0.14	***-2.61***	0.62	-1.41	0.97	*1.83*	*-1.75*	*1.87*	-1.19	0.60	-1.31	-0.74	-0.93
	***p*-value**	***0.00***	*0.07*	0.89	***0.02***	0.54	0.18	0.34	*0.08*	*0.10*	*0.08*	0.25	0.56	0.21	0.47	0.36
OLS-DE	**alfa**	***105.75***	-0.02	***-0.90***	-0.15	0.06	-0.15	-3.11	-0.29	0.61	0.17	*2.35*	*-1.89*	***15.53***	2.69	0.03
	***t*-stat.**	***29.64***	-0.12	***-6.38***	-0.68	0.16	-1.42	-1.41	-1.24	0.30	1.26	*1.77*	*-1.73*	***4.56***	1.20	0.02
	***p*-value**	***0.00***	0.90	***0.00***	0.51	0.87	0.17	0.18	0.23	0.77	0.22	*0.09*	*0.10*	***0.00***	0.25	0.98
OLS-IT	**alfa**	***241.85***	-2.02	***-5.39***	-3.14	-0.95	***-2.51***	***-12.36***	4.20	***-8.61***	***-2.41***	***-46.33***	***33.25***	***27.76***	-13.05	0.53
	***t*-stat.**	***9.95***	-1.20	***-2.39***	-1.24	-0.35	***-4.23***	***-6.14***	1.64	***-3.22***	***-2.45***	***-5.65***	***4.83***	***5.34***	-1.11	0.19
	***p*-value**	***0.00***	0.25	***0.03***	0.23	0.73	***0.00***	***0.00***	0.12	***0.00***	***0.02***	***0.00***	***0.00***	***0.00***	0.28	0.85
OLS-GB	**alfa**	***106.49***	0.21	***-8.90***	***-5.55***	-0.86	-0.29	4.53	-0.36	*-7.54*	***3.22***	*-5.55*	2.90	***132.71***	***44.97***	***-19.21***
	***t*-stat.**	***3.45***	0.15	***-4.05***	***-2.12***	-0.58	-1.16	1.32	-0.38	*-1.85*	***2.30***	*-1.78*	0.67	***8.03***	***3.30***	***-2.72***
	***p*-value**	***0.00***	0.88	***0.00***	***0.05***	0.57	0.26	0.20	0.71	*0.08*	***0.03***	*0.09*	0.51	***0.00***	***0.00***	***0.01***
OLS-PL	**alfa**	***417.21***	***-7.20***	***-13.91***	-0.22	3.55	***-10.10***	-0.38	0.65	6.01	0.40	***-13.91***	***10.44***	-81.93	-3.54	-8.45
	***t*-stat.**	***12.57***	***-2.31***	***-19.44***	-0.06	1.48	***-6.01***	-0.07	1.34	1.17	0.25	***-2.61***	***2.38***	-0.61	-0.15	-0.37
	***p*-value**	***0.00***	***0.03***	***0.00***	0.95	0.15	***0.00***	0.94	0.20	0.26	0.81	***0.02***	***0.03***	0.55	0.88	0.72
OLS-PT	**alfa**	***84.73***	-0.07	***1.68***	*1.06*	-0.23	*0.70*	*2.67*	*-0.80*	0.69	***-0.73***	-0.81	0.98	***-8.08***	-2.04	0.30
	***t*-stat.**	***11.61***	-0.21	***4.44***	*1.77*	-0.73	*1.86*	*1.83*	*-1.76*	0.92	***-3.03***	-1.21	1.32	***-3.83***	-0.72	0.37
	***p*-value**	***0.00***	0.83	***0.00***	*0.09*	0.47	*0.08*	*0.08*	*0.10*	0.37	***0.01***	0.24	0.20	***0.00***	0.48	0.72
OLS-IE	**alfa**	28.14	0.76	***-4.94***	1.83	-0.19	-0.08	***3.66***	***3.05***	***-9.52***	***-5.70***	***-4.64***	***6.52***	***64.55***	7.06	7.93
	***t*-stat.**	1.08	1.53	***-4.49***	1.02	-0.12	-0.17	***2.21***	***2.71***	***-2.71***	***-7.03***	***-2.46***	***2.41***	***5.91***	0.76	1.52
	***p*-value**	0.29	0.14	***0.00***	0.32	0.91	0.86	***0.04***	***0.01***	***0.01***	***0.00***	***0.02***	***0.03***	***0.00***	0.46	0.15
OLS-GR	**alfa**	***93.36***	0.00	***-6.25***	***1.93***	-0.31	-0.03	*-7.65*	-2.00	2.06	***1.78***	2.42	*-2.71*	***312.05***	-9.18	0.75
	***t*-stat.**	***2.03***	0.00	***-5.40***	***1.84***	-0.50	-0.12	*-1.92*	-1.05	0.50	***2.16***	1.23	*-1.97*	***4.16***	-0.78	0.34
	***p*-value**	***0.06***	1.00	***0.00***	***0.08***	0.62	0.91	*0.07*	0.31	0.62	***0.04***	0.24	*0.06*	***0.00***	0.45	0.74
OLS-ES	**alfa**	223.15	-13.15	-8.58	-1.30	0.40	***6.81***	2.62	-3.38	-33.11	9.03	104.77	-108.16	22.26	47.25	-19.98
	***t*-stat.**	0.93	-0.82	-1.25	-0.06	0.10	***2.34***	0.23	-0.20	-1.31	0.96	1.41	-1.39	0.27	0.41	-0.29
	***p*-value**	0.37	0.42	0.23	0.95	0.92	***0.03***	0.82	0.84	0.21	0.35	0.18	0.18	0.79	0.69	0.77

* bold - significant at the 0.05 level, italic - significant at the 0.10 level

ANNEX 3

Values of correlation coefficient (RPPI to all variables)

Predictor	GDP	UE	MEI	CPI	HICP_H	HICP_AR	HICP_M	HICP_HS	ANNI	FCE	HFCE	PG	GGD_FR	LTL
RPPI-FR	-0.28	-0.32	-0.08	-0.12	-0.04	-0.33	0.04	**-0.40**	**-0.44**	**-0.59**	**-0.53**	-0.25	-0.28	-0.13
RPPI-DE	-0.19	-0.07	**0.50**	-0.18	**-0.43**	0.21	**-0.46**	0.07	-0.11	**-0.52**	**-0.50**	**0.68**	0.17	**0.39**
RPPI-IT	-0.34	**-0.74**	0.21	-0.18	0.11	-0.12	**0.39**	**0.40**	**-0.46**	**-0.65**	**-0.53**	-0.21	-0.10	-0.26
RPPI-GB	0.26	**-0.44**	**0.59**	0.25	0.30	**0.77**	-0.03	**0.77**	**0.48**	0.27	0.34	0.30	0.08	-0.19
RPPI-PL	-0.09	**-0.99**	-0.02	0.28	**0.72**	**0.78**	0.11	**0.83**	**0.41**	**0.37**	**0.48**	**0.68**	-0.13	0.17
RPPI-PT	-0.12	-0.20	0.36	-0.03	**-0.44**	0.10	**-0.41**	0.35	0.15	0.24	0.21	0.10	-0.16	-0.12
RPPI-IE	0.11	-0.35	-0.26	0.35	**0.55**	**0.69**	0.10	**0.61**	0.26	**0.53**	**0.45**	**0.64**	0.07	0.18
RPPI-GR	-0.24	**-0.82**	**0.49**	-0.00	-0.07	**-0.68**	**0.45**	**-0.52**	**-0.46**	0.01	-0.27	**0.90**	-0.20	-0.16
RPPI-ES	-0.35	-0.03	0.00	-0.05	**0.38**	-0.08	0.12	-0.03	**-0.50**	-0.31	-0.32	-0.18	0.04	-0.08

* bold - correlation coefficients are significant with p < 0,05.

ANNEX 4

Sensitivity analysis for the independent variables in the models CANN and the CANNc

Predictor	Variables														
CANN-FR	-	PG-FR	ANNI-FR	FCE-FR	MEI-FR	HFCE-FR	UE-FR	HICP_M-FR	HICP_HS-FR	HICP_AR-FR	HICP_H-FR	GGD-FR	CPI-FR	LTL-FR	GDP-FR
% *	-	8.4%	8.4%	8.0%	7.5%	7.5%	7.1%	7.0%	6.9%	6.9%	6.6%	6.6%	6.5%	6.3%	6.2%
CANNc-FR	Crisis	PG-FR	ANNI-FR	HFCE-FR	UE-FR	HICP_AR-FR	MEI-FR	HICP_H-FR	FCE-FR	HICP_M-FR	CPI-FR	GGD-FR	HICP_HS-FR	GDP-FR	LTL-FR
% *	38.7%	6.2%	5.4%	4.8%	4.8%	4.3%	4.3%	4.2%	4.2%	4.1%	4.0%	4.0%	3.9%	3.8%	3.4%
CANN-DE	-	PG-DE	UE-DE	FCE-DE	HFCE-DE	HICP_M-DE	HICP_AR-DE	HICP_H-DE	ANNI-DE	MEI-DE	HICP_HS-DE	GGD-DE	LTL-DE	CPI-DE	GDP-DE
% *	-	33.9%	20.1%	9.4%	7.1%	6.1%	4.9%	3.1%	2.8%	2.5%	2.1%	2.0%	2.0%	2.0%	1.9%
CANNc-DE	Crisis	PG-DE	HICP_M-DE	FCE-DE	UE-DE	MEI-DE	HICP_AR-DE	HICP_H-DE	ANNI-DE	HICP_HS-DE	HFCE-DE	LTL-DE	CPI-DE	GGD-DE	GDP-DE
% *	28.0%	10.9%	9.7%	7.3%	7.2%	4.5%	4.3%	4.1%	3.7%	3.6%	3.6%	3.5%	3.4%	3.3%	3.0%
CANN-IT	-	FCE-IT	UE-IT	HFCE-IT	HICP_AR-IT	HICP_H-IT	ANNI-IT	MEI-IT	PG-IT	HICP_HS-IT	GDP-IT	LTL-IT	HICP_M-IT	CPI-IT	GGD-IT
% *	-	42.2%	15.5%	13.7%	6.5%	3.7%	3.3%	3.0%	2.9%	2.3%	1.9%	1.4%	1.3%	1.1%	1.0%
CANNc-IT	Crisis	UE-IT	FCE-IT	HICP_H-IT	PG-IT	HICP_HS-IT	HICP_AR-IT	MEI-IT	GDP-IT	HFCE-IT	HICP_M-IT	LTL-IT	ANNI-IT	CPI-IT	GGD-IT
% *	81.3%	9.5%	1.6%	1.2%	1.0%	0.6%	0.6%	0.6%	0.6%	0.6%	0.5%	0.5%	0.5%	0.5%	0.4%
CANN-GB	-	PG-GB	ANNI-GB	HICP_AR-GB	UE-GB	HICP_HS-GB	HFCE-GB	FCE-GB	MEI-GB	GGD-GB	HICP_M-GB	GDP-GB	LTL-GB	HICP_H-GB	CPI-GB
% *	-	26.1%	8.7%	7.3%	7.3%	6.0%	5.9%	5.5%	5.3%	5.1%	4.7%	4.7%	4.5%	4.5%	4.3%
CANNc-GB	Crisis	PG-GB	ANNI-GB	UE-GB	HICP_HS-GB	HFCE-GB	GGD-GB	LTL-GB	MEI-GB	HICP_AR-GB	CPI-GB	GDP-GB	HICP_M-GB	FCE-GB	HICP_H-GB
% *	42.3%	28.9%	6.4%	2.9%	2.9%	2.6%	2.4%	2.4%	2.2%	1.7%	1.2%	1.2%	1.1%	1.1%	0.9%
CANN-PL	-	UE-PL	FCE-PL	HFCE-PL	HICP_HS-PL	PG-PL	HICP_H-PL	ANNI-PL	HICP_AR-PL	HICP_M-PL	MEI-PL	GDP-PL	CPI-PL	GGD-PL	LTL-PL
% *	-	69.7%	4.9%	4.6%	4.5%	4.2%	4.1%	1.8%	1.2%	1.1%	1.0%	0.8%	0.8%	0.7%	0.7%
CANNc-PL	Crisis	UE-PL	HICP_AR-PL	HICP_H-PL	HFCE-PL	FCE-PL	ANNI-PL	HICP_HS-PL	HICP_M-PL	PG-PL	MEI-PL	CPI-PL	GGD-PL	GDP-PL	LTL-PL
% *	66.8%	20.3%	2.1%	1.9%	1.5%	1.5%	1.5%	0.9%	0.7%	0.7%	0.5%	0.4%	0.4%	0.4%	0.3%
CANN-PT	-	PG-PT	UE-PT	HICP_M-PT	ANNI-PT	MEI-PT	HICP_H-PT	HFCE-PT	GDP-PT	HICP_AR-PT	HICP_HS-PT	LTL-PT	FCE-PT	GGD-PT	CPI-PT
% *	-	26.1%	17.4%	6.5%	6.3%	5.5%	4.8%	4.6%	4.4%	4.3%	4.1%	4.0%	4.0%	4.0%	4.0%
CANNc-PT	Crisis	PG-PT	UE-PT	MEI-PT	ANNI-PT	HICP_H-PT	HFCE-PT	HICP_M-PT	HICP_AR-PT	GDP-PT	CPI-PT	LTL-PT	FCE-PT	GGD-PT	HICP_HS-PT
% *	67.6%	6.6%	3.1%	2.1%	2.1%	2.0%	2.0%	1.9%	1.9%	1.8%	1.8%	1.8%	1.8%	1.8%	1.6%
CANN-IE	-	PG-IE	HICP_AR-IE	UE-IE	ANNI-IE	HFCE-IE	HICP_HS-IE	HICP_M-IE	HICP_H-IE	CPI-IE	FCE-IE	MEI-IE	GDP-IE	LTL-IE	GGD-IE
% *	-	46.5%	12.7%	11.9%	9.5%	5.8%	4.7%	1.6%	1.5%	1.3%	1.3%	0.9%	0.8%	0.7%	0.7%
CANNc-IE	PG-IE	UE-IE	Crisis	ANNI-IE	HICP_AR-IE	HFCE-IE	HICP_HS-IE	HICP_H-IE	HICP_M-IE	CPI-IE	FCE-IE	MEI-IE	GDP-IE	GGD-IE	LTL-IE
% *	39.0%	15.5%	12.2%	9.6%	6.9%	5.6%	4.0%	1.3%	1.1%	1.1%	1.1%	0.8%	0.7%	0.7%	0.5%
CANN-GR	-	PG-GR	UE-GR	FCE-GR	HICP_AR-GR	MEI-GR	HICP_HS-GR	HICP_H-GR	GDP-GR	ANNI-GR	HFCE-GR	HICP_M-GR	LTL-GR	GGD-GR	CPI-GR
% *	-	26.1%	16.5%	7.9%	7.0%	5.3%	4.8%	4.6%	4.6%	4.4%	4.2%	3.9%	3.7%	3.6%	3.6%
CANNc-GR	Crisis	PG-GR	UE-GR	HICP_AR-GR	FCE-GR	HICP_M-GR	ANNI-GR	MEI-GR	HFCE-GR	HICP_H-GR	GDP-GR	LTL-GR	HICP_HS-GR	GGD-GR	CPI-GR
% *	37.8%	21.5%	7.6%	3.6%	3.1%	3.0%	2.9%	2.8%	2.8%	2.8%	2.6%	2.5%	2.5%	2.4%	2.2%
CANN-ES	-	UE-ES	HICP_HS-ES	ANNI-ES	HICP_H-ES	HICP_M-ES	GDP-ES	FCE-ES	PG-ES	HFCE-ES	HICP_AR-ES	LTL-ES	MEI-ES	CPI-ES	GGD-ES
% *	-	30.5%	17.8%	8.7%	5.9%	5.8%	5.4%	4.1%	4.0%	3.3%	3.1%	2.9%	2.9%	2.8%	2.7%
CANN-ES	Crisis	UE-ES	HICP_HS-ES	ANNI-ES	HICP_M-ES	HICP_H-ES	PG-ES	FCE-ES	GDP-ES	HFCE-ES	HICP_AR-ES	MEI-ES	CPI-ES	LTL-ES	GGD-ES
% *	68.0%	14.2%	4.0%	3.9%	2.1%	1.4%	1.3%	0.8%	0.8%	0.7%	0.6%	0.6%	0.6%	0.5%	0.5%

* - % contribution of the variable.