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Clustering and forecasting inflation expectations using the World Economic Survey: the case of the 2014 oil price shock on inflation targeting countries *

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Abstract

This paper examines inflation expectations of the World Economic Survey for ten inflation targeting countries. First, by a Self Organizing Maps methodology, we cluster the trajectory of agents inflation expectations using the beginning of the oil price shock occurred in June of 2014 as a benchmark in order to discriminate between those countries that anticipated the shock smoothly and those with brisk changes in expectations. Then, the expectations are modeled by artificial neural networks forecasting models. Second, for each country we investigate the information content of the quantitative survey forecast by comparing it to the average annual inflation based on national consumer price indices. The results indicate the presence of heterogeneity among countries to anticipate inflation under the oil shock and, also different patterns of accuracy to predict average annual inflation were found depending on the observed inflation trend.

Key Words: Inflation expectations, machine learning, self-organizing maps, nonlinear autoregressive neural network, expectation surveys
JEL Classification: C02, C222, C45, C63, E27

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1 Introduction

Subjective data from economic expectations surveys across countries has contributed recently on studying crucial empirical macroeconomic issues focused on expectations formation and forecasting. Expectations serves as guidance for real economic variables and policy decision makers and specifically, inflation expectations are crucial for countries where targeting inflation were implemented as the monetary policy rule. In general , their usefulness is considered on various kinds of tasks. For instance, to test theories of inflation rigidities, to estimate key structural parameters, to test the public understanding of the monetary policy. In addition, inflation expectations serve as a predictor variable in both macroeconomic models and business cycles turning points forecasting models.

Expectation surveys have been applied to different agents, which include economic experts, central bankers, financial agents, consumers, and firms. The implementation helps to provide a stock of data that could be converted into an informational source about the effectiveness of the economic policies and the economic agents level of institutional confidence. In the inflation expectations case, surveys advise to the monetary policy makers about anchoring of inflation. One source to obtain those expectations is through the World Economic Survey (WES), which is conducted among more than 1000 economic experts in approximately 120 countries. The respondents evaluate the present economic situation and the outlook of their own country given special attention to price trends answering qualitative and quantitative questions.

In this sense, we pay particular attention to analyze a sample of inflation targeting countries and take into account the oil price shock of 2014 on their inflation expectations and other macroeconomic indicators due to their oil dependency as exporters or importers. With this aim, the forecast evaluation takes place after the oil's shock period from the 2014.QIII to 2016.QII. Also, for a better understanding of agents' expectations behavior and to obtain optimal forecasts, the combination between clustering and forecasting analysis can be used synergistically. Thus, data visualization techniques are useful to discover relevant characteristics and to perform clustering of agents' expectations. Furthermore, machine learning methodologies could be employed to forecast inflation expectations based on qualitative questions of WES surveys.

The objective of this article is twofold: firstly, we rely on Claveria et al. (2016) (1) , and make use of the Self-organizing maps, SOM, as a clustering technique on the agent's expectations for some targeting countries to discriminate them after the oil's shock of 2014 between soft or brisk behaviors. Then, we predict the inflation expectations evaluating, at different horizons, the forecasts from different models specifications of the Non-linear Autoregressive Neural network (NAR-NN). Secondly, we examine the informational content of the quantitative prediction of the average annual inflation on the WES in order to obtain further reliable inflation forecasts.

This paper contains five sections apart from this introduction. In the second section, the methodologies of the models for clustering and forecasting are presented, emphasizing in the neural network techniques. Section 3 described the expert economic survey data and how the qualitative expectations indicators were aggregated. In section 4, we presented the main results, including the clustering analysis and forecasting accuracy. Next in section 5, the statistical evaluation of the quantitative inflation question is assessed. Finally, conclusions and future extensions are proposed.

2 Methodology

This section describes the clustering and forecasting methodologies from the point of view of machine learning methodologies from which artificial neural networks models have been widely used due to their abilities to fulfill these tasks. The most frequent model in clustering is the Kohoens Self-organizing maps, SOM, and to forecasting the multilayer perceptron from which the Non-linear autoregressive neuronal network, NAR-NN, is a subclass.

2.1 Artificial neural networks

In order to explain the ANNs framework, we start looking at the key points of the simple neural network model that are the base of the SOM and NAR-NN models.

ANNs are a kind of parallel computing systems consisting of a number of simple interconnected processors called neurons or nodes, which through a learning process adjust their parameters to approximate non-linear functions between a set of inputs (variables) and the output (results), see Jain et al. (1996) (2). Thus there is not required assumptions about the generating process data which allowed them to be a more flexible model.

Following Hagan et al. (2016) (3), the simplest neuron model is composed by a scalar input p, called a single variable, which is multiplied by a scalars weight w. Then, wp plus the bias b form the called net input n, which is send to the activation function f, to produce the scalar neuron output a. However, ANN's architecture may be more complex, they can have multiple inputs, layers and neurons as show the figure 1.

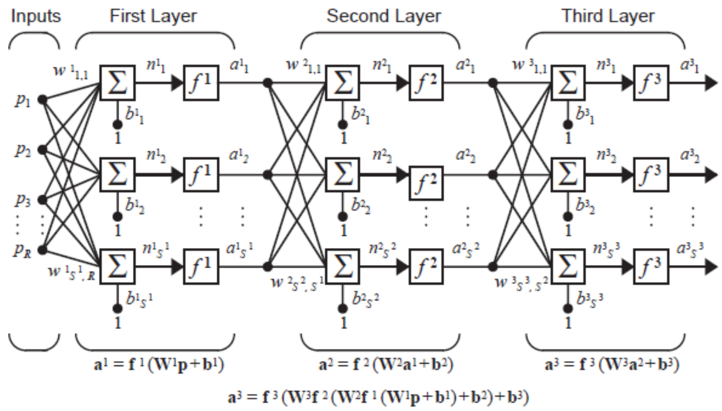


Figure 1: A three layer neural network. Based on Hagan et al (2014)

The parameters, weights and biases, are adjusted with some learning rule (eg. kohonen's learning rule), and the activation function is chosen according the task wanted to solve. For example, in the case of the SOM, were used the Competitive function. This networks are feed forward, which means that there no loops between outputs and inputs [1]. To see more details about ANNs see Hagan et al. (2016) (3).

2.2 Self-organizing maps

In this paper, the Self-organized Maps, proposed by Kohonen 1982, are used to cluster the economic agents' expectations before the oil's shock and mapping those expectations after the shock in the resulting cluster map. SOMs are competitive feed-forward networks based on unsupervised training with the property of topology preservation, which means that nearby input patterns should be represented on the map by nearby output units, see Kohonen (2001) (4).

The SOM architecture consists of a two layer network: in the first layer the inputs are multiplied with weights, that were initialized as small numbers. Then the results are evaluated by a competitive function that produce a wining neuron (Best Matching unit). The weights are updated according a learning rule, equation (1), and the neuron's neighborhood are updated too. See the figure (2) below.

$$\mathbf{w}_i(q) = (1-\alpha)\mathbf{w}_i(q-1) + \alpha(\mathbf{p}(q)) \tag{1}$$

The training stage for each iteration consists in adjusting the weighs of the winning neuron and its neighbors by using the learning rule. This process guarantees similarity between the inputs

[1]In the NAR-NN Model to perform multi-steps forecasts the network is transformed into a recurrent network after their parameters were trained as a feed forward network.

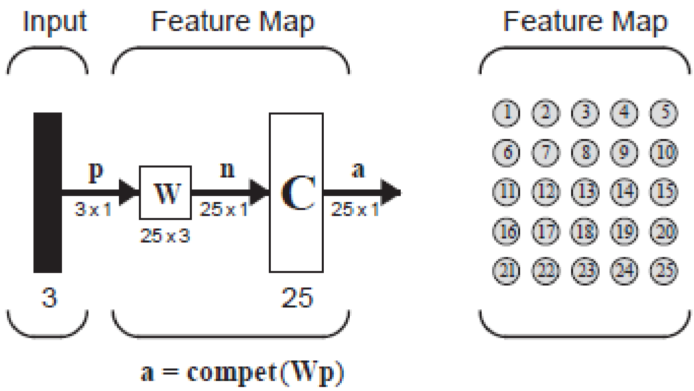


Figure 2: A Self-Organizing Map of 5x5 dimension. Based on Hagan et al (2014)

and the neurons that are represented on the feature map (the second layer of the map). At the end of the process the resulting learned weights capture the data characteristics on the feature map that have two dimensions (3).

Kohonen suggested to use rectangular and hexagonal neighborhoods. Furthermore, with the aim of improving the SOM's performance, we considered to gradually decrease the neighbor size during the training progresses, until it only includes the winning neuron. Also, to take into account the trade-off between fast learning and stability, the learning rate can be also decreased in this phase. This is given by the fact that a high learning rate at the beginning of the training phase allows a quick but unstable learning. On the other side, with a small rate, the learning becomes slow but more stable.

2.3 Nonlinear auto-regressive neural network

In this subsection we describe the main issues of the NAR-NN methodology which includes the training algorithm selected. The model assumes that the current observation could be explained by the compromise of two components: the signal and the noise. The first is an unknown function that is approximated by the neural network to the inflation expectation time series with an autoregressive structure. The second component is the noise, which is assumed to be independent with zero mean. The model equation is stated below:

$$Y_t = g(Y_{t-1} + Y_{t-2} + \ldots + Y_{t-p}) + e_t \tag{2}$$

In order to obtain the best approximation for g , the neural network architecture should meet the following three conditions: it has to avoid overfitting [2], the predicted error should be

[2] Overfitting is a characteristic that should be avoided and occurs when the neural network fit the data closely in

uncorrelated through time, and the cross-correlation function between the predicted errors and the observed time series should be close to zero. In this paper we rely on the Bayesian regularization framework to approximate g in a parsimonious way.

The objective function for the Bayesian regularization setup is given by:

$$F(x) = \beta \sum_{t=1}^{T} (Y_t - \hat{Y}_t)^T (Y_t - \hat{Y}_t) + \alpha \sum_{i=1}^{n} x_i^2 \tag{3}$$

Which is the weighted combination between the model fit and the smoothness. The parameter α penalizes the model complexity and β reflect the goodness of fit. The term x_i^2 is the sum squared of the parameters values of the network, weights and biases.

Using the Bayesian theorem sequentially, the joint posterior distribution of the parameters α and β given the data D and the neural network model chosen M, is computed by multiplying the likelihood times the joint a-priori distribution of α and β divided by the evidence:

$$P(\alpha, \beta | D, M) = \frac{P(D|\alpha, \beta, M) P(\alpha, B|M)}{P(D|M)} \tag{4}$$

The a priori joint density for α and β is assumed to come from the uniform distribution. Consequently, the posterior could be obtained by computing the following probabilities:

$$P(D|\alpha, \beta, M) = \frac{P(D|X, \beta, M) P(X|\alpha, M)}{P(X|D, \alpha, \beta, M)} \tag{5}$$

$$P(X|D, \alpha, \beta, M) = \frac{P(D|X, \beta, M) P(X|\alpha, M)}{P(D|\alpha, \beta, M)} \tag{6}$$

to see the technical details and the full training algorithm see Hagan et al (2016) (3)

The adaptation of the algorithm requires to set the neural network architecture, M, which means we have to pick the number of neurons in the input layer, the number of hidden layers, the number of neurons per hidden layer and the number of neurons in the output layer, to more details see Zhang et al (1998) (5).

Bayesian regularization guarantee that the parameters sum is optimal for the given data. In order to optimize the regularization parameters the objective function $F(x)$ should be minimized following the Levenberg-Marquardt Back propagation algorithm.

Given the Bayesian regularization results there is flexibility to model the architecture of the

the training set, but in the testing set and out of sample, the fitting is poor.

network. For the hidden layer, we set a fix number of nodes, where their parameters, weights and biases, always will sum a small amount. We used just one hidden layer due to the length of the series. We observed that an extra layer did not change significantly the results. With respect to the output layer, one node is used because the forecast is one-step-ahead. The selection of the adequate number of input nodes or lags will be explained in the NAR-NN results section. In order to improve the generalization of the network, the methodology usually requires to divide the data into three sets: the training, validation and testing. However, the Bayesian regularization avoid the validation stage because the solution is based on the optimization of the equation (3).

We employed the hyperbolic Tangent Sigmoid as activation function for the nodes in the hidden layer as is showed below, which is frequently used in forecasting.

$$a = \frac{e^n - e^{-n}}{e^n + e^{-n}} \tag{7}$$

$$a = n \tag{8}$$

To the output layer the linear function is used. Notice that before training the network, data normalization, which transform the data in the interval between [-1, 1], is required to faster the training algorithm.

$$p^n = \frac{2(p - p^{min})}{(p^{max} - p^{min})} - 1 \tag{9}$$

3 World economic survey data

The data source of our empirical analysis came from the World economic Survey (WES) applied by the IFO Institute for Economic Research.

The surveys contain qualitative and quantitative questions related to diagnostics and expectations covering different macroeconomic topics: economic growth, interest rates, consumption, capital, exchange rates and inflation, among others [3]. These opinion surveys are responded quarterly by economic experts mostly from public and private sector and academy. The subjective response could be classified as positive, neutral or negative. These opinions are analyzed by assigning values to the responses in the following way: where the response is considered positive a numerical value of 9 is coded. A value of 5 represent a neutral choice and a value of 1 express the negative response. Next, the average rating is calculated by country for each question. Traditionally the analysts divide by the following rule: a positive zone is related to an average greater than 5, and the negative is

[3] An example of the World economic survey WES questionnaire was include in the appendix A, see figure 12

below to 5. Nevertheless, the neutral zone depends on the subjectivity of the analyst. One of results of this paper is to establish the limits of the three zones by letting the data speaks for itself.

The WES survey also introduce a quantitative questions about the future inflation. This question is also evaluated through the forecasting error decomposition in the section 6. To see more about WES see Stangl (2007) (6, chap. 5), and Stangl(2007) (7).

For SOM and NAR-NN models we rely on the qualitative WES questions. Thus, we select expectations of the next six months for 16 inflation targeting countries around the world that ranges from 1991.QIII to 2016.QII. The sample of countries analyzed were Brazil, Canada, Switzerland, Chile, Colombia, Czech Republic, United Kingdom, Hungary, Korea Republic, Mexico, Norway, Philippines, Poland, Sweden, Thailand, South Africa. In figure 5 the inflation expectations indicator and the actual annual inflation are plotted for some countries of the sample [4] [5]. In addition we include a summarize of or data, their histograms, and their correlation, relevant to the SOM analysis [6]. Furthermore, we applied traditional unit root tests to study the properties of the inflation expectations time series, see the results on table A.7 in appendix A.

	Overall economy	Capital expenditures	Private consumption	Inflation rate
Min	1	1	1	1
1stQ	4.8	4.7	4.57	4
Median	5.8	5.7	5.5	5.5
Mean	5.79	5.59	5.44	5.32
3rdQ	6.8	6.6	6.5	6.8
Max	9	9	9	9

Table 1: Data Summary of WES expectations

[4]We did not include all the inflation targeting countries in our study because the survey for them stared at the different dates

[5]Figure 11 in Appendix A contains the full time series length

[6]Figure 3 shows that our variables have variation, figure 4 shows the correlation between them. Because we are interested in inflation expectation and the other variables do not show a linear correlation with it, we keep them to our analysis.

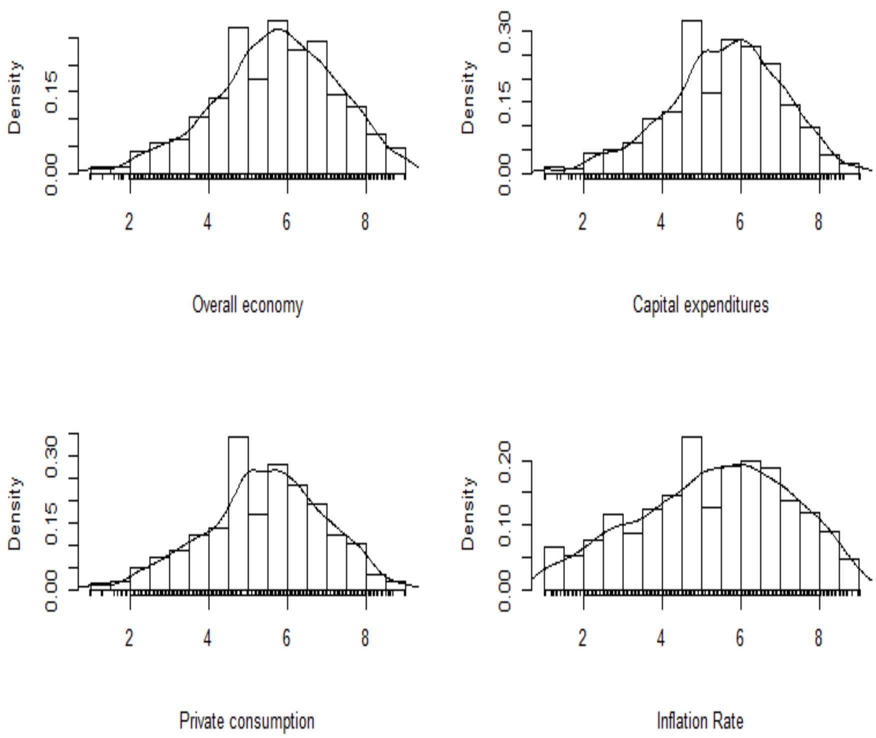


Figure 3: Histograms of Agents' expectations of economic situation for next 6 months in macroeconomic variables

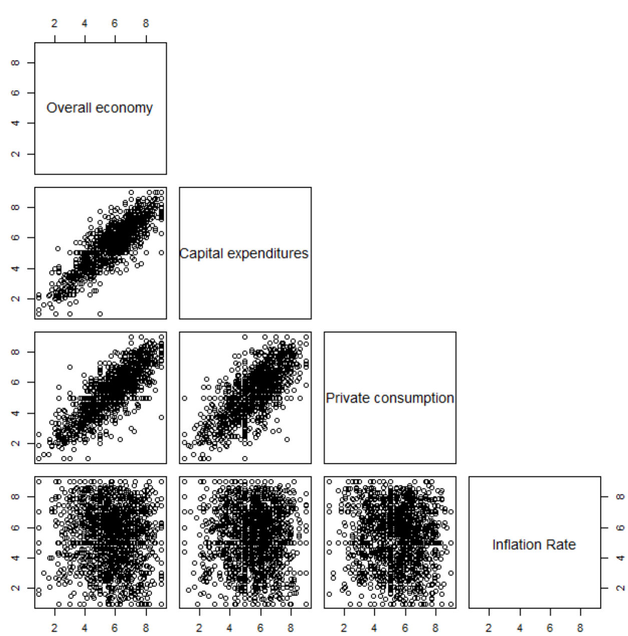
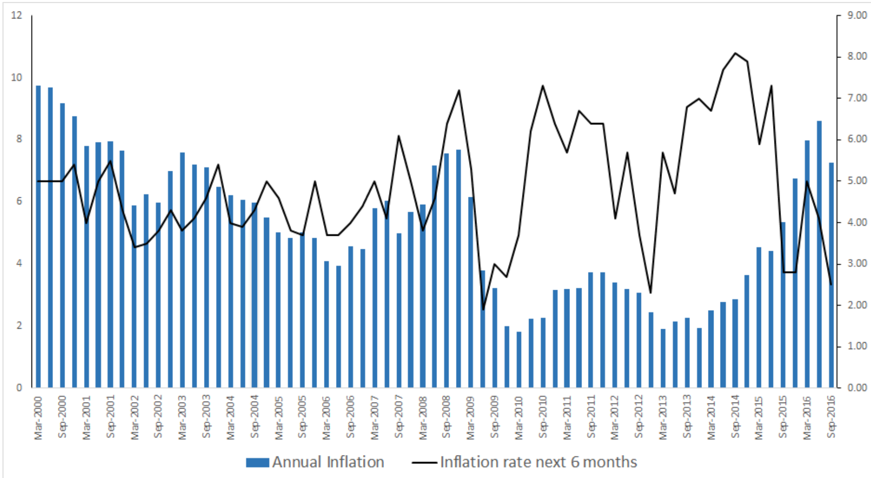
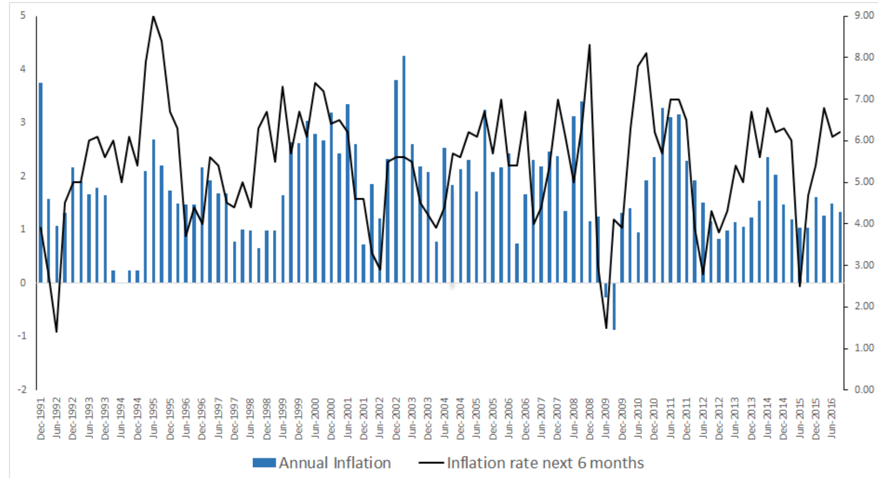


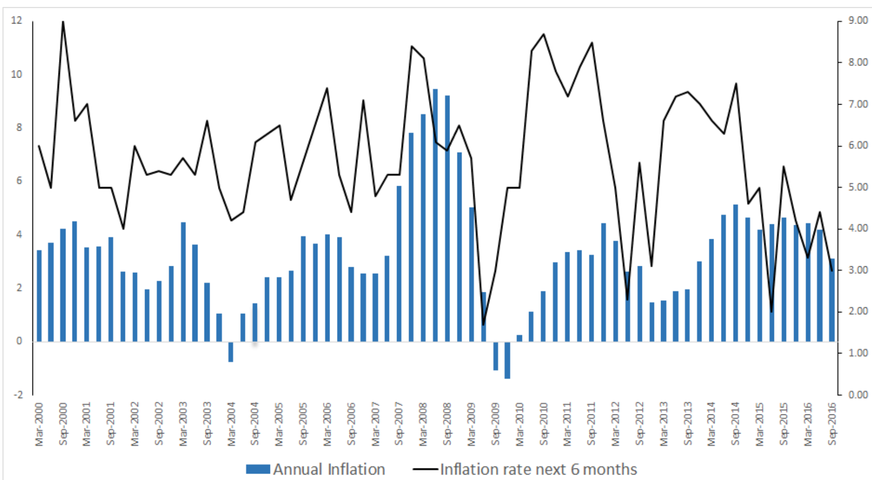
Figure 4: Scatter plot of of Agents' expectations of economic situation for next 6 months



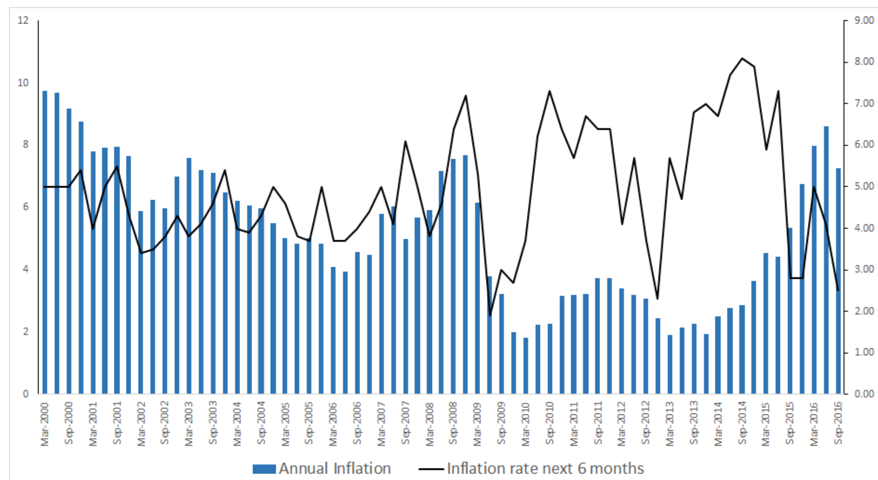
(a) Brazil



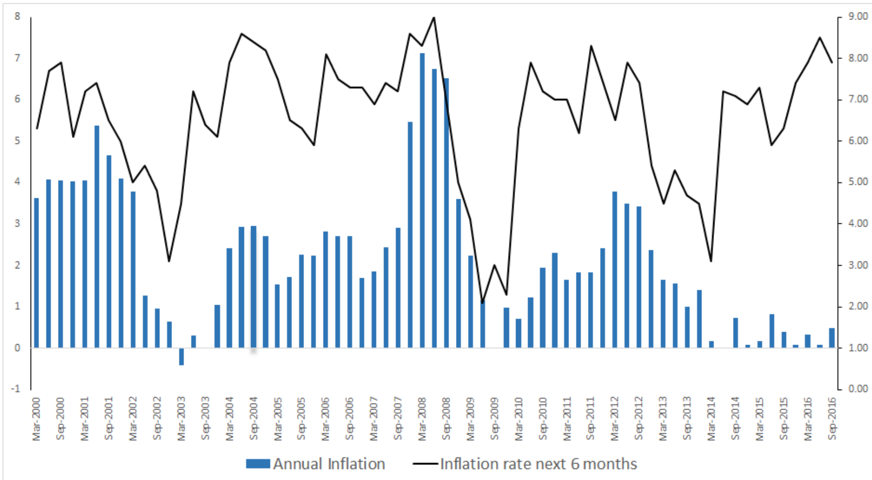
(b) Canada



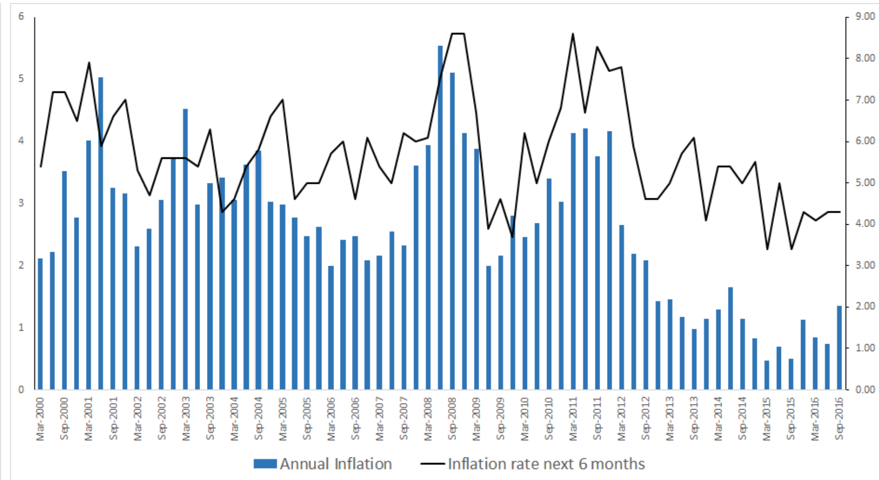
(c) Chile



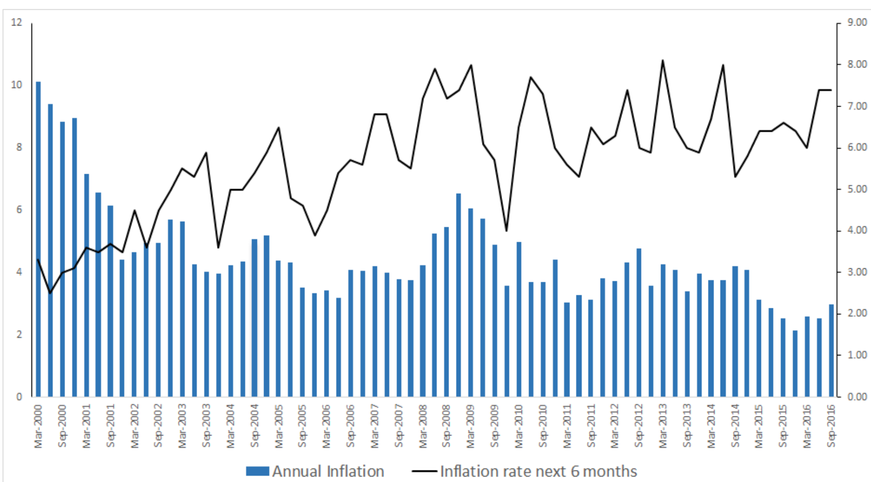
(d) Colombia



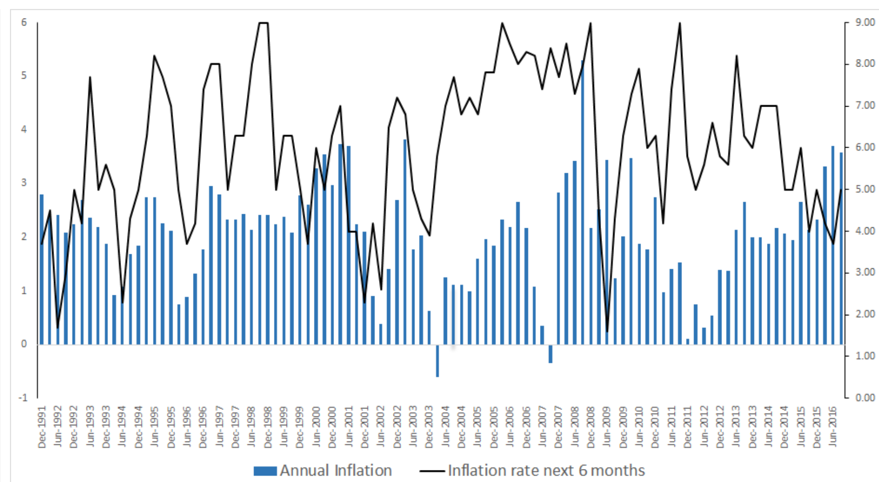
(e) Czech Republic



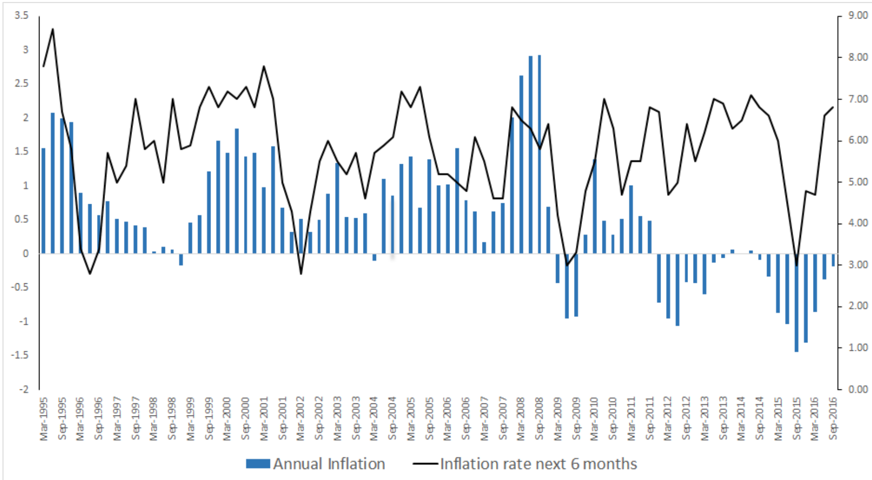
(f) Korea



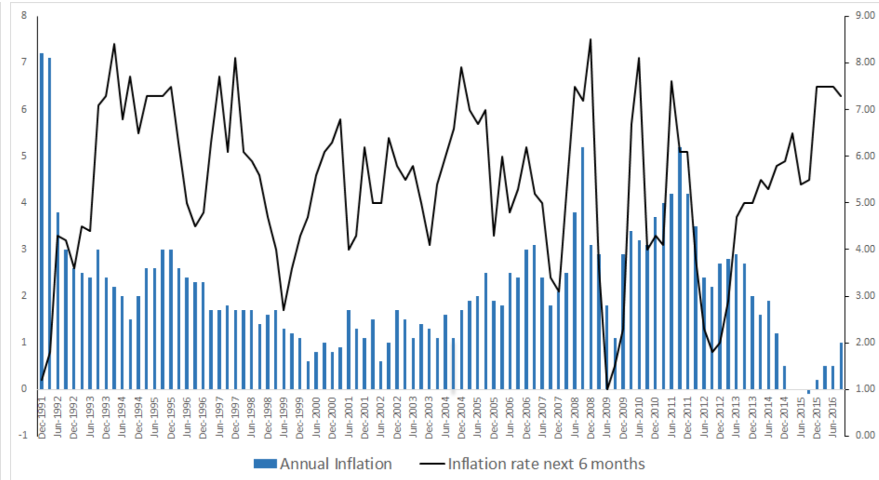
(g) Mexico



(h) Norway



(i) Switzerland



(j) United Kingdom

Figure 5: Countries Inflation Expectations and Annual inflation. Source WES survey and OECD statistics

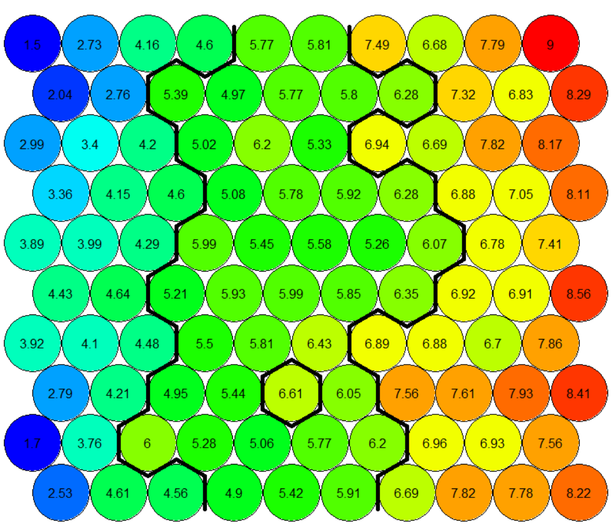
4 Results

In this section we present the main results of the different methodologies related to clustering and forecasting the inflation's expectation. First, we present the SOM analysis, which include sequential steps: the map topology choice based on data, the SOM neural network training and validation and finally the clustering map of agents expectations. These three steps are explained in detail in the appendix B. Then we overlap agents' inflation expectations on the resulting SOM map. By last, the NAR-NN results are developed.

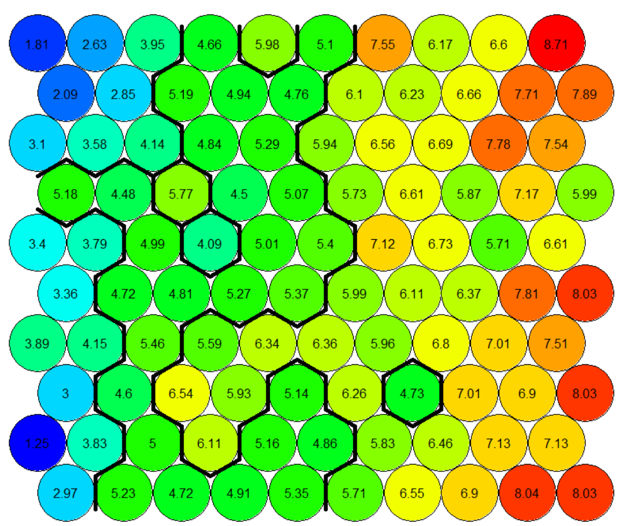
4.1 Self-organizing maps of agents' expectations

Based on the SOM analysis we set a 10X10 hexagonal map with a learning rate varying from 0.05 to 0.0001 and we used 1000 iterations. The computation was realized using the kohonen package in R developed by Wehrens et al. (2007) (8). The training step used observations before the oil shock identified on 2014.QII, which cover a sample of 84 observations per country for the expected situation by the end of the next 6 months of the overall economy, capital expenditures, private consumption and inflation.

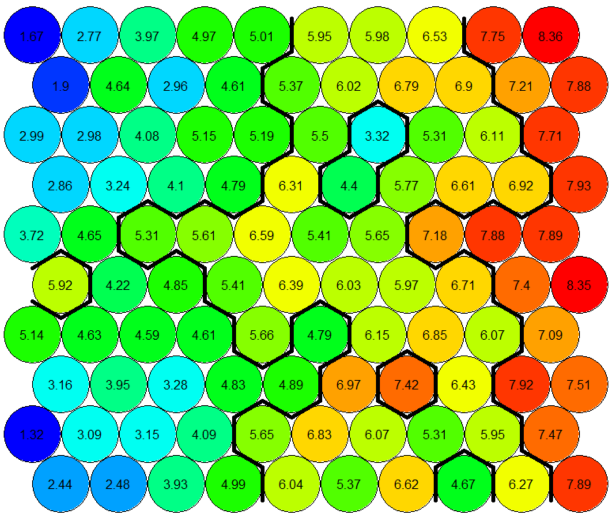
A key tool in this analysis is *the feature map* or *heat map* that is the representation of a single variable across the map (Figure 6). In this application, the colors identify the level of the indicator. For example: the blue color is associated with low expectations and the red with high expectations. Clustering can be performed by using hierarchical clustering on the weight learned vectors of the variable. This procedure requires to set the number of clusters. Thus, given the nature of the expectations we used 3 clusters that represents the low, neutral and high expectations.



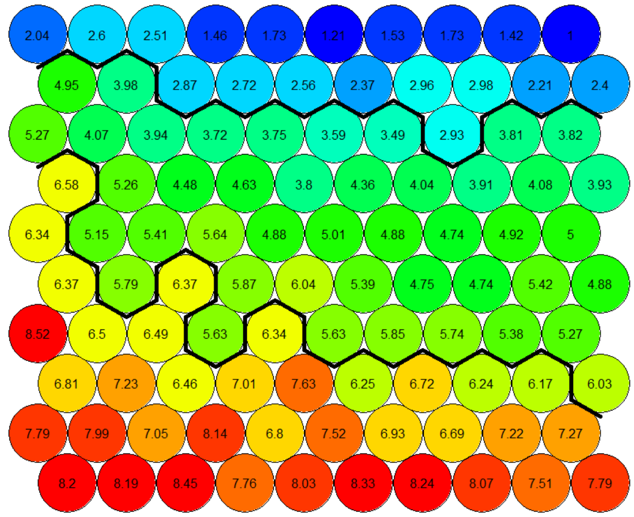
(a) Overall economy



(b) Capital expenditures



(c) Private consumption



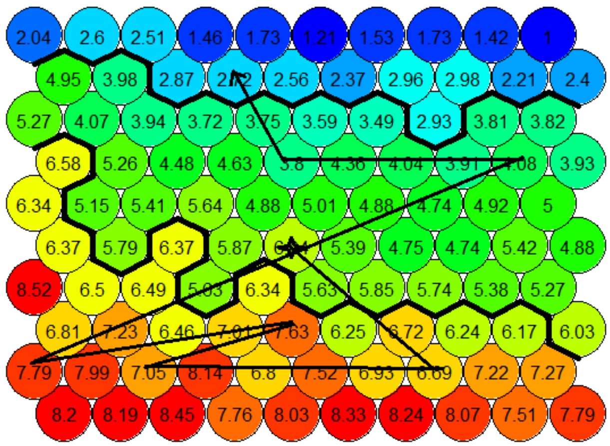
(d) Inflation rate

Figure 6: SOMs of countries economy situation expectations for the next 6 months (1991.QIII to 2014.QIV)

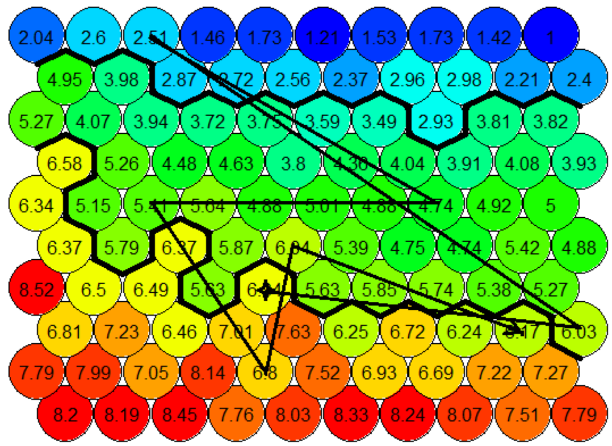
4.2 Overlapping agents' inflation expectations by country

In order to discriminate the agents' inflation expectation patterns after the oil price shock that took place on June of 2014, we overlap those expectation from the third quarter of 2014 to the second quarter of 2016 on the heatmap resulting from the SOM analysis. As a consequence, we classified the expectations patterns by country into two categories: smooth and brisk expectations trajectories. For smooth transitions we expected to found a path that moves through a single cluster. Otherwise, we identify a brisk trajectory by observing a changing path among several clusters. In The figure 7(a), the black arrow represent the trajectory of the inflation expectation with an initial node marked with a black start symbol.

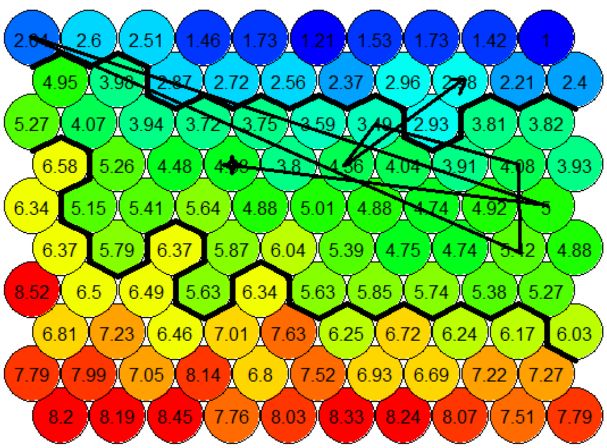
For example, in the case of Colombia, figure 7(d), the observed inflation expectations on July of 2014 are located in the higher expectation cluster, then moves through the Heatmap ending in the lower expectation cluster. We classified this pattern as having brisk expectations behavior. On the other hand, the Korea Republic Inflation expectations (f) remains in the same neutral cluster. Therefore it is classified with a smooth expectation path. Finally, the summary of the classification results for the sample of countries expectations is shown in table 2.



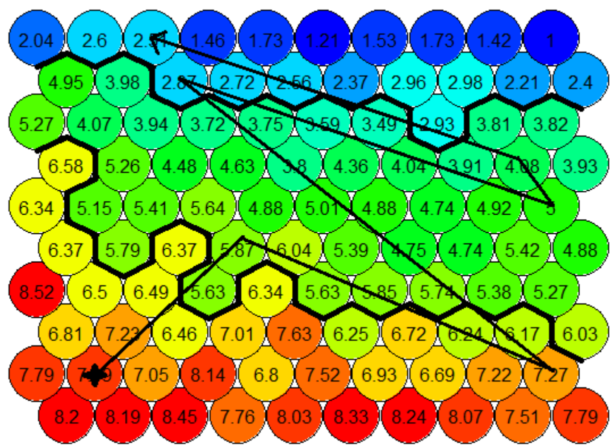
(a) Brazil



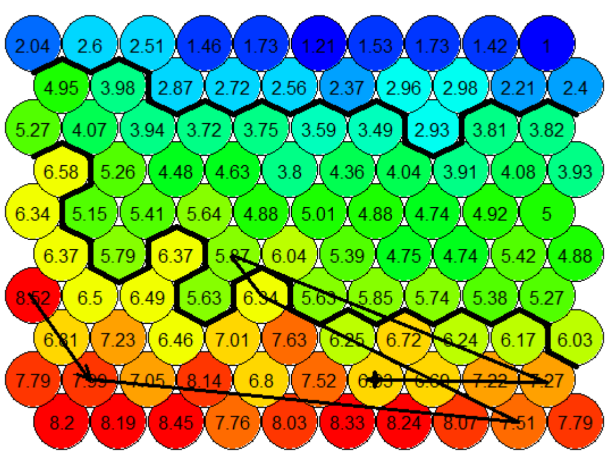
(b) Canada



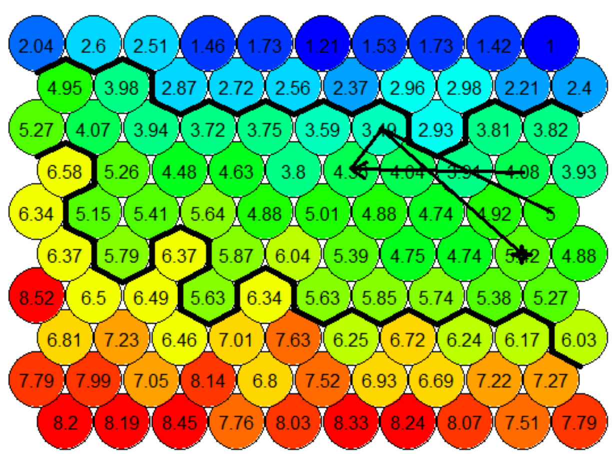
(c) Chile



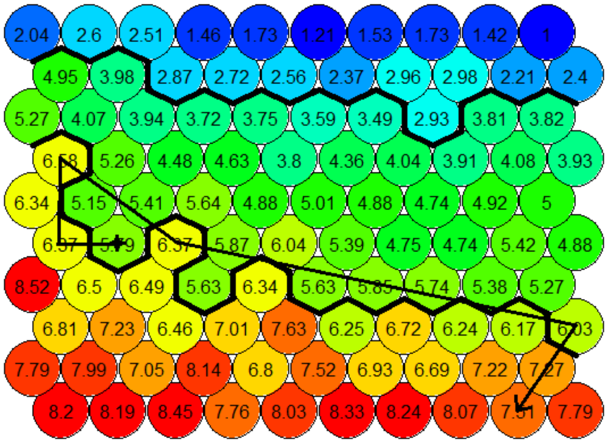
(d) Colombia



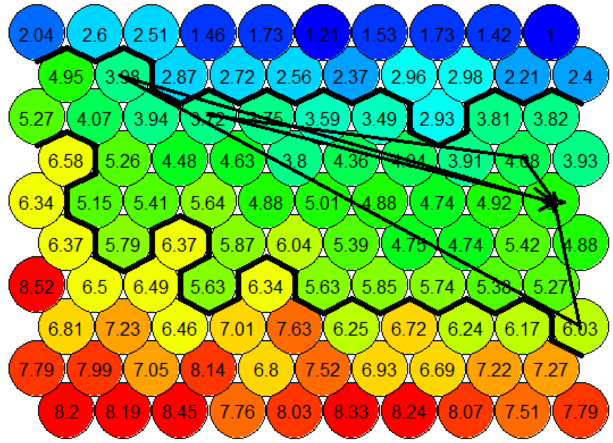
(e) Czech Republic



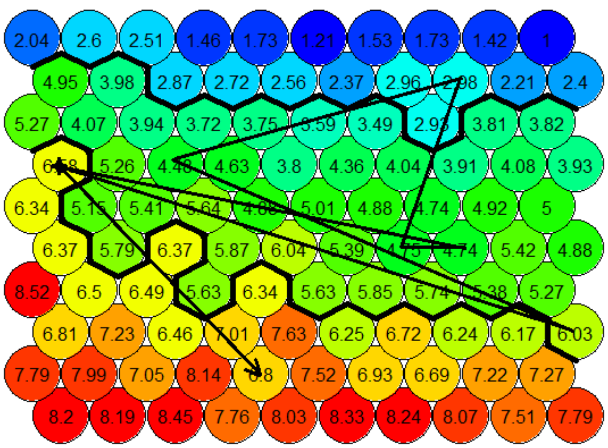
(f) Korea Republic



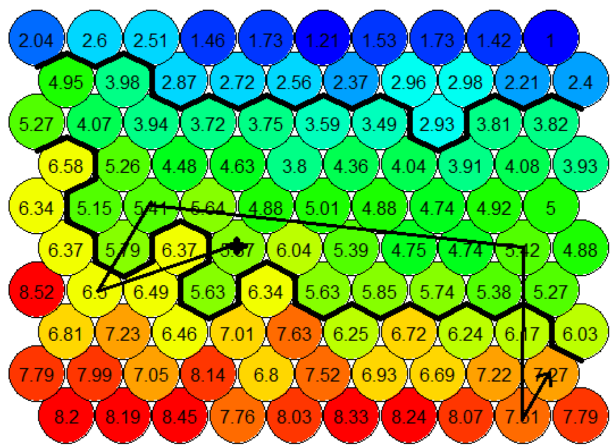
(g) Mexico



(h) Norway



(i) Switzerland



(j) United Kingdom

Figure 7: Countries Inflation rate next 6 months (III.2014 to II.2016) on the Expected Inflation rate SOM Map

Country	Inflation expectation	Lag selected
Brazil	Brisk	1
Canada	Brisk	8
Chile	Smooth	4
Colombia	Brisk	5
Czech R.	Smooth	6
Korea R.	Smooth	2
Mexico	Smooth	6
Norway	Smooth	1
Switzerland	Brisk	8
United K.	Smooth	6

Table 2: Classification of inflation expectations and lag selected in the NAR-NN model

4.3 Non linear autoregressive neural network results

From the Bayesian regulation framework applied to the NAR-NN methodology, we have to select a model M. For each country, the sum of parameters is conditional on the complexity of its data. In this context we chose a flexible network where regularization guarantee the minimum sum of parameters. Thus, we set an architecture with one hidden layer of 10 neurons. Moreover, at the input layer we have to specify the number of neurons, that corresponds to the lag order used to forecast one step ahead. We used the Neural Network Toolbox provided by Matlab (9) .

The lag order selection were based on different criterion's: The mean squared error resulting from the testing data, the error auto-correlation function, and the cross-correlation between the errors and the observed data. In this way, from lags 1 to 10 we generated 30 neural networks per lag and obtain the MSE for the training, testing, and the complete sample. Then, we select the lag that reports the smallest median from the testing data sample taking into account the auto-correlations diagnostics [7]. The lag chosen for each country is presented in table 2 and the overall results from lags 1 to 10 are shown in table 3 [8]. A similar procedure was developed by Ruiz et al. (2016) (10).

Figure 8 displays the observed data (Black line), the fit in the training set (Blue line), the forecasts in horizons 1 and 2 (green and orange lines respectively), and the out of sample forecasts 8 steps ahead (yellow line). Also, the figure 9 is divided into three blocks. The left corresponds to

[7] In most of the cases mean and median, of the lag chosen, are both the smallest. However, in Colombian, Czech R., and Switzerland is not the case, even though the lag's mean is closes to the smallest mean.

[8] These results for all data set, training set and testing set are presented in tables C.8, C.9, and C,10 respectively in appendix C.

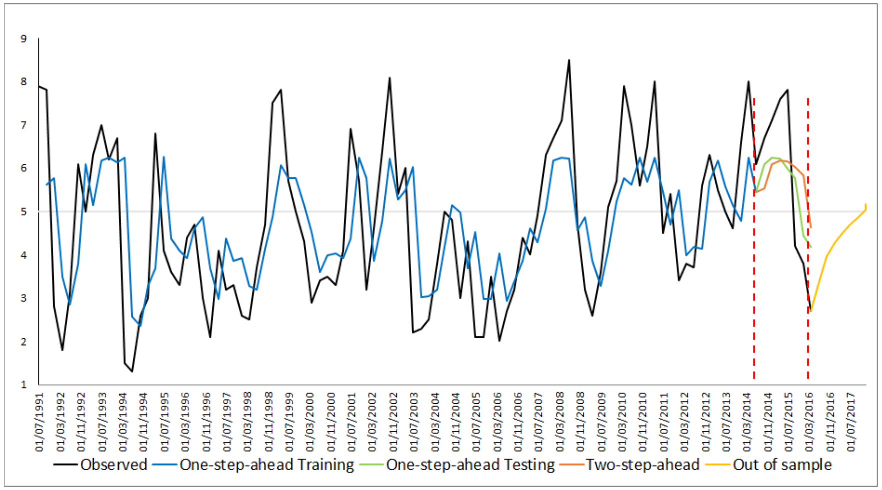
the training set (from 1991.QIII to 2014.QII), the center to the testing set, which is the after oil shock period (from 2014.QIII to 2016.QII), and the right block is the forecasted period. The table 4 contains the mean squared error at different time horizons for the selected countries [9] [10].

Countries	Lags	1	2	3	4	5	6	7	8	9	10
Brazil	mean	**1.70**	2.08	1.85	1.93	1.83	1.85	1.83	1.90	1.92	2.04
	median	**1.69**	2.07	1.85	1.86	1.83	1.85	1.83	1.84	1.92	2.04
Canada	mean	2.02	1.74	1.59	1.63	1.62	1.54	1.56	**1.52**	1.75	1.73
	median	2.03	1.74	1.59	1.63	1.62	1.54	1.56	**1.52**	1.75	1.73
Switzerland	mean	1.32	1.22	1.04	1.04	1.02	0.98	1.06	0.78	0.93	**0.77**
	median	1.31	1.22	1.04	1.04	1.02	0.98	1.06	**0.78**	0.94	0.83
Chile	mean	4.36	2.76	2.75	**2.69**	2.73	2.82	2.90	3.18	3.13	2.92
	median	4.38	2.76	2.79	**2.68**	2.76	2.81	2.88	3.28	3.08	2.91
Colombia	mean	4.94	2.88	2.91	2.95	2.89	**2.88**	2.96	3.26	3.20	3.30
	median	4.97	2.88	2.92	2.88	**2.78**	2.83	2.81	3.23	3.15	3.20
Czech R.	mean	0.73	0.74	0.73	**0.70**	0.93	0.72	1.20	1.24	2.21	1.61
	median	0.74	0.74	0.73	0.70	0.93	**0.67**	1.20	1.24	2.10	1.16
United K.	mean	0.86	0.87	0.95	0.95	0.88	**0.82**	0.84	1.21	0.87	0.85
	median	0.87	0.86	0.95	0.95	0.88	**0.82**	0.83	0.84	0.87	0.83
Korea R.	mean	2.21	**1.86**	1.99	2.02	2.03	2.21	2.40	2.06	2.06	2.05
	median	2.22	**1.86**	1.99	2.02	2.03	2.21	2.40	2.06	2.06	2.05
Mexico	mean	0.38	0.43	0.52	0.49	0.48	**0.34**	0.48	0.35	0.52	1.09
	median	0.38	0.42	0.52	0.49	0.48	**0.30**	0.57	0.37	0.31	0.53
Norway	mean	**1.41**	1.44	1.61	1.67	1.59	2.01	2.04	2.10	1.88	1.80
	median	**1.41**	1.44	1.61	1.67	1.59	2.01	2.04	2.10	1.88	1.80

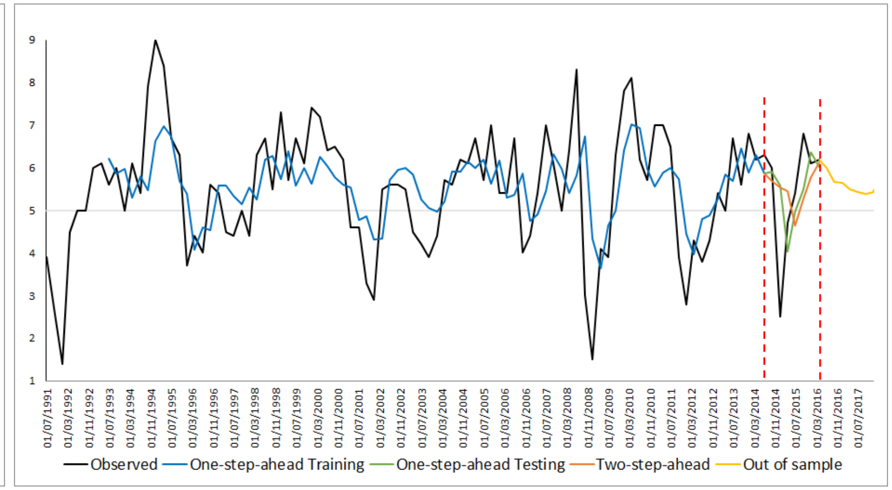
Table 3: Lag statistics test data - forecast one-step ahead. sample = 30

[9] A summary results of the neural networks parameters are presented in table C.11, appendix C

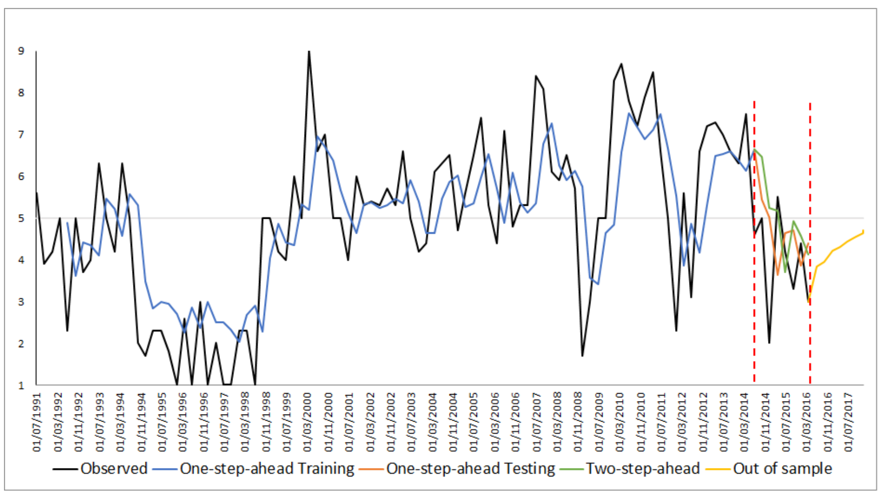
[10] A simulation of 1000 networks was performed to ensure that the MSE presented belongs to the average neural network find after specifying the model previous described. See table C.12, appendix C



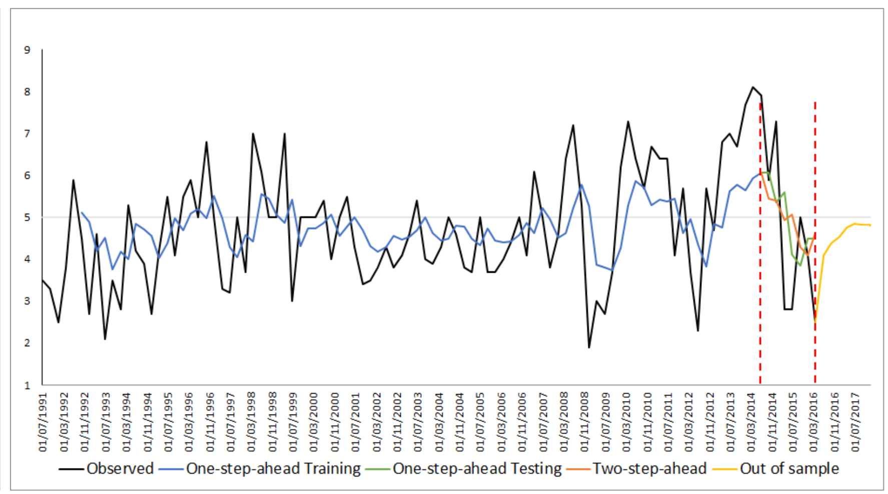
(a) Brazil



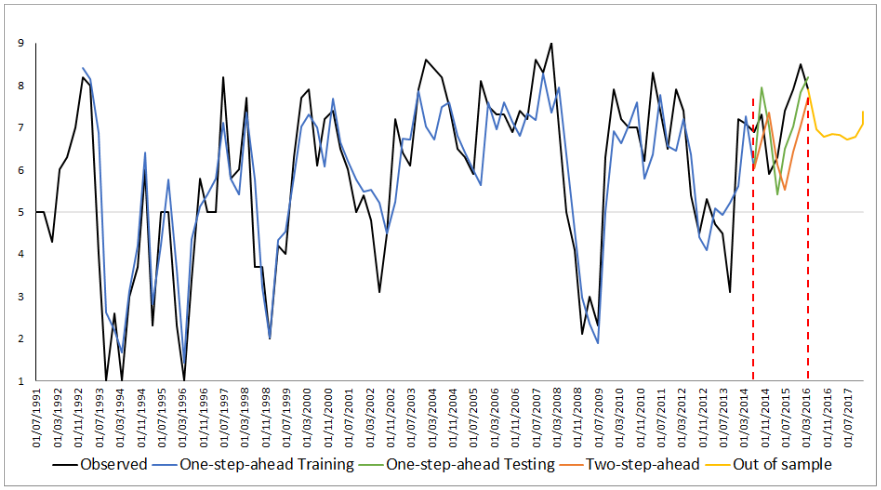
(b) Canada



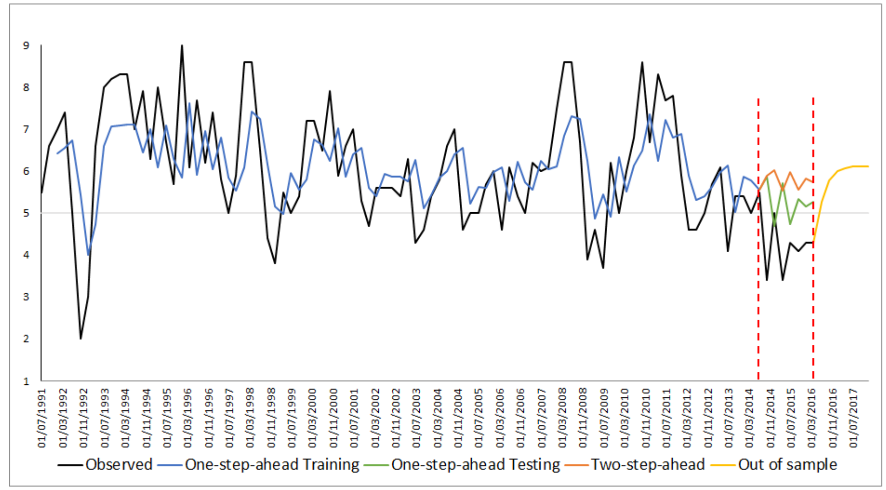
(c) Chile



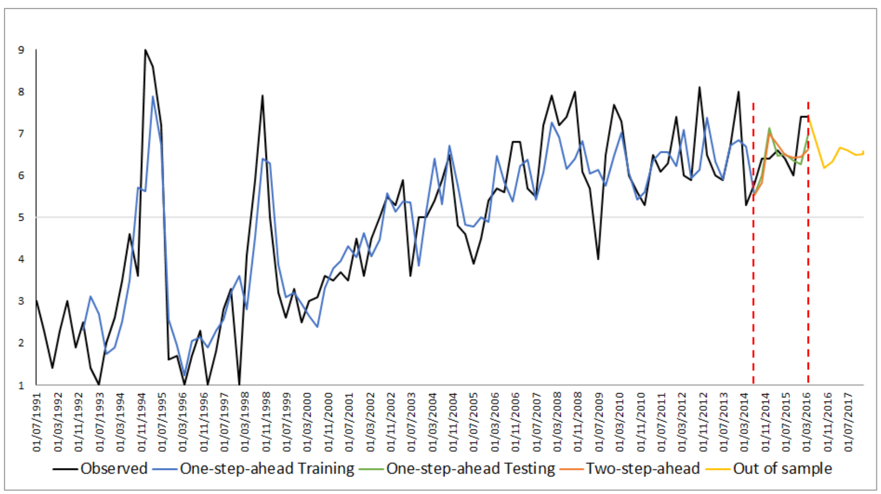
(d) Colombia



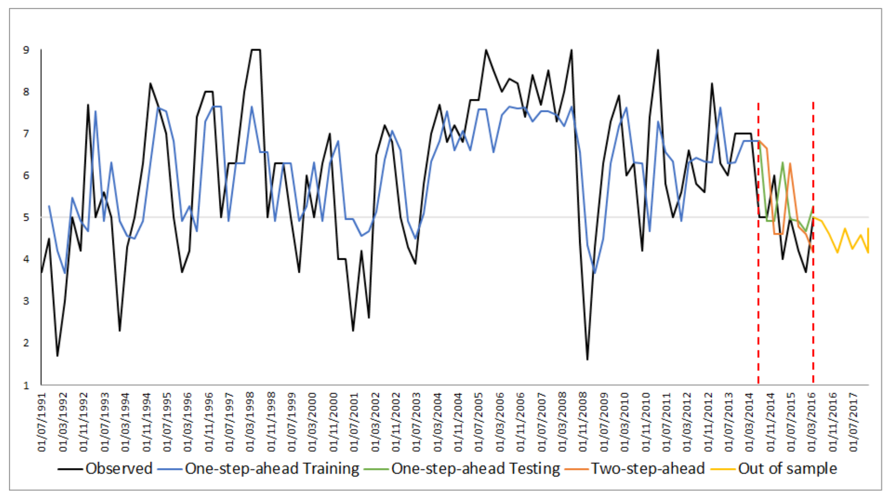
(e) Czech Republic



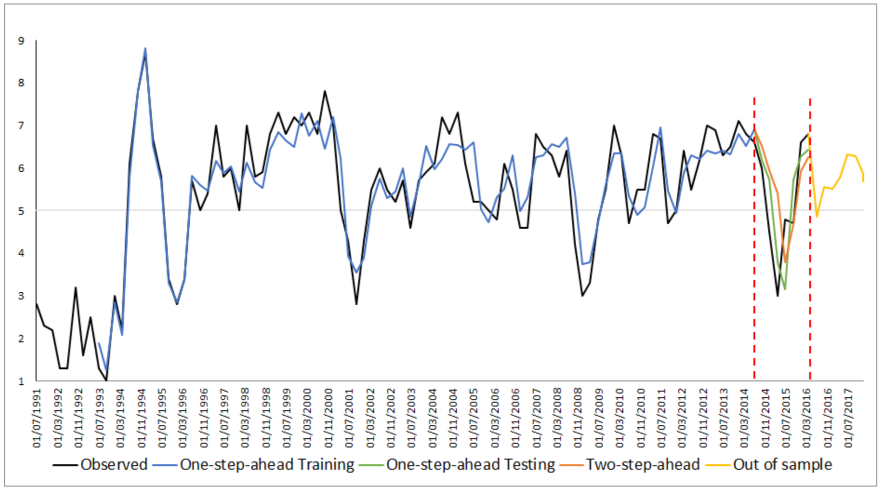
(f) Korea



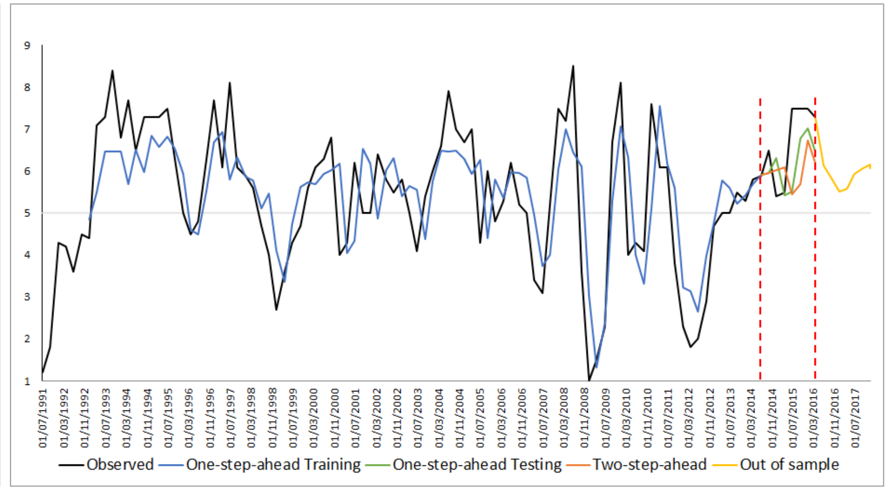
(g) Mexico



(h) Norway



(i) Switzerland



(j) United Kingdom

Figure 8: Countries forecasted Inflation rate next 6 months by NAR-NN

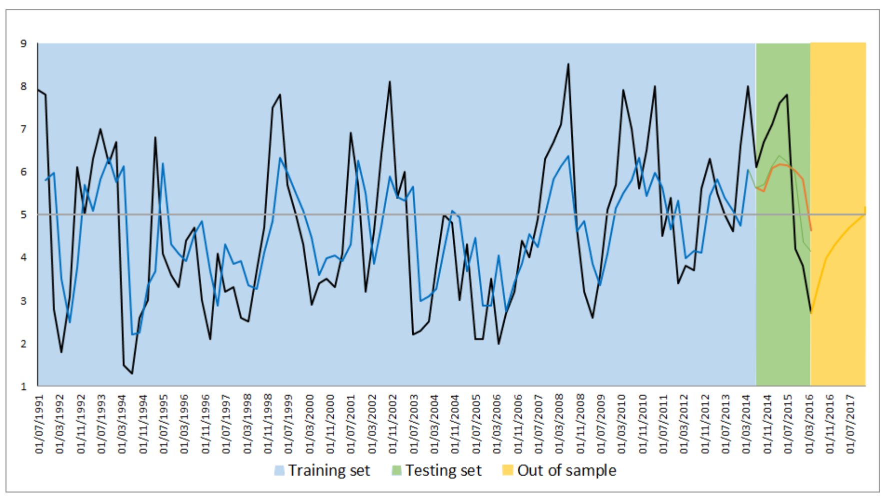


Figure 9: Data block division ant out of sample sets

	All data one steap-ahead	Training set one-step ahead	Testing set one-step ahead	Testing set two-step ahead
Brazil	1,993	2,039	1,470	2,616
Canada	1,320	1,301	1,519	1,834
Chile	2,226	2,185	2,680	2,429
Colombia	1,573	1,462	2,776	2,648
Czech R	0,887	0,908	0,665	1,464
Korea	1,474	1,440	1,857	3,028
Mexico	0,896	0,951	0,299	0,341
Norway	1,846	1,884	1,419	1,221
Switzerland	0,313	0,268	0,781	1,414
United K.	1,215	1,252	0,820	1,465

Table 4: MSE by period and time horizon

5 Quantitative forecasting inflation expectations

This section look at the comparison between annual average inflation based on the CPI and the correspondent quantitative WES inflation assessment which is obtained from the survey question "the rate of inflation on average this year will be: % p.a.". In this section we follow previous works by Fildes and Stekler (2002) (11) and Hammella and Haupt (2007) (6, chap. 9) in order to quantify and examine the accuracy of the WES forecasts at different horizons. It is worth to notice that the expert's information increase from quarter to quarter as data inflation is released.

5.1 Statistical analysis of the forecasting error

The forecast error is calculated in the following way:

$$e(L, Q(h), t) = \bar{p}(L, t) - q(L, Q(h), t) \tag{10}$$

Where L = countries, h = I,II,III,IV, and t = 1991,. . . , 2016 First, we compute different error statistics for each quarter that include the RMSFE (root mean squared forecast error), MAE (mean absolute error), and Theil U-statistic, See Hammella and Haupt 2007 [11].

Second, the error decomposition, based on the mean squared error and proposed by Theil in 1966 (12), is constructed . This illustrated how the error changes conditional on the different forecasting horizons and is divided into three factors: the bias share V_h, the spread share S_h, and

[11] The the respective statistics equations are presented in appendix D.1, also MAE and U-statistic results are in tables D.13 and D.14 respectively, see appendix

the covariance share K_h. The V_h bias component refers to the systematic distortions of the forecast, where bias should decrease through forecast horizons only if the expectations are anchored. The S_h measures the dispersion between the observed inflation and the WES forecast . Finally, K_h assess the linear association between the average inflation and the WES forecast, if the correlation is perfect then $K = 0$. Notice that The three components should add 1.

5.2 Quantitative inflation expectations results

The tables 5 and 6 summarize the RMSFE and its decomposition for the countries selected in previous sections at the different time horizons. According with the results the RMSFE decrease through the year for countries such as Switzerland, Colombia, Korea, and Norway. Nevertheless, there are some countries which shows another pattern where the last forecast is more uncertain such as Brazil, Canada, Chile, Czech Republic, and United Kingdom. These features remain observing the MAE and U-statistics. Figure 10 compare the respective observed annual inflation (bar line) and the WES expectation for each quarter by countries [12] [13].

In Colombia we observed that the actual annual inflation was overestimated during the period 2000 to 2003, then until 2007 the expectations were close to the observed inflation. The 2008 financial crises caused that expectations suffers a short period of underestimation and over estimation till 2014. Finally, the 2014 oil shock induce an underestimated inflation period. There are different patterns across the countries such as Mexico, where the expectations were close to the actual inflation until the oil shock, after the inflation was overestimate.

Countries	4-step forecast (QI)	3-step forecast (QII)	2-step forecast (QIII)	1-step forecast (QIV)
Brazil	182.71	321.48	354.44	431.01
Canada	0.70	0.57	0.42	0.58
Switzerland	0.75	0.50	0.41	0.38
Chile	1.23	1.46	1.36	1.66
Colombia	1.80	1.67	1.43	1.00
Czech R.	2.29	1.16	1.32	2.02
United K.	0.89	0.88	0.90	0.99
Korea	1.61	1.41	1.16	1.09
Mexico	3.37	2.03	4.48	3.62
Norway	0.78	0.65	0.52	0.39

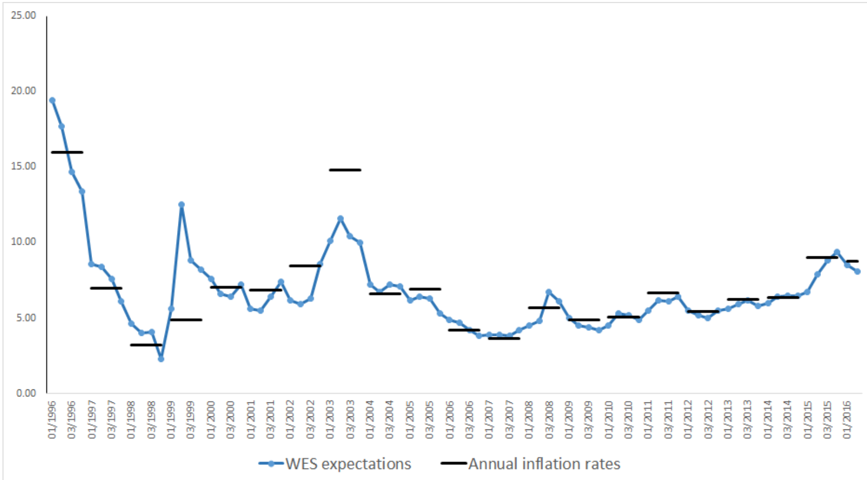
Table 5: Root mean squared forecast errors of WES survey quantitative inflation question

[12] Due to there are some countries with different monetary policies regimens the starting year of the series where adjusted for the scale

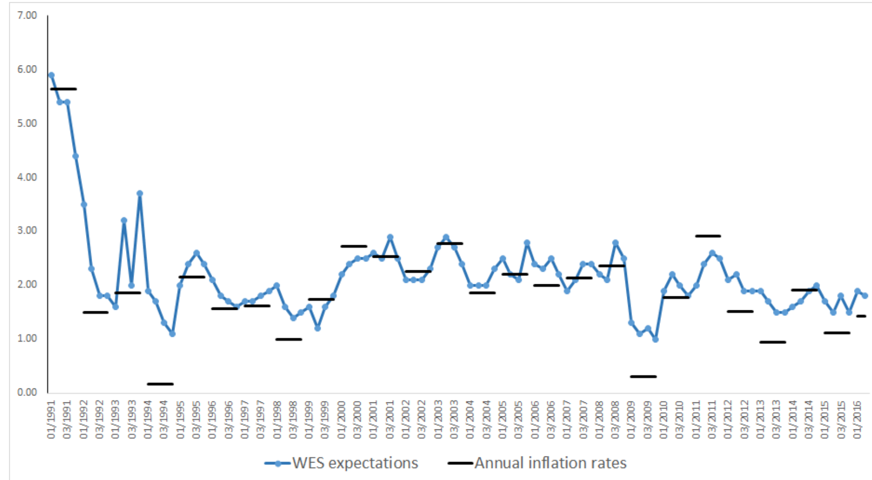
[13] The quarter-specific forecasting error by country is plotted in Figure 17, appendix D

Countries	Error descomposition	4-step forecast (QI)	3-step forecast (QII)	2-step forecast (QIII)	1-step forecast (QIV)
	V	0.13	0.06	0.07	0.01
Brazil	S	0.84	0.81	0.53	0.10
	K	0.06	0.14	0.45	0.92
	V	0.16	0.20	0.31	0.16
Canada	S	0.05	0.14	0.26	0.26
	K	0.83	0.70	0.46	0.61
	V	0.22	0.32	0.30	0.19
Switzerland	S	0.22	0.28	0.37	0.54
	K	0.60	0.55	0.35	0.31
	V	0.003	0.02	0.05	0.02
Chile	S	0.02	0.20	0.74	0.75
	K	1.02	0.84	0.25	0.27
	V	0.003	0.06	0.04	0.01
Colombia	S	0.08	0.02	0.05	0.33
	K	0.96	0.99	0.95	0.71
	V	0.10	0.17	0.05	0.0001
Czech R.	S	0.05	0.38	0.35	0.36
	K	0.88	0.60	0.64	0.68
	V	0.23	0.26	0.18	0.14
United K.	S	0.16	0.28	0.43	0.30
	K	0.64	0.56	0.43	0.60
	V	0.37	0.44	0.52	0.39
Korea	S	0.03	0.002	0.0003	0.02
	K	0.62	0.45	0.50	0.62
	V	0.03	0.13	0.01	0.01
Mexico	S	0.43	0.002	0.11	0.03
	K	0.57	1.04	0.92	1.01
	V	0.06	0.02	0.08	0.02
Norway	S	0.19	0.14	0.13	0.18
	K	0.79	0.79	0.83	0.84

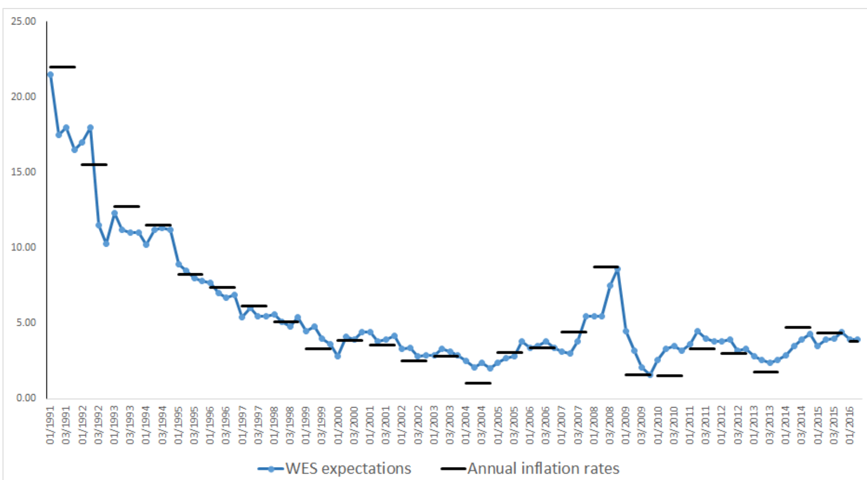
Table 6: Theil error decomposition of the WES forecast errors 1991.I to 2016.II



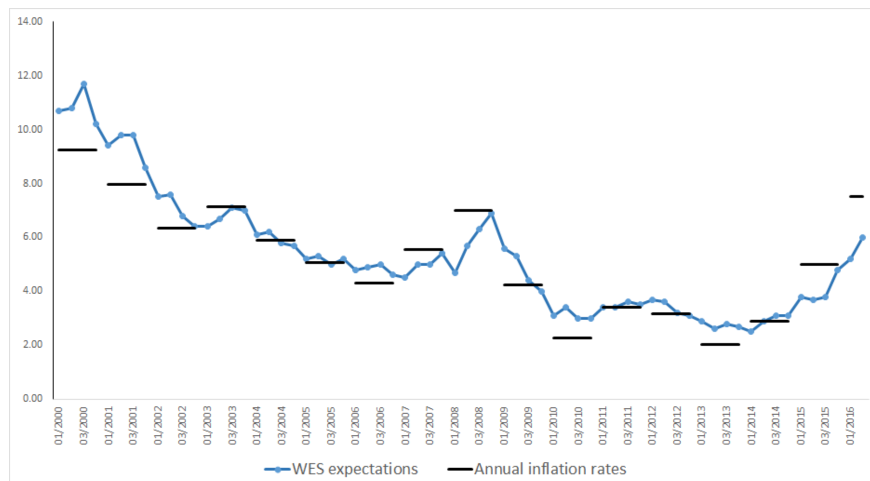
(a) Brazil



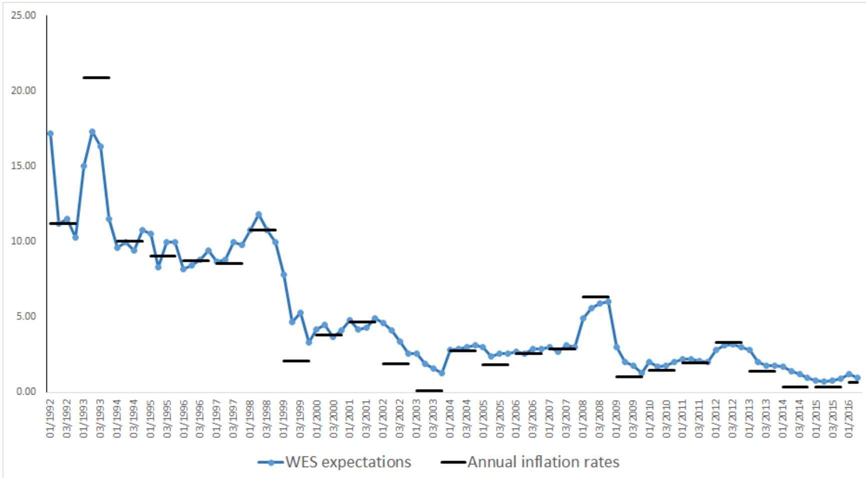
(b) Canada



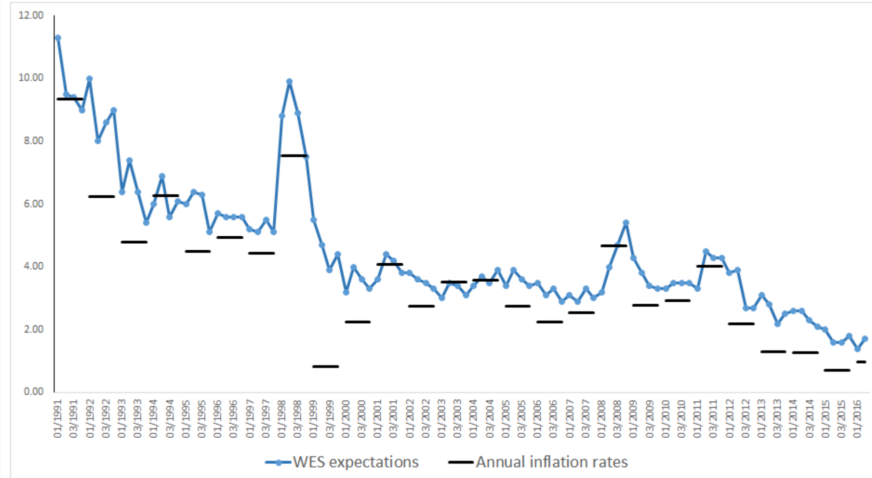
(c) Chile



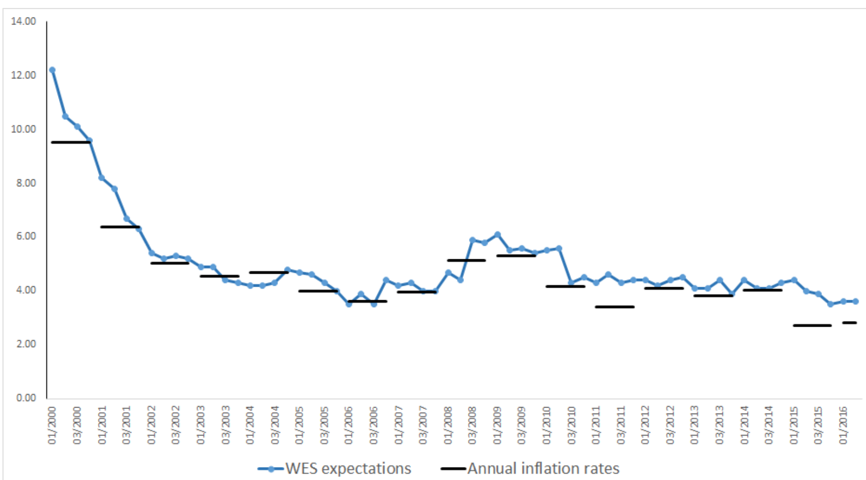
(d) Colombia



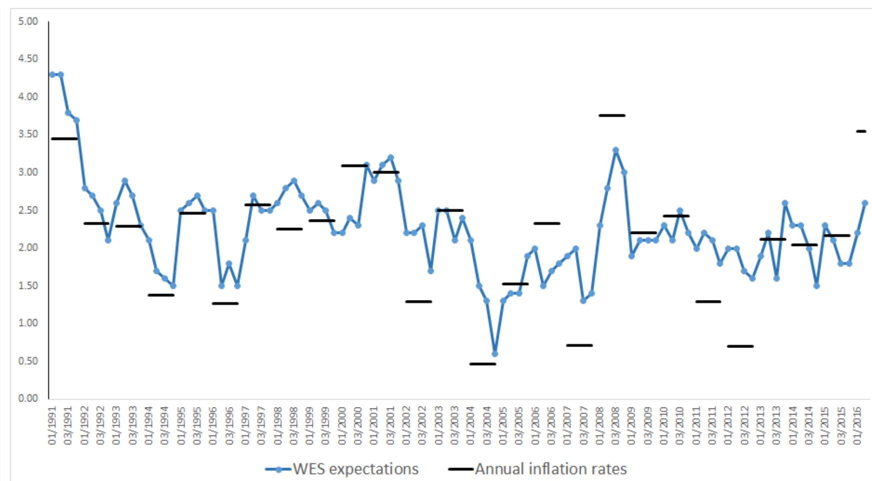
(e) Czech Republic



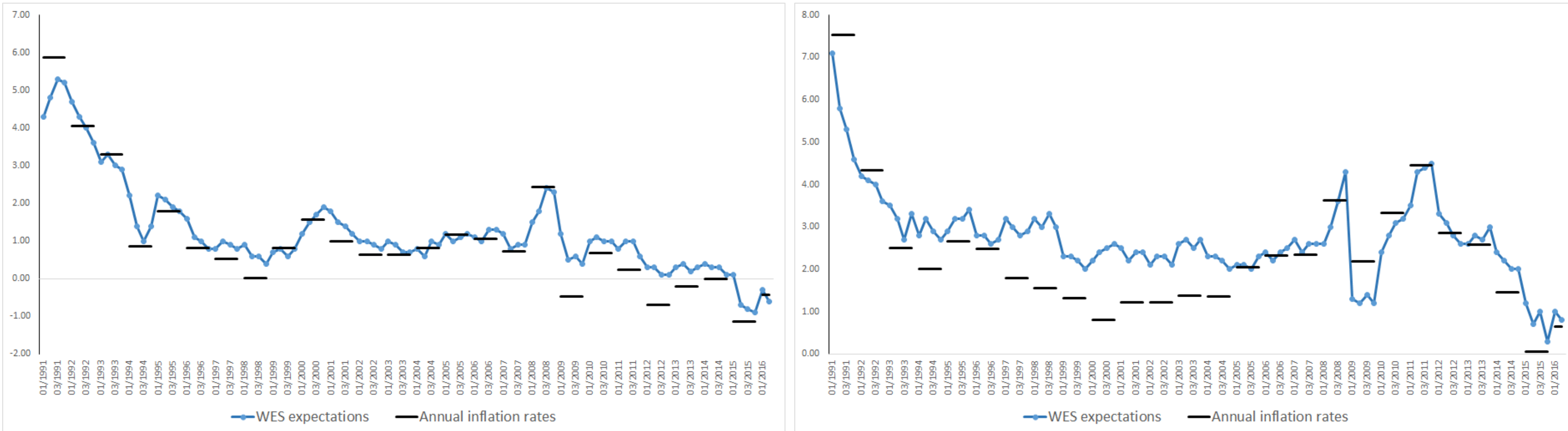
(f) Korea



(g) Mexico



(h) Norway



(i) Switzerland

(j) United Kingdom

Figure 10: Countries Inflation Expectations and Annual inflation. Source WES survey and OECD statistics

6 Conclusions

Predicting inflation expectations from international survey data applied to economics agents is a valuable goal in some empirical topics of monetary macroeconomics. The quarterly questions about the evolution of prices in these surveys consider both qualitative and quantitative answers. In this research, we started with analyzing the informational content of the subjective question by finding different patterns of expectations among countries and forecasting it. Secondly, we evaluate the suitability of the quantitative WES inflation forecasts by accomplishing a statistical decomposition of the forecasting errors.

Thus, we first rely on explorative techniques situated inside the machine learning methods to cluster and predict inflation's expectations in a sample of countries that have implemented the inflation targeting scheme as their monetary policy. Therefore, by using a clustering technique known as Self-Organizing Maps and a predictive model based on artificial neuronal networks, we visualize and predict different patterns of inflation expectations according to their perceptions before the imminent coming oil shock that took place in the middle of 2014.

We cluster 16 countries according to the evolution of their inflation expectations during the transition period to the recent minimum oil price mark. Then we generate forecasts of survey expectations by the NAR-NN model for selected countries. Regarding to the SOM analysis, we find that some countries exhibited a brisk behavior that is associated with signs that inflation expectations were deanchoring. On the other side, there were countries with a soft evolution of inflation expectations.

Concerning to the statistical evaluation of the quantitative inflation expectation, we detected that the uncertainty of the predictions of the average annual inflation across countries could be classified into two groups of countries with different patterns through the year. The first group is characterized by the fact that the closer the economic agent is to the end of the year the smaller the prediction bias is. It includes Colombia and Switzerland among others. The other group of countries which attract attention by displaying an increasing bias in the last quarter of the prediction are Brazil, Canada and Chile. However, we have to notice that overestimation of inflation is observed for some countries in periods when inflation is going down.

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Appendix A Data

A.1 Qualitative series

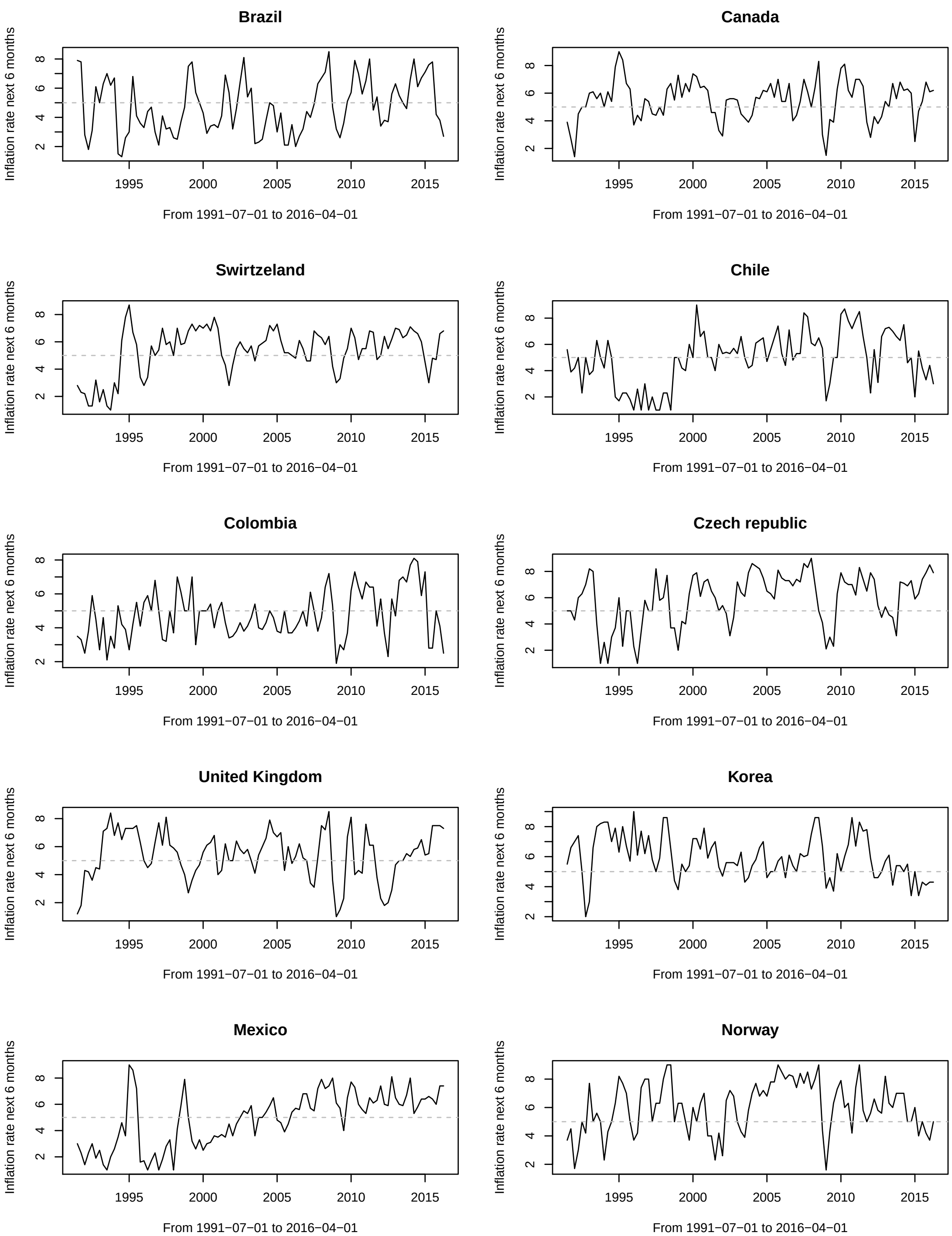

Figure 11: Expected Inflation Rate for the next 6 months

A.2 WES Survey questionnaire

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Telefax: + 49 (0)89 985369 or + 49 (0)89 9224-1463 or -2227

World Economic Survey WES

The individual survey results will be treated as absolutely confidential. Please mark the appropriate boxes. No mark means: "Not applicable" or "no judgement". The answer "no change" implies no remarkable change.

Data requested for **Code-Nr.:**

1. This country's **general situation** regarding

	present judgement			compared to the same time last year			from now on: expected situation by the end of the next 6 months		
	good	satis-factory	bad	better	about the same	worse	better	about the same	worse
- overall economy	☐	☐	☐	☐	☐	☐	☐	☐	☐
- capital expenditures	☐	☐	☐	☐	☐	☐	☐	☐	☐
- private consumption	☐	☐	☐	☐	☐	☐	☐	☐	☐

2. Expected **foreign trade volume** by the end of the next 6 months (in convertible currency)

	higher	about the same	lower
exports	☐	☐	☐
imports	☐	☐	☐

3. Expected **trade balance** within the next 6 months (in convertible currency)

improve-ment (a)	no change	deterio-ration (b)
☐	☐	☐

(a) increasing surplus or decreasing deficit
(b) decreasing surplus or increasing deficit

4. Expected **inflation rate** by the end of the next 6 months (change of consumer prices compared to the same month previous year)

higher	about the same	lower
☐	☐	☐

The rate of inflation on average of 2004 will be ________ % (p.a.)

5. Expected **interest rates** by the end of the next 6 months

	higher	about the same	lower
- short term rates (3-month money market rates)	☐	☐	☐
- long-term rates (government bonds with 10 and more years of maturity)	☐	☐	☐

6. At present, **in relation to this country's currency** the following currencies (US-$; Euro; UK £, Yen) are...

	US $	Euro	UK	Yen
overvalued	☐	☐	☐	☐
about at proper value	☐	☐	☐	☐
undervalued	☐	☐	☐	☐

7. The **value of the US $** in relation to this country's currency by the end of the next 6 months will be

higher	about the same	lower
☐	☐	☐

8. The level of **domestic share prices** by the end of the next 6 months will be

higher	about the same	lower
☐	☐	☐

9. Please try to asses the **importance** of the following **problems** the economy of your country is facing **at present**

	most important	important	not so important
- Lack of confidence in the government's economic policy	☐	☐	☐
- Insufficient demand	☐	☐	☐
- Unemployment	☐	☐	☐
- Inflation	☐	☐	☐
- Lack of international competitiveness	☐	☐	☐
- Trade barriers to exports	☐	☐	☐
- Lack of skilled labour	☐	☐	☐
- Public deficits	☐	☐	☐
- Foreign debts	☐	☐	☐
- Capital shortage	☐	☐	☐

- Others: ____________________

10. **ICC Special Question**
The current round of **multilateral trade** negotiations, launched in Doha in 2001, is stalled. Leaders of the world's major industrial democracies are meeting in June 2004 at the G8 Summit in the US to **discuss** world trade and protectionist pressures.

1. How important is it to your business / the economy of your country that the **Doha Round gets back on track**?

very important	important	not important	no answer
☐	☐	☐	☐

2. How satisfied are you with the **efforts of the world's political leaders to contain protectionist pressures** and to promote a better understanding among electorates of the benefits of an open international trade system?

fully satisfied	satisfied	dissatisfied	no answer
☐	☐	☐	☐

11. Expected growth of **real Gross Domestic Product (GDP)** this year in % ________

Please return the questionnaire by April 14, 2004

Figure 12: Example of the World economic survey WES questionnaire

A.3 Unit root tests

		ADF		Phillips-Perron	
		t-Stat	Prob.	t-Stat	Prob.
Brazil		-5.32	0.0001	-5.25	0.0002
Canada		-5.37	0.0001	-5.40	0.0001
Switzerland		-4.49	0.0026	-4.09	0.009
Chile		-4.97	0.0005	-4.97	0.0005
Colombia		-6.15	0.0000	-6.14	0
Czech Republic		-4.62	0.0017	-4.73	0.0012
United Kingdom		-4.89	0.0007	-4.63	0.0016
Korea		-5.62	0.0000	-5.55	0.0001
Mexico		-5.06	0.0004	-4.89	0.0007
Norway		-5.21	0.0002	-5.03	0.0004
Test critical values:	1% level		-4.04		-4.053392
	5% level		-3.45		-3.455842
	10% level		-3.15		-3.15371

Table 7: Unit root test

Appendix B Self- organizing map validation

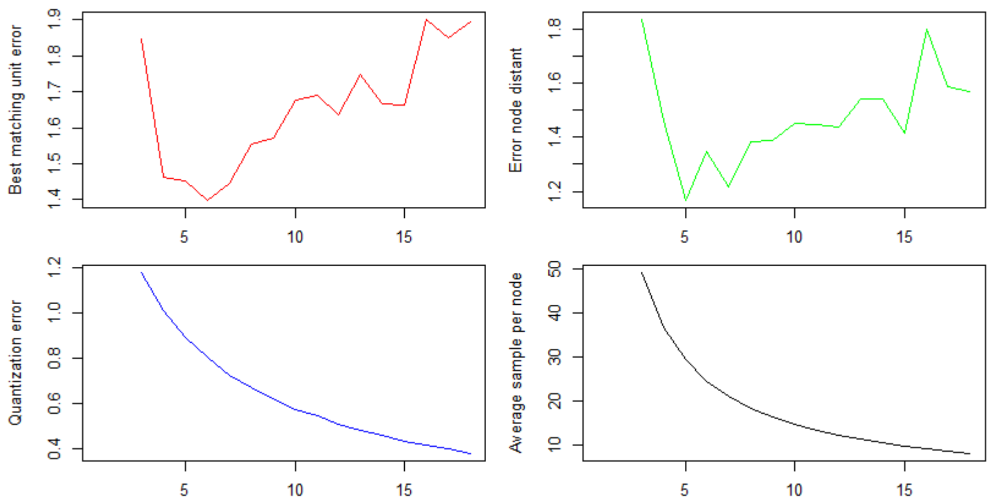
B.1 Choice of Topology

In this section we set the for the best topology according with the available data. It includes finding the dimensions of the map and the form of the neighbourhood. In order to have more neighbors around the winning neuron, we choose the hexagonal topology that allocate six neurons around . for the dimensions we found several empirical rules. The first rule is to have the number of neurons increase as the square root y of the number of data points. This give us a map of 40 neurons. The second rule said to have 10 samples per neuron, that give of 192 neurons around.

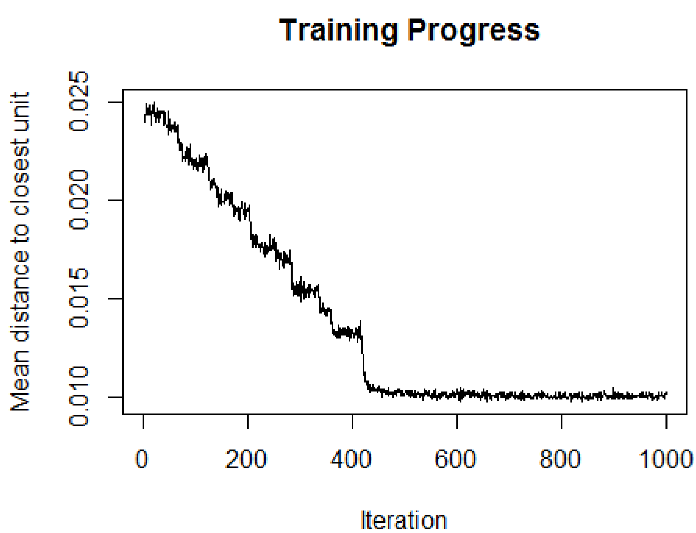
Trying to get enough granularity on the map with also a small topographic error, we tried different architectures. Unfortunately, there is not a firm criterion for the best performance in SOM networks. Due the goal of finding the agent's clusters before the oil's shock price, we divide our data into two sets, before and after the shock. Thus, the training data will be from the third quarter of 1991 to the second quarter of 2014.

While The first rule suggest a map of 16x12, by the square rule suggested to have a map with

38 neurons around. Using the R software, we analyzed various architectures: from 3x10 to 18x10, from which their topographic errors where stored, and taking into account the granularity and their errors [14].Figure 3(a) bring us to choose hexagonal topology of 10x10.



(a) Best Matching unit error, error node distance, quantization error and sample per neuron vs map width node size



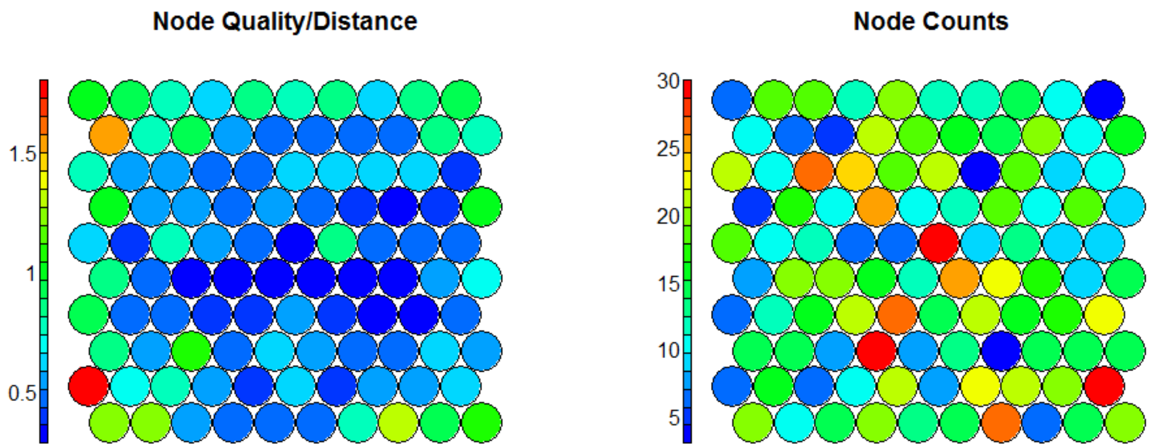
(b)

Figure 13

[14]The quantization error is not comparable between maps because is susceptible to map size. To see more about topographic error see Post-training analysisi section

B.2 Post-training analysis

Following Wehrens (2007) (8) and Lynn (2014) (13) we analysis the results from the trained map to validated the previous results. The training progress shows the mean distance between neuron's weights to the samples represented through each iteration. When the training progress reach a minimum, no more iterations are required, see figure 3(b).

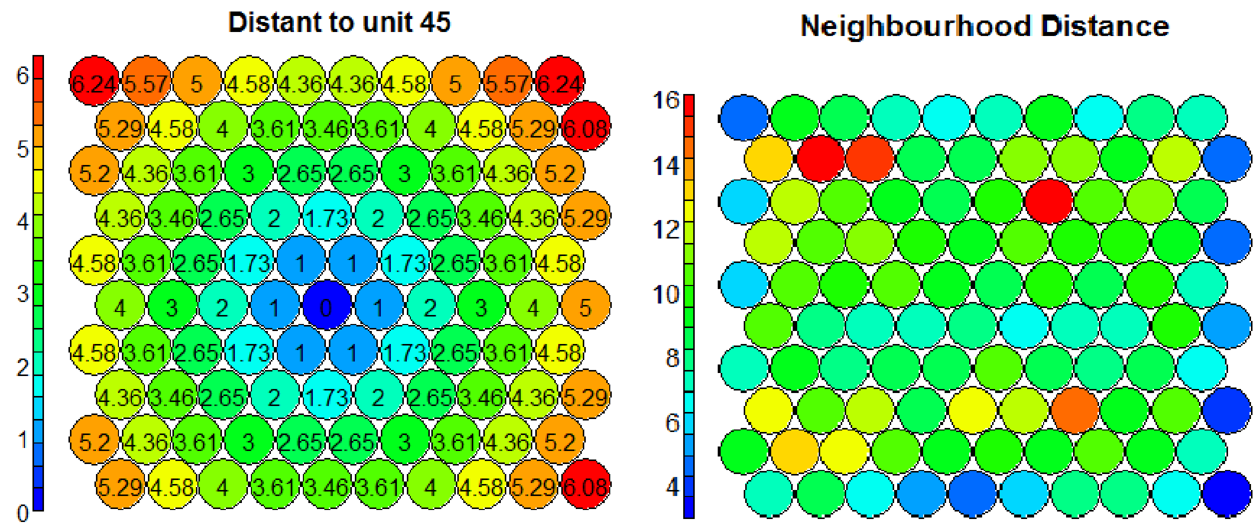


(a) (b)

Figure 14

In figure 4(a) the node or quality distance map is shown. This map displays an approximation of the distance per node to the sample that their are representing. The smallest the distance,a better map is found. This error is called the quantization error. When it is large, there are some inputs vectors that are not adequately represented on the map. However it is susceptible to the map sizes: if the map is too large, it could be near to zero. This would represent overfitting because the number of neurons on the map should be significantly smaller that the sample size. the mean quantization error found is 0.5888693.

In the figure 4(b) can analyse how many samples are mapped to each node on the map. Ideally we want that the sample distributions be relatively uniform. Our map is relatively uniform, and it is mapping between 10 to 15 samples per neuron. Also, there are non empty neurons.



(a) (b)

Figure 15

The figure 5(b) map is also named the U-matrix, and shows the distance between each neuron and its immediate neighbours. Because we choose a hexagonal neighbour, each neuron have six neurons on their neighbourhood. This maps also assists to identify similar neurons. Before analyse our Neighbourhood distance, it is helpful the figure 5(a) that shows neighbourhood distance per neuron on the total map, in this case the neuron number 45.

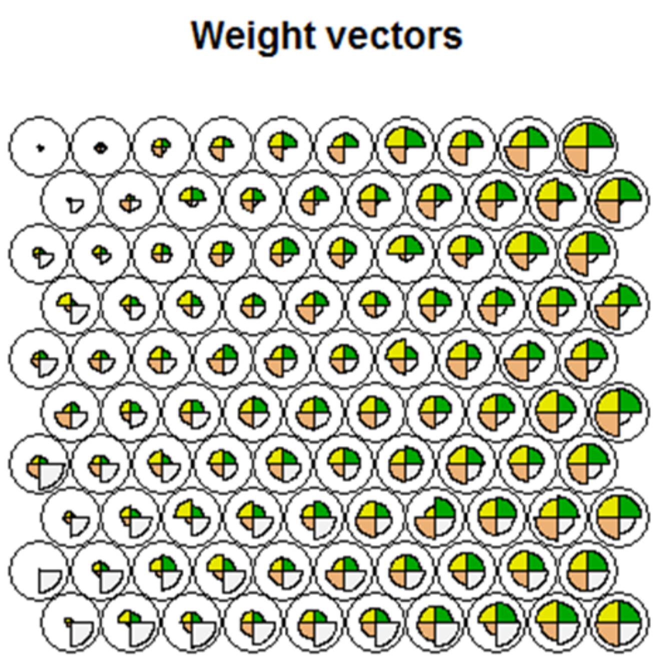


Figure 16: Weight vectors

The weight vectors plot, figure 6, shows the weights associated to each neuron. Each weight vector is similar to the variable that is representing due to the kohonen's learning rule. Looking the weights distribution on the map, green for economy over all, yellow for Capital expenditures, orange for private consumption, and white for inflation expectations, we can distinguish patterns of the variables. In our map we can see how the inflation expectations is dissimilar to the other Agent's expectations, and the latter how they are similar to each others.

Finally we present three measures of topographic errors. We already saw the first one,the quantization error, that is average distance between each variable and the closest neuron , again our quantization error is 0.5888693. The Best-matching error is the average distance between the best matching unit and the following, which is 1.568656, this is in terms of coordinates in the map. Similarly, the node distant error is the average distance between all pairs of most similar codebook vectors., which is 1.387984.

Appendix C Non Linear Autorregresive neural networks validation

C.1 Lag selection

Countries	Lags	1	2	3	4	5	6	7	8	9	10
Brazil	mean	2.02	1.99	1.88	1.94	1.90	**1.86**	1.87	1.92	1.89	1.88
	median	2.01	1.99	1.88	1.90	1.90	**1.86**	1.87	1.88	1.89	1.88
Canada	mean	**1.17**	1.38	1.31	1.29	1.33	1.30	1.31	1.32	1.29	1.32
	median	**1.15**	1.38	1.31	1.29	1.30	1.30	1.31	1.32	1.29	1.30
Switzerland	mean	1.03	1.09	1.04	1.04	1.03	1.03	0.76	**0.31**	0.50	0.63
	median	1.03	1.09	1.04	1.04	1.03	1.03	0.87	**0.31**	0.50	0.83
Chile	mean	2.22	2.09	2.10	2.22	2.09	**1.97**	2.08	2.05	2.05	2.10
	median	2.22	2.09	2.05	2.23	2.17	1.95	**1.93**	1.97	2.11	2.10
Colombia	mean	**1.56**	1.58	1.58	1.62	1.62	1.60	1.61	1.60	1.57	1.62
	median	1.56	1.58	1.58	1.59	1.57	1.59	1.55	1.58	**1.54**	1.57
Czech Republic	mean	1.85	2.05	1.99	1.94	1.85	0.93	1.73	1.78	0.36	**0.26**
	median	1.87	2.06	1.99	1.94	1.85	0.89	1.73	1.78	0.32	**0.25**
United Kingdom	mean	1.27	1.40	1.39	1.38	1.26	1.21	1.10	**0.96**	1.15	0.96
	median	1.27	1.41	1.39	1.38	1.26	1.21	1.10	1.00	1.16	**0.92**
Korea	mean	1.36	1.47	1.45	1.46	1.45	1.35	1.36	1.30	**1.29**	1.31
	median	1.36	1.47	1.45	1.46	1.45	1.35	1.36	1.30	**1.29**	1.31
Mexico	mean	1.26	1.36	1.33	1.14	1.12	0.99	1.21	1.26	0.95	**0.27**
	median	1.25	1.37	1.32	1.14	1.12	0.90	1.44	1.35	1.21	**0.25**
Norway	mean	1.87	2.08	1.97	1.98	1.92	1.91	1.83	1.81	1.76	**1.75**
	median	1.86	2.08	1.97	1.98	1.92	1.91	1.83	1.81	1.76	**1.75**

Table 8: Lag statistics all data - forecast one step ahead- sample = 30

Countries	Lags	1	2	3	4	5	6	7	8	9	10
Brazil	mean	2.05	1.98	1.88	1.94	1.90	1.86	1.88	1.92	1.89	**1.86**
	median	2.05	1.98	1.88	1.90	1.90	1.86	1.88	1.89	1.89	**1.86**
Canada	mean	**1.10**	1.34	1.28	1.26	1.31	1.27	1.28	1.30	1.24	1.28
	median	**1.07**	1.34	1.28	1.26	1.27	1.27	1.28	1.30	1.24	1.26
Switzerland	mean	1.01	1.07	1.05	1.04	1.03	1.03	0.73	**0.27**	0.46	0.61
	median	1.01	1.07	1.05	1.04	1.03	1.03	0.85	**0.27**	0.46	0.83
Chile	mean	2.04	2.03	2.05	2.17	2.03	**1.89**	2.01	1.95	1.95	2.02
	median	2.03	2.03	1.99	2.18	2.11	1.87	1.84	**1.84**	2.02	2.02
Colombia	mean	**1.26**	1.46	1.46	1.50	1.50	1.49	1.48	1.45	1.41	1.46
	median	**1.27**	1.46	1.46	1.48	1.46	1.47	1.43	1.43	1.38	1.41
Czech Republic	mean	1.95	2.17	2.11	2.05	1.94	0.95	1.78	1.83	0.18	**0.13**
	median	1.96	2.17	2.10	2.05	1.94	0.91	1.78	1.83	**0.15**	0.16
United Kingdom	mean	1.31	1.45	1.43	1.42	1.29	1.25	1.13	**0.93**	1.18	0.97
	median	1.31	1.46	1.43	1.42	1.29	1.25	1.13	1.01	1.18	**0.92**
Korea	mean	1.29	1.44	1.40	1.41	1.39	1.27	1.26	1.23	**1.22**	1.23
	median	1.28	1.44	1.40	1.41	1.39	1.27	1.26	1.23	**1.22**	1.23
Mexico	mean	1.34	1.44	1.40	1.20	1.18	1.05	1.28	1.34	0.99	**0.19**
	median	1.32	1.45	1.39	1.20	1.18	0.95	1.53	1.44	1.29	**0.23**
Norway	mean	1.91	2.14	2.00	2.01	1.95	1.90	1.81	1.79	**1.75**	1.75
	median	1.90	2.14	2.00	2.01	1.95	1.90	1.81	1.79	**1.75**	1.75

Table 9: Lag statistics train data - forecast one step ahead- sample = 30

Countries	Lags	1	2	3	4	5	6	7	8	9	10
Brazil	mean	**1.70**	2.08	1.85	1.93	1.83	1.85	1.83	1.90	1.92	2.04
	median	**1.69**	2.07	1.85	1.86	1.83	1.85	1.83	1.84	1.92	2.04
Canada	mean	2.02	1.74	1.59	1.63	1.62	1.54	1.56	**1.52**	1.75	1.73
	median	2.03	1.74	1.59	1.63	1.62	1.54	1.56	**1.52**	1.75	1.73
Switzerland	mean	1.32	1.22	1.04	1.04	1.02	0.98	1.06	0.78	0.93	**0.77**
	median	1.31	1.22	1.04	1.04	1.02	0.98	1.06	**0.78**	0.94	0.83
Chile	mean	4.36	2.76	2.75	**2.69**	2.73	2.82	2.90	3.18	3.13	2.92
	median	4.38	2.76	2.79	**2.68**	2.76	2.81	2.88	3.28	3.08	2.91
Colombia	mean	4.94	2.88	2.91	2.95	2.89	**2.88**	2.96	3.26	3.20	3.30
	median	4.97	2.88	2.92	2.88	**2.78**	2.83	2.81	3.23	3.15	3.20
Czech R.	mean	0.73	0.74	0.73	**0.70**	0.93	0.72	1.20	1.24	2.21	1.61
	median	0.74	0.74	0.73	0.70	0.93	**0.67**	1.20	1.24	2.10	1.16
United K.	mean	0.86	0.87	0.95	0.95	0.88	**0.82**	0.84	1.21	0.87	0.85
	median	0.87	0.86	0.95	0.95	0.88	**0.82**	0.83	0.84	0.87	0.83
Korea R.	mean	2.21	**1.86**	1.99	2.02	2.03	2.21	2.40	2.06	2.06	2.05
	median	2.22	**1.86**	1.99	2.02	2.03	2.21	2.40	2.06	2.06	2.05
Mexico	mean	0.38	0.43	0.52	0.49	0.48	**0.34**	0.48	0.35	0.52	1.09
	median	0.38	0.42	0.52	0.49	0.48	**0.30**	0.57	0.37	0.31	0.53
Norway	mean	**1.41**	1.44	1.61	1.67	1.59	2.01	2.04	2.10	1.88	1.80
	median	**1.41**	1.44	1.61	1.67	1.59	2.01	2.04	2.10	1.88	1.80

Table 10: Lag statistics test data - forecast one step ahead- sample = 30

C.2 Post training analysis

Countries	Total number of parameters	Effective number of parameters	maximum sum squared of parameters	Sum squared of parameters	Total epoch
Brazil	31	2.88	2760	1.74	355
Canada	101	7.66	53	1.01	622
Chile	61	4.68	91.3	1.11	228
Colombia	71	5.02	72	0.72	1000
Czech Republic	81	31.17	61.6	20.96	314
Korea	41	2.99	280	1.10	1000
Mexico	81	20.71	61.7	9.91	114
Norway	31	2.96	2760	1.49	70
Switzerland	101	38.81	53.4	22.16	330
United Kingdom	81	10.20	64.7	3.39	245

Countries	Best epoch	Error autocorrelation	Input-error correlation	Correlation coefficient Trainig R	Testing R	All R
Brazil	2	1	0	0.605	0.877	0.632
Canada	99	1	0	0.570	0.334	0.551
Chile	56	1	0	0.702	-0.049	0.678
Colombia	429	1	0	0.445	0.560	0.463
Czech Republic	253	1	0	0.885	0.607	0.884
Korea	1000	1	0	0.523	-0.464	0.554
Mexico	64	1	0	0.875	0.474	0.879
Norway	4	1	0	0.641	-0.041	0.640
Switzerland	240	1	0	0.935	0.759	0.921
United Kingdom	77	1	0	0.740	0.473	0.743

Table 11: Neural networks resume results of training phase

C.3 MSE evaluation

	Brazil			Korea		
	All data	Training set	Testing set	All data	Training set	Testing set
mean	2.01	2.05	1.65	1.47	1.44	1.86
median	2.00	2.04	1.61	1.47	1.44	1.86
std	0.04	0.03	0.18	0.01	0.01	0.03
maximum	2.09	2.09	2.11	1.52	1.44	2.51
minimum	1.92	1.97	1.24	1.36	1.34	1.62

	Canada			Mexico		
	All data	Training set	Testing set	All data	Training set	Testing set
mean	1.33	1.31	1.52	0.97	1.03	0.34
median	1.32	1.30	1.52	0.90	0.95	0.30
std	0.06	0.06	0.01	0.24	0.24	0.17
maximum	2.09	2.09	2.11	3.91	4.00	2.94
minimum	1.92	1.97	1.24	0.90	0.95	0.30

	Chile			Norway		
	All data	Training set	Testing set	All data	Training set	Testing set
mean	2.21	2.17	2.69	1.87	1.91	1.41
median	2.23	2.18	2.68	1.86	1.90	1.42
std	0.06	0.07	0.03	0.04	0.04	0.03
maximum	1.33	1.36	1.01	2.06	2.12	1.51
minimum	0.55	0.54	0.67	1.82	1.86	1.25

	Colombia			Switzerland		
	All data	Training set	Testing set	All data	Training set	Testing set
mean	1.59	1.48	2.83	0.31	0.27	0.78
median	1.57	1.46	2.78	0.31	0.27	0.78
std	0.08	0.07	0.21	0.00	0.00	0.00
maximum	1.93	1.76	3.69	0.31	0.27	0.78
minimum	1.57	1.46	2.77	0.31	0.27	0.78

	Czech Republic			United Kigdom		
	All data	Training set	Testing set	All data	Training set	Testing set
mean	0.90	0.92	0.69	1.21	1.25	0.82
median	0.89	0.91	0.67	1.21	1.25	0.82
std	0.08	0.08	0.08	0.00	0.00	0.00
maximun	1.21	1.25	0.82	1.21	1.25	0.82
minimum	1.21	1.25	0.82	1.21	1.25	0.82

Table 12: Neural network simulations statistics by data sets, sample = 1000

Appendix D Quantitative forecasting inflation expectations

D.1 Equations of the statistical analysis forecasting error

Root mean squared forecast error (RMSFE):

$$\sqrt{\frac{1}{26}\sum_{1991}^{2016} e(L,Q(h),t)^2} \tag{11}$$

Mean absolute error (MAE):

$$\frac{1}{26}\sum_{1991}^{2016} \mid e(L,Q(h),t) \tag{12}$$

Theil U.statistic:

$$\frac{\sqrt{\frac{1}{26}\sum_{1991}^{2016} e(L,Q(h),t)^2}}{\sqrt{\frac{1}{26}\sum_{1991}^{2016} q(L,Q(h),t)^2}\sqrt{\frac{1}{26}\sum_{1991}^{2016} \bar{p}(L,t)^2}} \tag{13}$$

Bias share:

$$V(h) = \frac{\left[\frac{1}{26}\sum_{1991}^{2016} q(L,Q(h),t)^2 - \frac{1}{26}\sum_{1991}^{2016} \bar{p}(L,t)\right]^2}{\frac{1}{26}\sum_{1991}^{2016} e(L,Q(h),t)^2} \tag{14}$$

The spread share:

$$S(h) = \frac{\left[S_q(h) - S_{\bar{p}}(h)\right]^2}{\frac{1}{26}\sum_{1991}^{2016} e(L,Q(h),t)^2} \tag{15}$$

where $S_q(h)$ and $S_{\bar{p}}(h)$ are the standard deviations of the respective quarter.

The covariance share:

$$K(h) = \frac{2(1 - r_{q,\bar{p}}(h))S_q(h) - S(h)}{\frac{1}{26}\sum_{1991}^{2016} e(L,Q(h),t)^2} \tag{16}$$

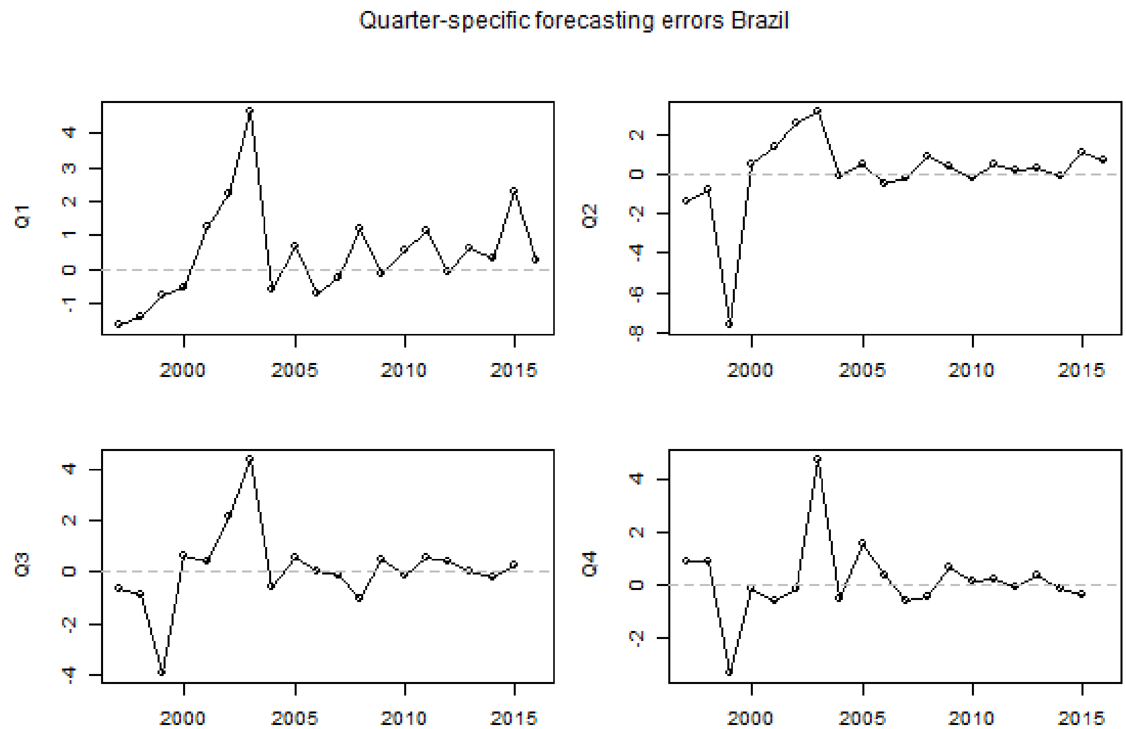
where $r_{q,\bar{p}}(h)$ is the correlation coefficient between q and $\bar{p}$. Thus $V(h) + S(h) + K(h) = 1$

	4-step forecast (QI)	3-step forecast (QII)	2-step forecast (QIII)	1-step forecast (QIV)
Brazil	67.52	99.05	94.00	122.19
Canada	0.51	0.43	0.34	0.41
Switzerland	0.59	0.41	0.32	0.30
Chile	0.97	1.04	0.89	0.93
Colombia	1.33	1.14	0.92	0.65
Czech R.	1.43	0.78	0.82	0.95
United K.	0.76	0.72	0.68	0.77
Korea	1.26	1.11	0.91	0.78
Mexico	1.63	1.22	2.14	1.79
Norway	0.61	0.51	0.43	0.31

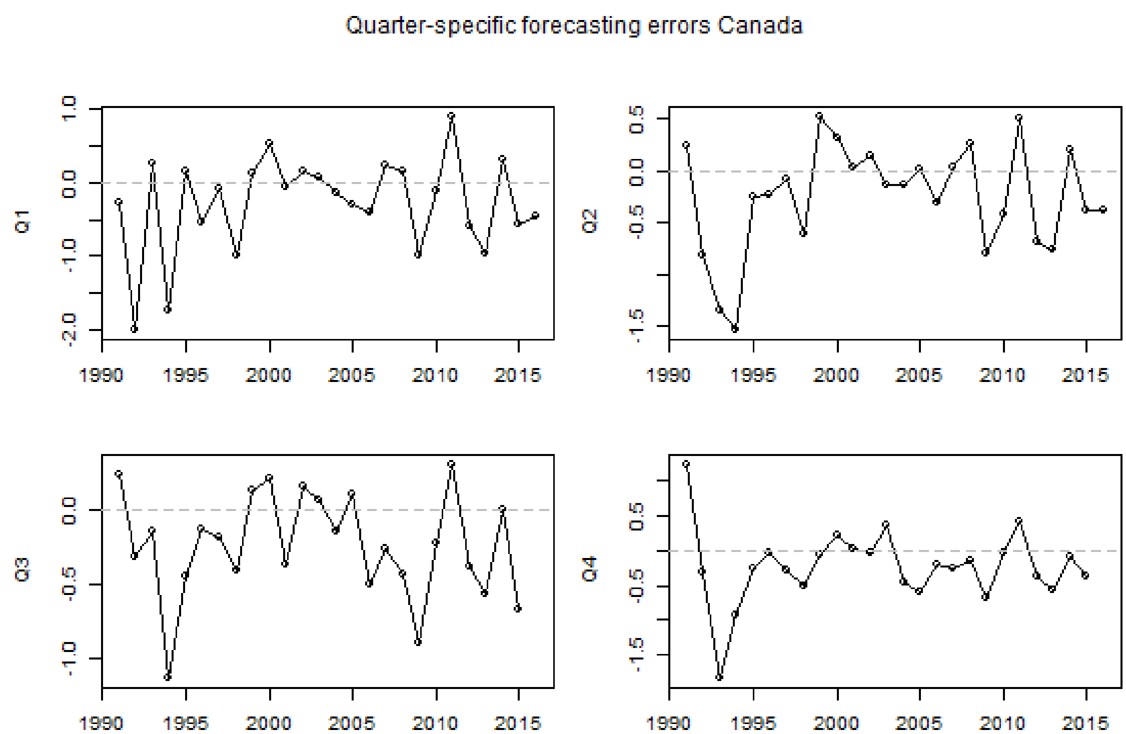
Table 13: MAE of WES survey quantitative inflation question

	4-step forecast (QI)	3-step forecast (QII)	2-step forecast (QIII)	1-step forecast (QIV)
Brazil	0.001	0.001	0.001	0.001
Canada	0.138	0.113	0.083	0.115
Switzerland	0.237	0.162	0.126	0.120
Chile	0.022	0.028	0.027	0.033
Colombia	0.010	0.009	0.007	0.005
Czech R.	0.049	0.026	0.029	0.048
United K.	0.110	0.111	0.112	0.122
Korea	0.075	0.067	0.055	0.054
Mexico	0.022	0.011	0.022	0.019
Norway	0.143	0.118	0.101	0.079

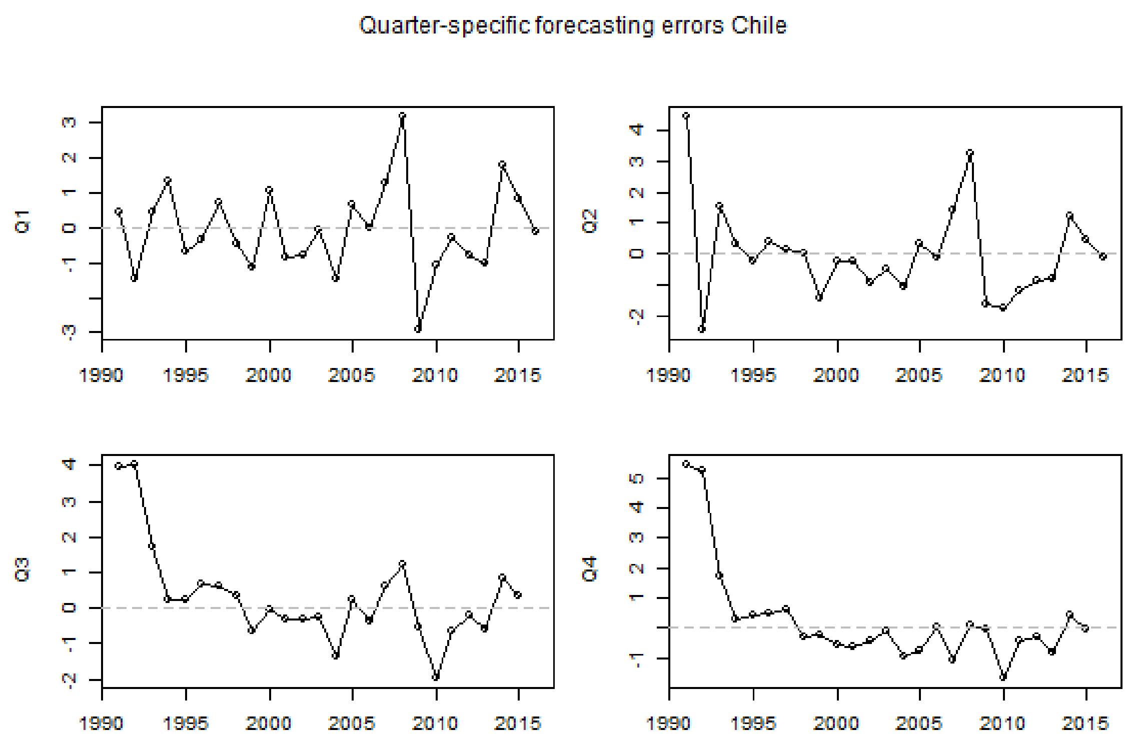
Table 14: U-statistic of WES survey quantitative inflation question


Quarter-specific forecasting errors Brazil
Q1
Q2
Q3
Q4
2000
2005
2010
2015

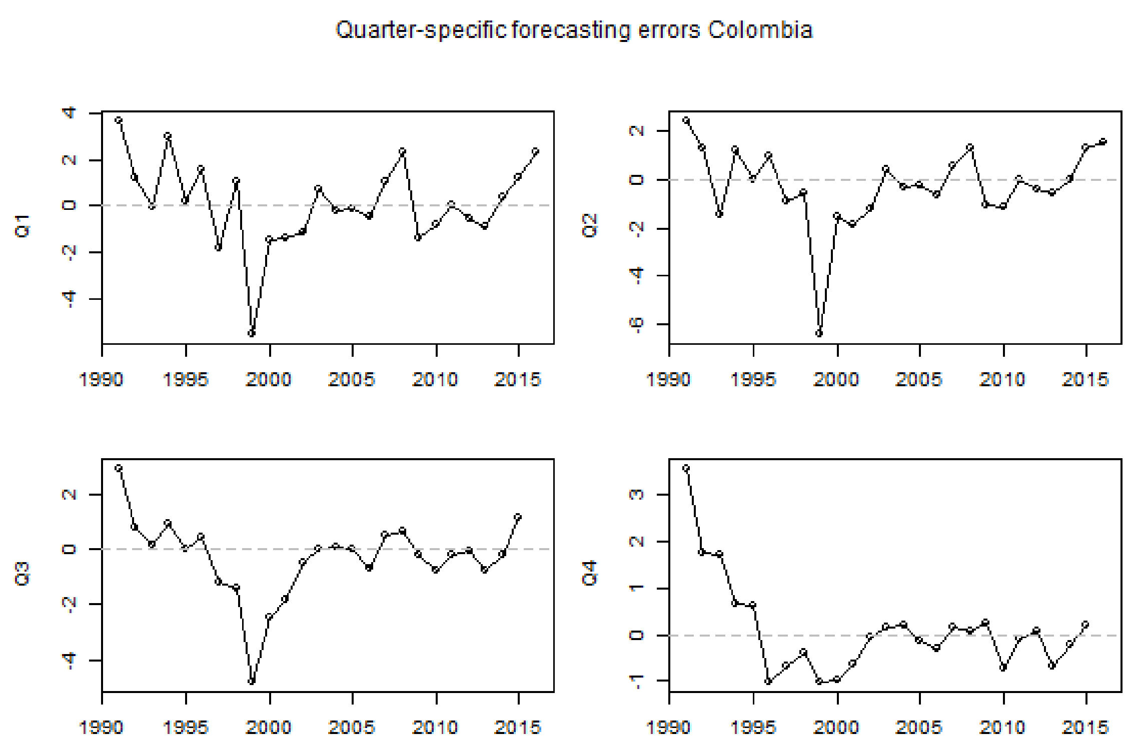
(a)


Quarter-specific forecasting errors Canada
Q1
Q2
Q3
Q4
1990
1995
2000
2005
2010
2015

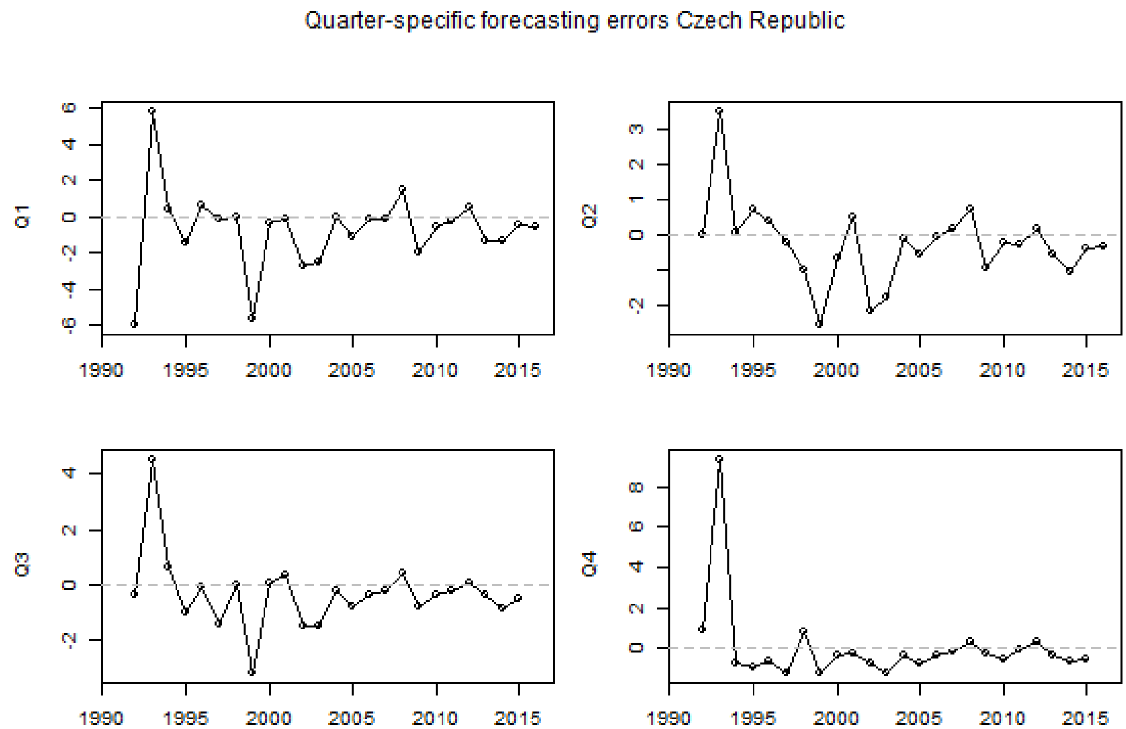
(b)


Quarter-specific forecasting errors Chile
Q1
Q2
Q3
Q4
1990
1995
2000
2005
2010
2015

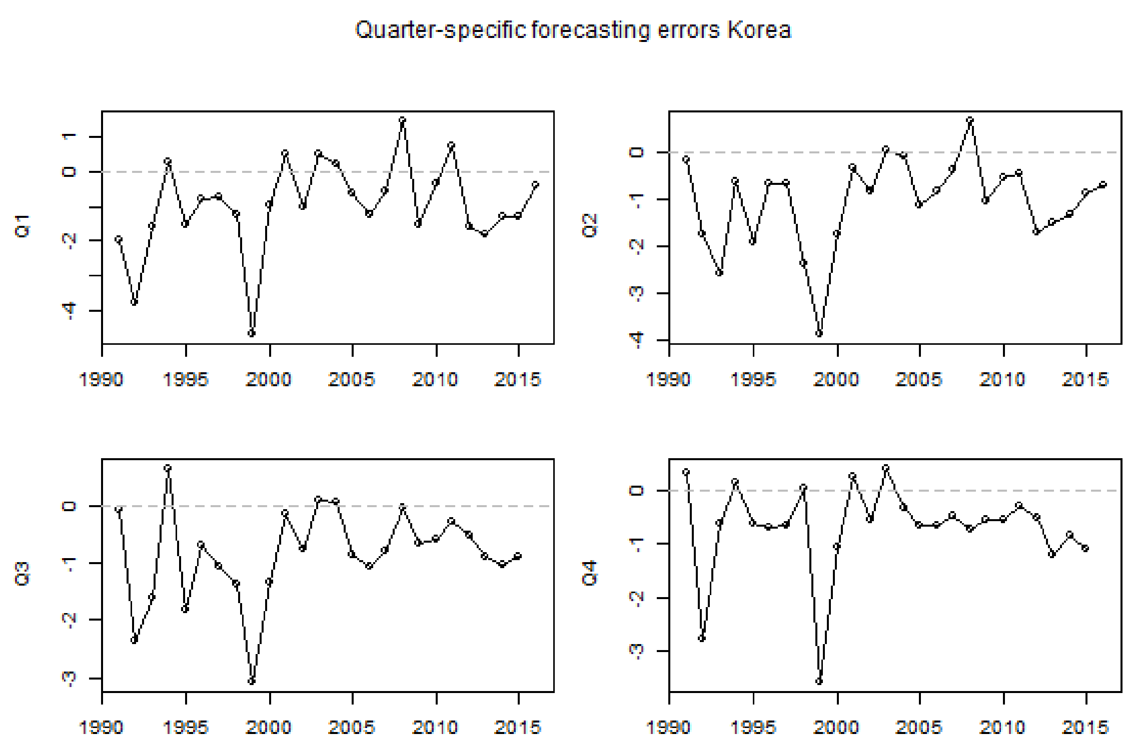
(c)


Quarter-specific forecasting errors Colombia
Q1
Q2
Q3
Q4
1990
1995
2000
2005
2010
2015

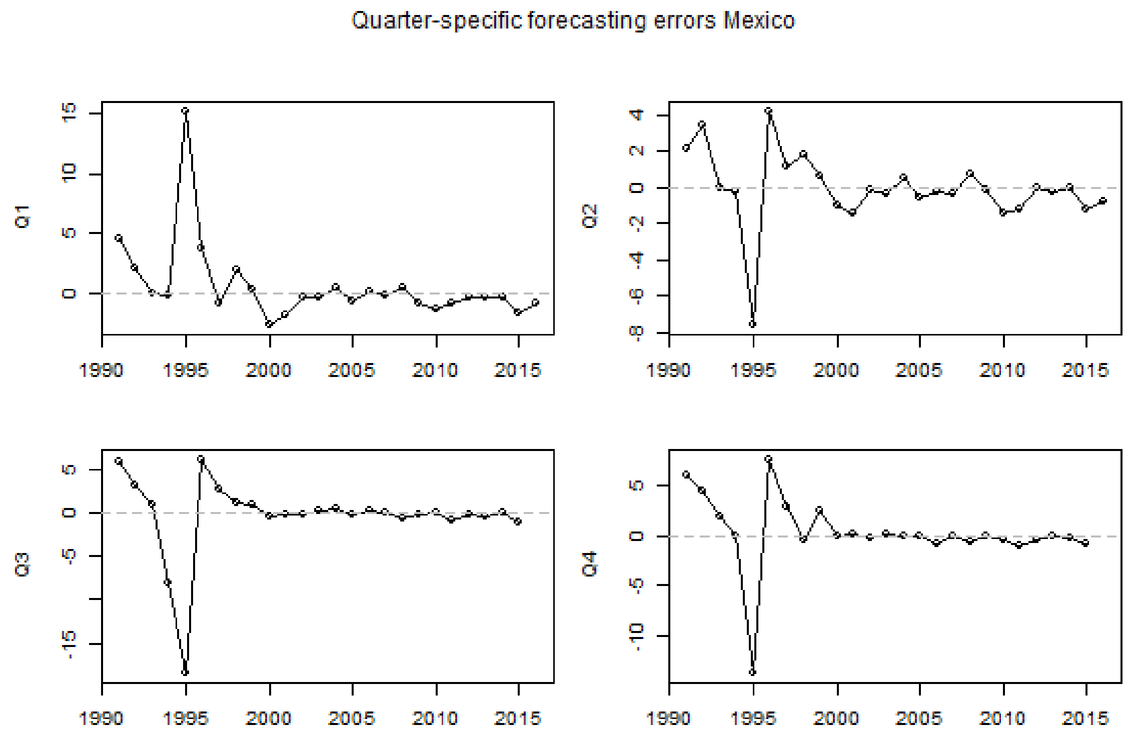
(d)


Quarter-specific forecasting errors Czech Republic
Q1
Q2
Q3
Q4
1990
1995
2000
2005
2010
2015

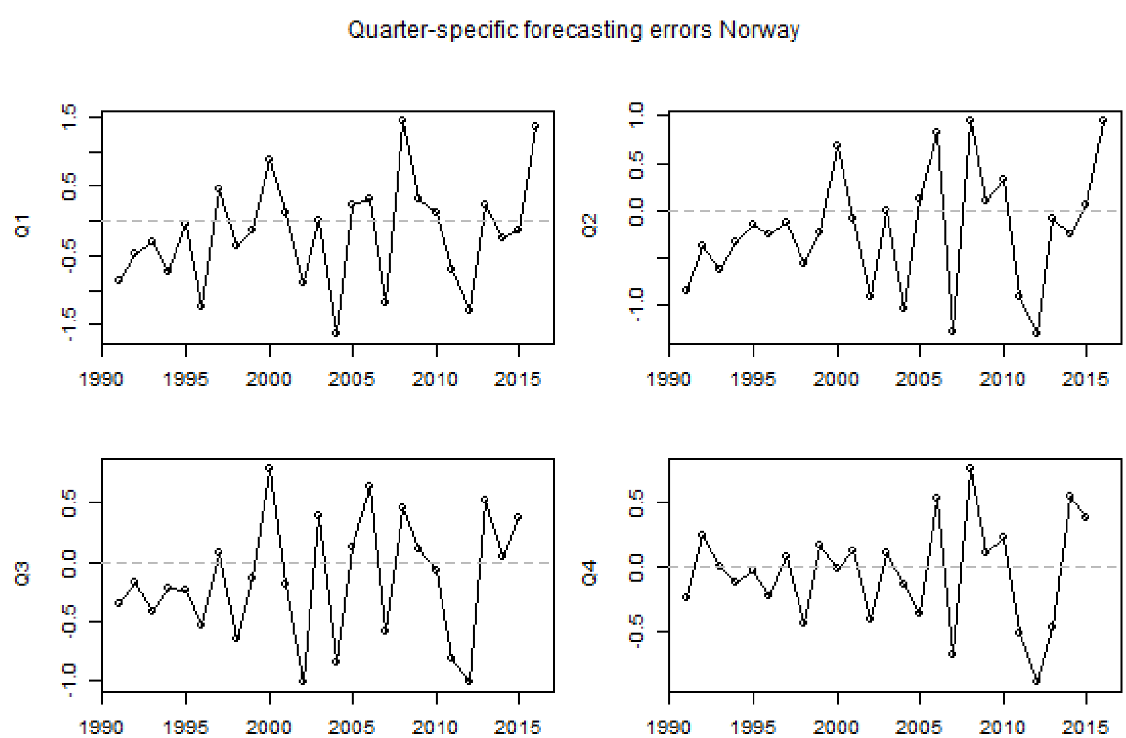
(e)


Quarter-specific forecasting errors Korea
Q1
Q2
Q3
Q4
1990
1995
2000
2005
2010
2015

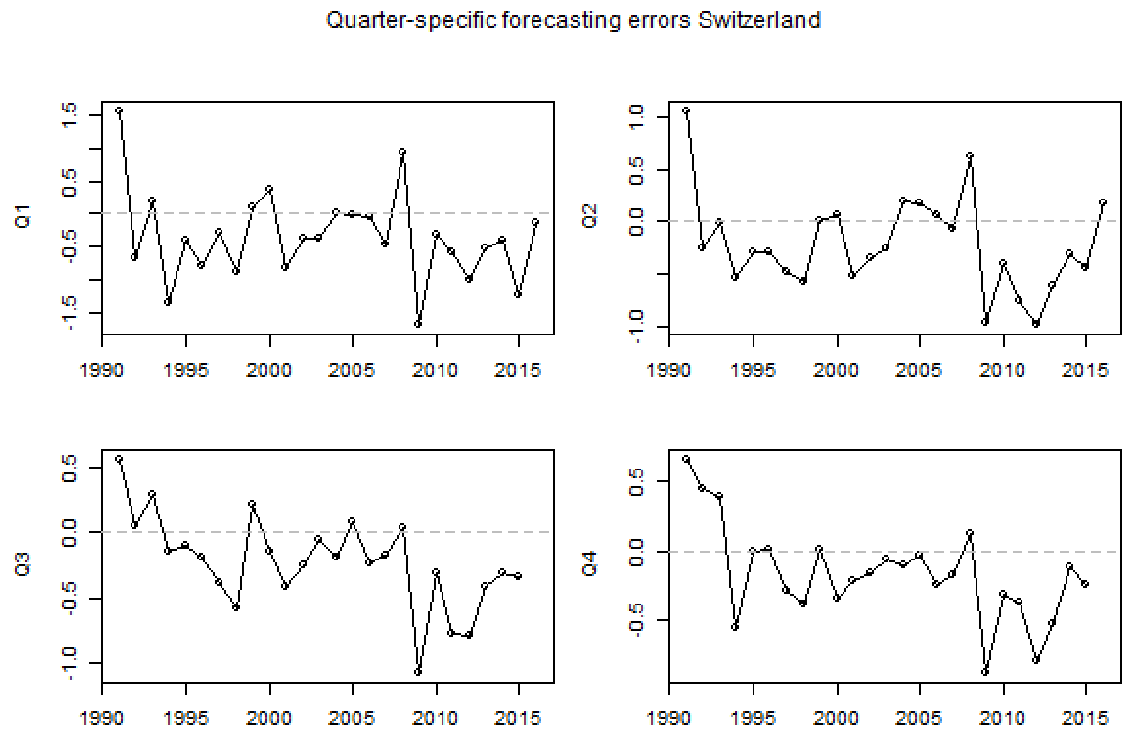
(f)


Quarter-specific forecasting errors Mexico
Q1
Q2
Q3
Q4

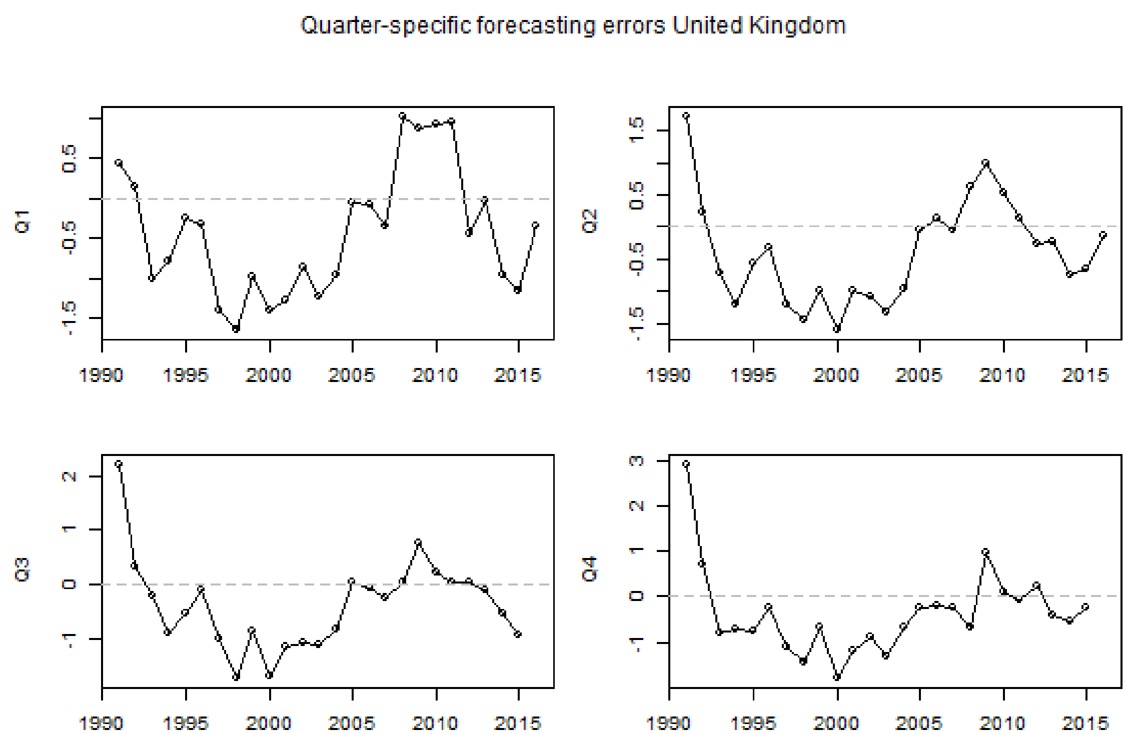
(g)


Quarter-specific forecasting errors Norway
Q1
Q2
Q3
Q4

(h)



(i)



(j)

Figure 17: Quarter-specific forecasting error by country


BANCO DE LA REPÚBLICA
COLOMBIA