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C O N T E N T S

THE USEFULNESS OF ARTIFICIAL NEURAL NETWORKS IN FORECASTING EXCHANGE RATES

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ABSTRACT

This article contributes to the neural network literature by demonstrating how potent and useful they can be as a tool in the process of economic and financial decision making. We probe into the usefulness of Nonlinear Autoregressive Networks (NAR) in comparison to the ARIMA models that are commonly used as a benchmark for forecasting exchange rates. To demonstrate it, we chose the USD/EUR exchange rate, as a considerably volatile and a highly transacted asset in the international financial market, yet very disputed in academic works due to its often large divergences from the fundamental levels suggested by economic theories. Although through a modest application, our findings show that neural network models can add value and possibly outperform traditional models used to forecast exchange rates. The results were affirmative that the nonlinear autoregressive net consistently beat the ARIMA (and the random walk) static forecasts of the USD/EUR exchange rate.

Keywords: artificial neural network; ARIMA model; exchange rate forecasting.

INTRODUCTION

Time series forecasting is increasingly used as a valuable tool to provide information in the decision-making process. It is important for fund managers, corporate treasurers, global traders and policy makers, to mention a few. However, forecasting of financial series has proven a very challenging task, especially for volatile time series such as exchange rates. Being the largest and the most liquid market with trillions of US dollars transacted every day, the empirical literature based on theoretical models has often found it difficult to beat forecasts from more naïve random walk processes.

Because exchange rates are influenced by many economic, political and psychological factors, it has been hard to identify a unique economic model that can provide reliable forecasts. Some authors state that "the poor explanatory power of existing theories of the exchange rate is most likely the major weakness of international macroeconomics" (Bacchetta & Wincoop, 2006), and that empirical exchange rate models "…generally fail badly in out-of-sample forecasting tests in the sense that they fail to outperform a random walk" (Sarno & Taylor, 2002). Even if exchange rate theories look fundamentally sound, many researchers blame the empirical implementation as a linear statistical model for the dismal forecast performance. Thus, they propose the use of time-varying or non-linear methods, which could help to better capture the exchange rate adjustment toward its long-term equilibrium in a nonlinear fashion (Kilian & Taylor, 2001).

As a matter of fact, exchange rate series often display signs of nonlinearity, which traditional linear forecasting techniques are ill equipped to handle, often producing unsatisfactory results (Philip, Taofiki, & Bidem, 2011). Researchers confronted with these characteristics turn to techniques that are heuristic and nonlinear. In this rather short article, we first estimate a linear autoregressive model that resembles the random walk to forecast the monthly USD/EUR exchange rate, and then generate a nonlinear autoregressive artificial neural network in an attempt to improve the traditional univariate model forecasting. Both types of models will finally be compared on their forecast performance, where the focus is on minimizing out-of-sample forecast error rather than maximizing in-sample 'goodness of fit'.

Indeed, the random walk modeling (of the form $y_t = y_{t-1} + e_t$, where e_t is the random error term) may not effectively handle the uncertainty or instability that characterizes exchange rate movements. Instead, we employ the autoregressive integrated moving average (ARIMA) model, which is widely used as a benchmark in time series forecasting and analysis. ARIMA is a specific subset of univariate modeling, which assumes that the historical characteristics of a time series (i.e. its systematic structural features) will be present in the future; therefore, they can be convenient for forecasting purposes.

On the other side, artificial neural networks (ANNs) have in the past decade emerged as a powerful alternative method for time series forecasting due to their higher capabilities. ANNs are nonparametric data-driven approaches that can capture nonlinear data structures without a prior assumption about the underlying relationship in a particular problem. ANNs can learn from examples and demonstrate some capability for generalization, beyond the training data. A large number of papers that make use of ANNs for predictions can be found in the literature. Nevertheless, the reported results are often mixed.

To give a brief overview on the results, the forecast evaluation based on the ME, MAE and RMSE indicates the neural network model has been able to provide better one-month ahead forecasts than the ARIMA model throughout the 2014. These findings can lend support to the ANN literature for its applicability in exchange rate forecasting techniques. In what follows, we begin by describing the basic facts about the two methodologies we used in the forecasting process and then we present and compare the respective results.

COMPETING METHODOLOGIES

The univariate ARIMA and ANN models are applied on the monthly USD/EUR exchange rate, as published online in the Thomson Reuters website. The data analysis starts from January 1994 till December 2014 – a total of 252 data points. The EViews 7 software was used for the ARIMA modeling. Whereas all partial measurements for the ANNs models are implemented directly in the core of MATLAB 2010b environment, which was used for the experiments. Below we describe separately the two methodologies applied in this article and show the preferred models in each of them. The chosen models are then compared on the basis of their one-month-ahead forecast performance.

ARIMA MODELING

Contrary to multivariate models with explanatory variables that are based on economic theories, ARIMA is a purely statistical model, in which a time series is regressed on its own past values (the autoregressive component) plus current and lagged values of a 'white noise' error term (the moving average component) (Meylar, Kenny, & Quinn, 1998). So by their nature, ARIMA models offer very little economic logic; future predictions are formed exclusively from the information contained on past movements and forecast errors. But, despite being "backward-looking" and not very good at predicting turning points, ARIMA models often outperform multivariate model predictions, particularly in the short term.

A general notation of ARIMA models is ARIMA (p, d, q), where p is the number of autoregressive terms, d denotes the difference operator (the number of differences needed to convert the series to a stationary level), and q is the order of moving average terms in the model. As many economic data, including exchange rates, contain changeable and unclear seasonality, it could be worthy to test the standard ARIMA representation with additional seasonal dummy variables.

In practice, we have followed these steps to determine the best forecast ARIMA model. We begin by testing the order of integration, whether the data is stationary or differencing the series is required. Next, we run various regressions until the best ARMA combination is identified based on certain diagnostic tests. In this step, particular attention is paid not only to the models' good in-sample characteristics, but also to their forecast performance and to the number of parameters that appear in the model.

Figure 1 plots the USD/EUR exchange rate from January 1994 to December 2014. It can be seen that the euro currency followed a depreciating trend until 2000; then it gradually reversed its losses till 2007, and has fluctuated around that level thereafter. In other words, the euro exchange rate averaged at about USD1.33 in the first half of this decade, as compared to the much lower level of USD1.19 in the previous 16 years. Meanwhile, its coefficient of variation has been fairly in control at only 4.1 during the post-global crisis period, which is nearly four times lower than the earlier period.

Likewise, the unit root tests indicate that the USD/EUR exchange rate is non-stationary in level. The ADF and Phillips-Perron tests show, however, that the series can become stationary around a constant (and trend) if differenced once. The different test results hold for the whole sample period, as well as for the sub-period starting from the year 2000. Therefore, the euro exchange rate will enter the ARIMA model in the first difference.

Having determined the order of integration, I(1), we now try to identify the appropriate AR and MA components in our model based on formal assessments of certain diagnostic checking and the forecasting ability for every competing form. Out of a number of alternative identification methods to determine parameters p and q we follow the penalty function criteria, which although offer no theoretical guidelines for choosing the maximum order of ARIMA they are asymptotically consistent and not based on subjective interpretation. Penalty function criteria, such as Akaike, Schwarz and Hannan-Quinn statistics, help in selecting a model with minimized sum of squared residuals. Nevertheless, our emphasis was finally put on the forecast performance, which suggests more focus on minimizing out-of-sample forecast errors than on maximizing the in-sample 'goodness of fit' – or the adjusted R2 (Meylar, Kenny, & Quinn, 1998).

Figure 1. The Daily USD-EUR Exchange Rate

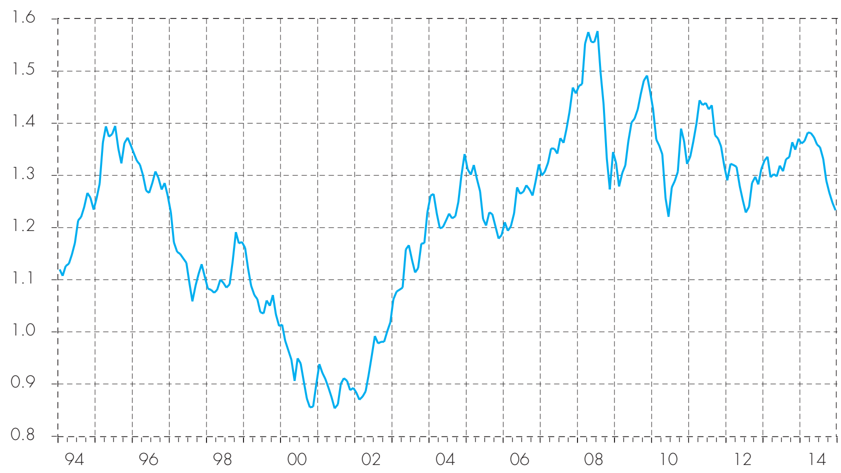


Table 1: Unit Root Tests on the USD/EUR exchange rate

Variables	ADF test results				Phillips-Perron test results			
	Null Hypothesis: Unit root				Null Hypothesis: Unit root			
	Levels		1st difference		Levels		1st difference	
	Prob.	Lag[a]	Prob.	Lag[a]	Prob.	Bandwidth[b]	Prob.	Bandwidth[b]
1994M01:2014M12								
With constant		1	0.0000	0	0.3854	5	0.0000	1
With constant and trend		1	0.0000	0	0.6542	5	0.0000	1
None		1	0.0000	0	0.6672	5	0.0000	1
2000M01:2014M12								
With constant		1	0.0000	0	0.4649	4	0.0000	1
With constant and trend		1	0.0000	0	0.7898	4	0.0000	1
None		1	0.0000	0	0.7443	4	0.0000	2

[a]Automatic selection of lags based on SIC; [b]Newey-West bandwidth selection using Bartlett kernel

In practice, we estimated numerous ARIMA forms with dozens of AR and MA lags and seasonal dummies, which were constantly tested for normal distribution, serial correlation and heteroskedasticity in the residuals. The sample estimation period covered January 1994 - December 2013, whereas observations in 2014 were saved to evaluate the out-of-sample forecast performance. It turned out that overfitting the model with too many parameters increased the in-sample explanatory power but weakened the diagnostic tests and/or the out-of-sample forecasting ability. Thus, we eventually retained a more parsimonious model with the smallest possible number of parameters. The constant term as well as the seasonal dummies stayed in the model because, although hardly statistically significant, they were found to help to satisfy the aforementioned criteria. The structure of our preferred model is seasonal ARIMA (7,1,48), estimated as a parsimonious ARMA Conditional Least Squares (Marquardt) method in the following specification:

Δ(USDEUR)	= 0.35*AR(1)	– 0.16*AR(2)	+ 0.08*AR(3)	– 0.12*AR(7)	– 0.28*MA(48)	+ 0.01*c	+ seas
Coefs prob.	0.00	0.02	0.23	0.07	0.00	0.16	0.36
Adj. R2 = 0.12		S.E. of regression = 0.0277					
Normal distribution: JB test prob. = 0.15							
Serial correlation: LM test, probability Chi-sq(12) = 0.55							
Heteroskedasticity: BPG test, probability Chi-sq(11) = 0.53							

where 'Δ' represents the change operator; c indicates the constant; and seas stands for the eleven seasonal dummies included in the specification. Most of the selected autoregressive and moving average terms are statistically significant, as shown by the probabilities below each coefficient. Also, the diagnostic tests suggest that errors are normally distributed and do not have serial correlation or heteroskedasticity. In what follows, we describe the nonlinear autoregressive model as part of the neural network and then compare the forecasting ability between ARIMA and NAR approaches.

NEURAL NETWORKS MODELING

This section gives a brief description of the artificial neural networks methodology, starting with basic issues in ANNs for time series forecasting and continuing with the nonlinear autoregressive construction (NAR) to predict the USD/EUR exchange rate. As previously mentioned this technique is a data driven approach, and it is nonparametric in the sense that is not necessary to know any prior information regarding the process that generates the signal. In an ARIMA model, we forecast future observation by using a certain function of past observations. Whereas, a network is trained through general-purpose algorithms based on time-series data and focusing on the computation of weighted neuron connections in a feed-forward network to accomplish a desired input-output mapping (Zhang & Hu, 1998).

The common feed-forward architecture of a neural network (NN) is organized into several layers of nodes. The first layer is the input layer; then comes the number of nodes in this layer that corresponds to the lagged data observations; and the last layer, also known as output layer, is the forecasting values. Between the input and the output layer, we put one or more hidden layers. The layers have unidirectional connection between them (Janil & Mao, 1996), that is, the information must flow from input to output in only one direction with no back-loops. Each connection has a numeric weight, which signifies its strength. Many authors have rigorously demonstrated that a three-layer neural network with a logistic activation function in the hidden units is a universal approximation (Gonzalez, Steven; Canada Economic and Fiscal Policy Branch, 2000).

The most challenging task is how to design a network of appropriate size for capturing the underlying patterns in the training data. Ultimately, for a network model to be useful, it should have generalization or forecasting capability. Hidden nodes are used to capture the nonlinear structures in a time series. Determination of how many hidden nodes to use is another difficult issue in the ANN model construction process. Since no theoretical basis exists to guide the selection, in practice, the number of input and hidden nodes is often chosen through experimentation or by trial-and-error (Zhang, Patuwo, & Hu, 1998). The NN learns by adjusting the weights. Various learning algorithms have been used to train the network. After the nets are trained, for each ANN model we choose the best architecture based on a certain performance criterion.

The general process used for training the network is done in three basic steps:

1. Inputting the training data and the target data
2. Learning the 'rules' from the given data collection
3. Improving the network performance by iteratively adjusting the weights.

The neural networks can be trained to predict future values of the exchange rate by relying on their own past values. But, unlike the linear estimation in the ARIMA method, the architectural approach to construct our neural network will be based on the "Nonlinear Autoregressive models (NAR)". Our main interest is to systematically examine how the forecasting performance of the neural network is affected by various factors, where a number of input nodes and hidden layer nodes are selected for the experimental process.

As in the ARIMA regression, the NAR analysis uses average monthly data of the USD/EUR exchange rate, spanning from January 1994 to December 2014, a total of 252 observations. The data is divided into two periods: we use the period from January 1994 to December 2013 (240 observations) to estimate and evaluate the model, and retain the twelve months in 2014 (5% of the date) for out-of-sample forecast analysis. Also, the in-sample data used for model estimation and evaluation is divided into three parts: the training period consists of 70 per cent of the total, while the rest is divided equally between the validation (15%) and the testing (15%) periods. The NAR networks are trained for 1,000 epochs. The Levenberg-Marquardt optimization was employed to train these networks, in which the weights and bias values are updated after each epoch in order to find the best configuration of the weights.

To determine the best architecture of the NAR model, we examined a number of neurons in the input and the hidden layers. The delayed data used as input neurons in the input layer for our analysis are in the range of one to twelve; the number of neurons in the hidden layer is similarly tried one through twelve; so, 144 different architectures (12x12) are examined in the process. For each network architecture, the training was repeated ten times using different starting values for the weights; they were randomly assigned in order to find the global minimum. Finally, each architecture is evaluated on the basis of their predictive power, and the one with lowest forecast errors in the out-of-sample forecast evaluation is selected.

Table 2 shows the 144 estimated NN structures and their respective one-month ahead forecast performance during 2014. It appears that the NN structure 11—12—1, i.e. involving eleven time lags of the variable and twelve hidden layers, is the finest network in terms of providing the most accurate exchange rate forecast for the next month. Both measures of the forecast evaluation, the RMSE and MAE, indicate that the forecast errors derived by the 11—12—1 net are the lowest in comparison to the rest of the NAR networks. The next discussion reviews how this compares with the forecast performance of the ARIMA (7,1,48) approach that we developed above.

Table 2: Statistical performance of NAR networks for the USD/EUR exchange rate

NR	NN Structure	RMSE	MAE	NR	NN Structure	RMSE	MAE	NR	NN Structure	RMSE	MAE	NR	NN Structure	RMSE	MAE
1	1−1−1	0.015710	0.012287	37	4−1−1	0.016188	0.013644	73	7−1−1	0.012342	0.009278	109	10−1−1	0.014704	0.011919
2	1−2−1	0.017768	0.014449	38	4−2−1	0.014853	0.012237	74	7−2−1	0.013914	0.011264	110	10−2−1	0.012535	0.009585
3	1−3−1	0.016610	0.013337	39	4−3−1	0.012466	0.010662	75	7−3−1	0.013670	0.011081	111	10−3−1	0.013972	0.012055
4	1−4−1	0.015954	0.012758	40	4−4−1	0.013793	0.011261	76	7−4−1	0.012009	0.010100	112	10−4−1	0.012959	0.010914
5	1−5−1	0.017590	0.014146	41	4−5−1	0.014217	0.011659	77	7−5−1	0.012813	0.010092	113	10−5−1	0.012075	0.009316
6	1−6−1	0.016867	0.013318	42	4−6−1	0.013037	0.011258	78	7−6−1	0.013180	0.009956	114	10−6−1	0.013078	0.011412
7	1−7−1	0.016548	0.013270	43	4−7−1	0.013760	0.010932	79	7−7−1	0.014702	0.013540	115	10−7−1	0.011964	0.009814
8	1−8−1	0.017827	0.014415	44	4−8−1	0.012896	0.010144	80	7−8−1	0.015939	0.012398	116	10−8−1	0.014126	0.009856
9	1−9−1	0.019239	0.014971	45	4−9−1	0.013793	0.011466	81	7−9−1	0.012950	0.010541	117	10−9−1	0.011758	0.009090
10	1−10−1	0.017826	0.014687	46	4−10−1	0.012797	0.010132	82	7−10−1	0.013824	0.010035	118	10−10−1	0.011842	0.009278
11	1−11−1	0.017532	0.014999	47	4−11−1	0.014072	0.011302	83	7−11−1	0.011680	0.009426	119	10−11−1	0.012074	0.009503
12	1−12−1	0.018063	0.015193	48	4−12−1	0.013481	0.010860	84	7−12−1	0.013590	0.010736	120	10−12−1	0.011341	0.008279
13	2−1−1	0.014919	0.012295	49	5−1−1	0.015406	0.012823	85	8−1−1	0.013313	0.010180	121	11−1−1	0.012882	0.010433
14	2−2−1	0.013743	0.010359	50	5−2−1	0.014011	0.011269	86	8−2−1	0.013289	0.010231	122	11−2−1	0.013455	0.010238
15	2−3−1	0.013962	0.011441	51	5−3−1	0.013974	0.011400	87	8−3−1	0.012169	0.008697	123	11−3−1	0.010644	0.008272
16	2−4−1	0.013932	0.011426	52	5−4−1	0.012856	0.010866	88	8−4−1	0.012687	0.010269	124	11−4−1	0.013214	0.010525
17	2−5−1	0.012333	0.008975	53	5−5−1	0.013778	0.011402	89	8−5−1	0.012401	0.009478	125	11−5−1	0.012604	0.009022
18	2−6−1	0.012452	0.009133	54	5−6−1	0.011619	0.009048	90	8−6−1	0.012237	0.009808	126	11−6−1	0.011521	0.009611
19	2−7−1	0.012913	0.010165	55	5−7−1	0.012717	0.010425	91	8−7−1	0.017478	0.014638	127	11−7−1	0.013214	0.010609
20	2−8−1	0.013241	0.010211	56	5−8−1	0.013844	0.011412	92	8−8−1	0.012049	0.009734	128	11−8−1	0.012603	0.011360
21	2−9−1	0.012485	0.010599	57	5−9−1	0.012224	0.010054	93	8−9−1	0.015219	0.012222	129	11−9−1	0.013391	0.011427
22	2−10−1	0.014374	0.011719	58	5−10−1	0.012505	0.010001	94	8−10−1	0.013783	0.011194	130	11−10−1	0.011057	0.008723
23	2−11−1	0.012907	0.010927	59	5−11−1	0.012696	0.010784	95	8−11−1	0.013309	0.009951	131	11−11−1	0.014931	0.011133
24	2−12−1	0.012543	0.009411	60	5−12−1	0.013538	0.011346	96	8−12−1	0.013190	0.010211	132	11−12−1	0.010514	0.007930
25	3−1−1	0.015692	0.013017	61	6−1−1	0.015371	0.012787	97	9−1−1	0.015019	0.012661	133	12−1−1	0.015653	0.013547
26	3−2−1	0.014438	0.011461	62	6−2−1	0.014961	0.012306	98	9−2−1	0.013387	0.010773	134	12−2−1	0.015573	0.013455
27	3−3−1	0.014292	0.011612	63	6−3−1	0.013024	0.010392	99	9−3−1	0.014736	0.012244	135	12−3−1	0.013502	0.010492
28	3−4−1	0.016304	0.013872	64	6−4−1	0.012575	0.009861	100	9−4−1	0.014580	0.010847	136	12−4−1	0.012885	0.011625
29	3−5−1	0.014639	0.011857	65	6−5−1	0.013417	0.010692	101	9−5−1	0.015710	0.012831	137	12−5−1	0.012555	0.008578
30	3−6−1	0.014344	0.011593	66	6−6−1	0.011860	0.010007	102	9−6−1	0.012554	0.010088	138	12−6−1	0.011591	0.009256
31	3−7−1	0.013127	0.009858	67	6−7−1	0.013226	0.010681	103	9−7−1	0.012328	0.009893	139	12−7−1	0.012035	0.009051
32	3−8−1	0.013862	0.011190	68	6−8−1	0.012449	0.009869	104	9−8−1	0.015647	0.012812	140	12−8−1	0.013303	0.009512
33	3−9−1	0.014468	0.011955	69	6−9−1	0.013702	0.011021	105	9−9−1	0.017664	0.013836	141	12−9−1	0.018062	0.015051
34	3−10−1	0.014647	0.011965	70	6−10−1	0.014009	0.011779	106	9−10−1	0.013458	0.010811	142	12−10−1	0.013773	0.009954
35	3−11−1	0.012644	0.010261	71	6−11−1	0.011271	0.008966	107	9−11−1	0.012031	0.009883	143	12−11−1	0.012607	0.008638
36	3−12−1	0.015436	0.013219	72	6−12−1	0.012490	0.010333	108	9−12−1	0.012632	0.010206	144	12−12−1	0.015885	0.013502

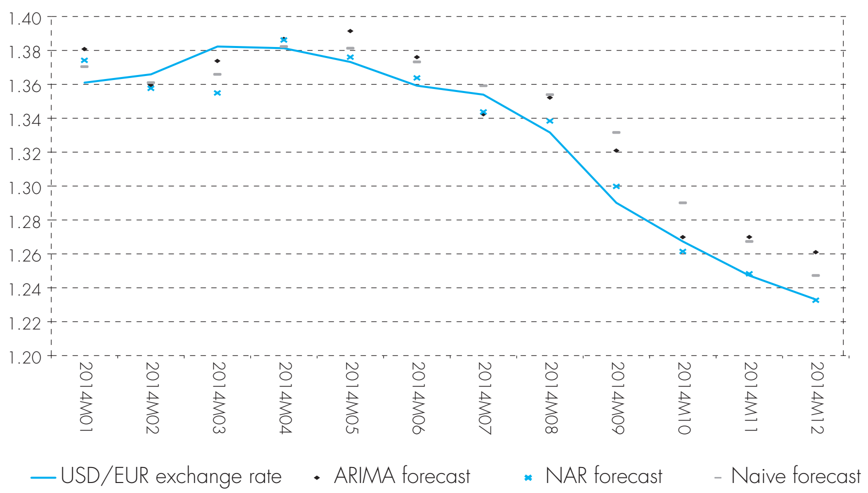
COMPARISON BETWEEN MODELS' FORECAST ABILITIES

Common measures to evaluate and compare the predictive power of a model are the Mean Error, Mean Absolute Error, the Root Mean Squared Error, and the Theil's U statistic. The first measure, ME, hints on the presence and the direction of the bias in the forecasts. A high and positive (negative) ME indicates a tendency to overshoot (undershoot) the actual exchange rate developments. The next two measures, MAE and RMSE, are useful in examining the size of the forecast errors. The mean absolute error implies that severity of errors increases in proportion to the MAE (e.g. 2 per cent error is 2 times as serious a 1 per cent error), while RMSE assumes that larger forecast errors are worse than smaller ones. The final measure, Theil's U, is an attractive indicator about relative accuracy that allows us to infer whether the applied forecasting techniques are better, as good as, or worse than simple guessing.

As mentioned before, the forecast evaluation period for the two competing models, ARIMA and NAR net, was purposely done on the out-of sample data. This is a common procedure among forecasters, who presume that in-sample evidence of predictability does not guarantee significant out-of-sample predictability (Inoue & Kilian, 2002). Therefore to avoid any possibility of spurious conclusions, the comparison of the predictive power of our chosen models will be conducted for the period from January to December 2014, which was not used in the regression estimation or the testing process.

Figure 2 exhibits the USD/EUR exchange rate during 2014 and its 12 one-month ahead forecasts based on the ARIMA (7,1,48) and NAR (11-12-1), as well as a naïve prediction that assumes 'no change' in the next month. A quick visual inspection suggests a better performance of the neural network model, since the NAR forecasts appear generally closer than other forecasts values to the actual observations. On the other hand, there is no clear view of the ARIMA predictions to outperform the naïve guessing values. Indeed, the ARIMA forecast values tend to alternate their position till July, but remain above actuals

Figure 2. Static forecasts of the USD/EUR exchange rate



(i.e. positive errors) thereafter. This implies that the ARIMA model has provided robust forecasts in a more normal time, but it has consistently overpredicted the USD/EUR exchange rate and was slow to catch up with the new trend in the second half of the year, during which the European Central Bank was rallying the markets with hints on initiating a quantitative easing programme[1].

Table 3. Evaluation of Static Forecasts of the USD/EUR exchange rate 12 one-month ahead periods, January to December 2014

	ARIMA(7,1,48)	NAR 11-12-1
Mean Error	0.0115	-0.0008
Mean Absolute Error	0.0159	0.0079
Root Mean Squared Error	0.0181	0.0105
Theil's U statistic	0.9921	0.5748

Table 3 presents the forecast evaluation measures for the ARIMA and NAR models. Obviously, the results confirm the superiority of the NAR technique by all measures. Its mean error is close to zero – or more precisely, less than a tenth of a cent – suggesting that NAR has on average neither overshot, nor undershot the exchange rate in 2014. On the contrary, the mean forecast error of the chosen ARIMA model, though moderate, has overpredicted the actuals by 1.15 cent in the same period.

The size of ME in ARIMA is around three-fourth of MAE, indicating the model is not predicting consistently too high. But again, that ratio is only one-tenth for the NAR. Similarly, the magnitudes of MAE and RMSE point out that larger forecast errors are to be taken more seriously in the case of ARIMA, and less for the neural network model.

Finally, the Theil's statistic in the last row of the table shows how both models compare to a naïve prediction (i.e. assuming the exchange rate in the next month will be the same as in the current period). Calculated as the ratio of the RMSE of the ARIMA (NAR) model to the RMSE of the naïve model, a Theil statistic greater than one would suggest our estimated model forecasts perform worse than a random walk model. This statistic for the ARIMA model is close to one, which – likewise the graphical inspection – suggests that predictions generated in 2014 were, on average, no better than the 'no change' method. On the other hand, the NAR predictions appear again to outperform even the naïve model, whose inferences for the next month exchange rate are about twice more erroneous.

CONCLUDING REMARKS

This article contributes to the neural network literature by demonstrating how potent and useful they can be as a tool in the process of economic and financial

[1] *"Markets rally after Draghi QE hint", article in Financial Times, August 25, 2014. Also see "ECB meeting recap: Draghi hints at more easing action next year", article in blogs.marketwatch.com, December 4, 2014.*

decision makings. To demonstrate it we chose the USD/EUR exchange rate, as a considerably volatile and a highly transacted asset in the international financial market, yet very disputed in academic works due to its often large divergences from the fundamental levels suggested by economic theories.

We were able to show that, while through a modest application, neural network models can add value and possibly outperform traditional models used to forecast exchange rates. The results were affirmative that the nonlinear autoregressive net consistently beat the ARIMA (and the random walk) static forecasts of the USD/EUR exchange rate. Nonetheless, in addition to autoregressive techniques and static forecasts, this research analysis can be further extended by employing more advanced models that are based on economic fundamentals as well as dynamic forecasts.

REFERENCES

Bacchetta, P., & Wincoop, E. v. (2006). Can information heterogeneity explain the exchange rate determination puzzle? American Economic Review 96, 552-576.

Gonzalez, Steven; Canada Economic and Fiscal Policy Branch. (2000). Neural networks for macroeconomic forecasting: a complementary approach to linear regression models.

Inoue, A., & Kilian, L. (2002). In-sample or out-of-sample tests of predicability: which one should we use? European Central Bank, Working Paper no. 195.

Janil, A. K., & Mao, J. (1996). Artificial Neural Networks: A Tutorial. IEEE Transactions on Computer, 29(3 (March)), 31-44; doi:10.1109/2.485891. doi:10.1109/2.485891

Kilian, L., & Taylor, M. P. (2001). Why is it so difficult to beat the random walk forecast of exchange rates?

Meylar, A., Kenny, G., & Quinn, T. (1998). Forecasting Irish inflation using ARIMA models. Munich Personal RePEs Archive (MPRA) paper no 11359 (December).

Philip, A., Taofiki, A., & Bidem, A. (2011). Artificial Neural Network Model for Forecasting Foreign Exchange Rate. 1(No. 3), 110-118.

Sarno, L., & Taylor, M. P. (2002). The Economics of Exchange Rates. Cambridge University Press.

Zhang, G., & Hu, M. Y. (1998). Neural network forecasting of the British pound/US dollar exchange rate. Omega 26.4, 495-506.

Zhang, G., Patuwo, B., & Hu, M. Y. (1998). Forecasting with artificial neural networks: The state of the art. International Journal of Forecasting(14 (1)), 35-62.

SIMILARITY ON ALBANIAN BANK CREDIT PORTFOLIO- APPLICATION ON CREDIT STOCK AND QUALITY

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INTRODUCTION

The international financial crisis (2007/2008) brought important academic contributions, which are focused on the sources of systemic importance of financial institutions. The newest concepts encountered in literature regarding the systemic importance are "too big to fail", "too connected to fail" and "too similar to fail". The latter is the subject of a recent study of the Czech National Bank[1] which emphasizes the importance of financial difficulties arising from the similarity of the banks' balance sheets and their exposure to similar macroeconomic shocks. The study proposes a toolkit of methods to address empirically this aspect in the context of their banking sector and assess the existence of clusters of similar banks based on both their balance sheet structure and their credit portfolio performance. The authors study the overall banking system diversification (similarity) and discuss potential implications on financial stability. High similarity in certain sectors brings high risk, as banks are similarly exposed to credit risk, as a result of similar macroeconomic shocks.

Their findings suggest that the overall similarity of individual banks was relatively stable and not excessively high over the period 2002-2013, driven mainly by large and well-established banks. They have identified specific clusters of banks, whose market share is small when assessed individually, but may become systemically important under adverse circumstances, when considered as a group.

Their study contributes to the existing literature in several ways. From the methodological point of view, they contribute to an empirical measurement of the cross-sectional dimension of systemic risk by proposing a simple measure of indirect interconnectedness between banks via common exposures. From the financial supervisor's point of view, this constitutes a practicable and applicable monitoring tool, which avoids many problems associated with empirical methods relying on the capital market data.

Within the discussion arising from the gap analysis with the European Central Bank (ECB) about addressing and European Systemic Risk Board (ESRB) recommendations on the diversification of investments by EU-based banks, it was necessary to implement a similar methodology in the case of the Albanian banking sector on similarity (diversification) of the loan portfolio by economy sectors.

1 *"Similarity and Clustering of Banks: the Application on the Credit Exposures of the Czech Banking Sector", J. Brechler, V. Hausenblas, Z. Komárková, M. Plašil.*

The methodology applied in our case showed that banks in Albania have invested in the same economic sectors, rendering them similar, thus increasing risk exposure. The similarity results higher when, in the application, we include the ratio of non-performing loans as a risk factor. The sectorial structure of the economy identifies some specific sectors that have contributed positively to the economic growth. Their rapid expansion in years, supported by favorable macroeconomic conditions and strong domestic demand, make these sectors attractive for the banks to invest. Among these business sectors, we identify the extractive industry, production and distribution of electric energy, construction, transport and agriculture. However, the households sector was also financially supported by the banking sector, namely in the form of consumer credit and mortgage credit.

In the following sections, we will briefly present the literature review, the methodology used to quantify the similarity of banks for their loan portfolio and the judgment on risk exposure arising from this application. Results and conclusions represent the concluding sections.

1. LITERATURE REVIEW

A part of literature focuses on measuring the systemic importance. One of the most used approaches often determines the level of market risk against institutions, based on the traditional financial modeling methods of market asset movements, for example Co-Value-at-Risk and MES (Acharya et al. 2010). In general, this approach may suffer from the lack of market prices, necessary to identify the empirical models, especially when describing a financial system with a less developed capital market. Another weakness of these models is that they usually do not rely on market efficiency. Another research source is the stress test used as a proxy. It is based on the simulation of shocks and their spread through the financial system. Stress tests use assets of individual banks (such as loans, interbank lending, and securities) and evaluate the resilience of the financial system against a wide range of shocks. These may be either random failures of banks (Hausenblas et al., 2012), or macroeconomic shocks (Elsinger et al., 2006a).

The concept of "too complex to fail" is closely linked to the market failures as a result of the moral hazard. Acharya and Yorulmazer (2007) conclude that banks get stronger incentives when the number of banks that are on the brink of bankruptcy is large and when survived institutions have sufficient capacity to acquire them, their need for salvation from bankruptcy is evaluated. The concept of interconnection by (Cai et al., 2014) is similar to the measurement of similarity in our research. The authors use the data for syndicated loans to calculate the Euclidean distance between pairs of banks for loan portfolios.
Correlation indicators at both bank and market level are calculated by aggregating the distance measurement. The empirical part of the study focuses on evaluating the factors affecting the formation of a syndicated loan and on finding interbank correlation. The study also offers models that address interbank correlation and different methods of measuring the systemic risk,

such as Covar, SRISK or DIP. (Kalluci, 2012) analyses, mainly since 2004, the behaviour of lending, and tries to identify two different behaviours, before and after the crisis. It lists several possible reasons behind these behaviours and then provides an analysis for the period of rapid credit growth during 2004-2008, as well as of credit slowdown during the years that followed the global financial crisis. After these analyses, the paper identifies an equilibrium of the credit/GDP ratio, which would represent a possible potential level, where lending to the economy should stand.

2. METHODOLOGY

In the following section, we present several concepts of similarity between bank portfolios and show how they can be combined into a unified framework. First, we design a measure of the portfolio similarity, which takes into account the correspondence of shares of selected asset categories in total assets between individual banks, but ignores the actual (credit) risk profiles of these assets. Selected categories refer to sectors of the economy, which will be explained in details in the next section. Such a measure may indicate seeds of potential vulnerabilities; nevertheless, the system can still remain stable in the absence of negative shocks and elevated risks. The analysis of common risks may thus be necessary to get a more realistic picture of the banking system. In particular, it may provide relevant indication whether a state of vulnerability turns into a state of financial instability. For this reason, we investigate how the similarity in the risk profile changes in time across the selected asset categories as well as across the banking sector. While this information may be interesting in its own right, it is first of all used to derive the risk weights for individual asset categories. These are, in turn, used for the calculation of the risk-adjusted version of the portfolio similarity measure. The main intuition behind the risk-adjusted indicator is that the portfolio similarity is more dangerous if all banks tend to hold similar and, at the same time, more risky assets. The measures under review can be used for monitoring the overall changes in the asset diversification within the banking sector or for identifying clusters of very similar banks at the given time point.

First concept relates to balance sheet similarity of assets, without considering their risk performance.

In practice, bank "a" can be described by a real-valued vector containing various characteristics, such as: portfolio structure of its loans and securities, funding structure, liquidity mismatch profile, and off-balance sheet business. Since our study is primarily concerned with the credit risk, we limit our attention to the asset-side of the balance sheet. Namely, a vector: a =(a1,….ak), where k stands for data granularity (characterizing sectors of economy), represents the asset portfolio characterized by the aggregate gross nominal value of each asset category i ε 1,…k. Asset categories are defined as exposures to different institutional sectors (debtors) that may be further broken down by financial instruments or branches of activity. Following (Blocher, 2011), we measure the similarity between the portfolios of any two banks (e.g. a and b) by the cosine similarity function. The cosine similarity between two vectors is defined as the cosine of the angle between the vectors:

Formula 1:

$$Similiarity\ (a, b) = cos\ (\theta) = \frac{\Sigma\ ai * bi}{\sqrt{(\Sigma ai^2 * \Sigma bi^2)}} \quad (1)$$

Cosine similarity is limited as follows:

(a;b ε R) -> [-1;1]

"a" and "b" represent individual banks, coupled with one-another. Given that on-balance-sheet assets can only take positive values, we further receive (a; (a; b ε R) -> [0, 1], 0 for orthogonal vectors (complete dissimilarity) and 1 for identically oriented vectors (completely identical portfolios composition). This highly facilitates the interpretation of the results obtained.

If it is necessary to put higher weight on the similarity between some of the asset categories, we may use the weighted form of the cosine similarity (in our case, varying weights will reflect different risk profile of individual asset categories):

Formula 2:

$$Similiarity\ (a, b, w) = \frac{\Sigma wiai * bi}{\sqrt{(\Sigma wiai^2 * \Sigma wibi^2)}} \quad (2)$$

Where: "a" and "b" represent individual banks of the system; w= risk weight, (whose measurement is explained below, where the analysis of the similarity include credit risk).

If we compute a similarity measure (according to the first formula), for each pair of "x" banks, we get a symmetric similarity matrix S=(si,j), which represents a key input for deriving several characteristics of the banking system.

In particular, based on the matrix S, we:

i) propose a measure of the overall similarity of banks in the system, and
ii) detect clusters of banks exposed to the common (systemic) risks.

To obtain the measure of overall similarity among banks, we stick to a simple solution and define it as a weighted-average of the pairwise similarities. We consider three different weighting schemes for computing the average similarity. (1) The trivial way is to consider equal weights (a unit matrix). This may, however, not be the desirable choice for heterogeneous banking systems, where data on smaller banks (yet to start to diversify their portfolios) can potentially noise the measurement. In order to get an estimate representative for the system in terms of total assets, we alternatively use (2) the weights computed as the sum of total assets of the bank i and j or even as (3) the total assets of the smaller of the two measured banks.

In our exercise, we chose the second way (2) to compute the similarity of banks. More specifically, the similarity of each pair of banks is multiplied by the weight that the pair of banks holds in the total assets of the banking sector. Similarity of the credit portfolio for the banking sector is the weighted sum of bank's similarity and bank's weight.

The results of similarity for each pair of banks are performed in the form of a matrix table. Given that the Albanian banking sector appears very similar to the orientation of their investments (credit given to the same sectors of the economy), the distribution of values of "similarity" does not have significant fluctuations among couples. So, we judge the current values of cosine similarity to be categorized by percentile (10th percentile, 50th percentile, and 90th percentile).

- *10th Percentile* represents those pairs of banks that are characterized by low similarity. These are pairs of banks that are considered heterogeneous and have not focused their lending activity to the same economic sectors. The values on the 10th percentile show that 10% of banks are not similar to each other. These are pairs of banks which are heterogeneous and their lending is focused on different sectors of economy.
- *50th Percentile* represents the value in which 50% of bank pairs are categorised. In other words, 50% of pairs are similar to each other at a medium level (neither very similar, nor dissimilar at all).
- *90th Percentile* represents the value above which we find 10% of the bank-pairs. Above the value defined in the 90th percentile, we find pairs of banks that are very similar to each other, which we consider as homogenous. These pairs of banks are supposed to have given credit to the same sectors of the economy. In times of crisis to certain sectors, the more homogeneous the banks are to each other, the more exposed to risk the system is.

To visually present the exercise, we used Excel conditional formatting.

Second Concept relates to similarity in credit risk performance.

In our exercise, we aim to include some measure of the credit risk materialization in the analysis of similarity. Therefore, we used the ratio of non-performing loans (NPL), as a measure. This choice was motivated by some practical reasons. First of all, it is a simple, easily and widely understandable measure, which exhibits relatively smooth changes over the time. Secondly, the NPL is probably the single measure available from all banks; it gives detailed information about the bank and comes with sufficient granularity. In particular, the NPL ratio does not only reflect the risk profile of a given asset category, but may also mirror internal processes of a bank (e.g. the work-out phase) and its risk appetite. In addition, contrary to other measures (such as provisions), it does not take into account recovery rates and thus ignores the real size of losses related to a given asset category.

The level of credit risk related to a given asset category at time "t", μt, is measured by the aggregate value for the banking sector in a given period (i.e. levels for individual banks are neglected). The overall similarity of NPL ratios across individual banks is then proxied by the coefficient of variation Vt = st/μt, where "st" denotes standard deviation of NPL ratios across individual banks at time "t". The lower is its value, the more similar credit risk levels are observed across banks for a given asset category in a given period and consequently higher exposure to credit risk.

* μit - The ratio of non-performing loans of the banking sector in a certain period of time for a specific category, named "i".

For example, the ratio of NPL for the agriculture category.

Vt- the coefficient of variation calculated as the ratio of standard deviation (St) to μt.

St- standard deviation is calculated as follows:

$$Wt = \mu t * Vt^{-1} = \frac{\mu t^2}{st} \tag{3}$$

where NPLai refers to the ratio of non-performing loans for bank "a" in the category "i". N refers to the number of banks participating in the exercise, in our case 15 banks (as Credit Bank of Albania has an almost non-existent activity in lending and a negligible level of non-performing loans).

It might be worth adjusting the portfolio similarity measure for risk characteristics so that more risky assets receive higher weight. To follow this track, we apply information on both the level of credit risk and its dispersion (coefficient of variation). In general, we assume that a high level of the NPL ratio, associated with a certain asset category, combined with a low dispersion of its values across banks, imply higher risk of indirect contagion stemming from exposures to such a category. Applying this reasoning, we define risk weights as an interaction term of the level and dispersion. Since higher levels of dispersion indicate lower similarity, we use its inverse to derive the weights of the form.

$$St = \frac{\sqrt{\Sigma(RKPai - \mu it)^2}}{N} \tag{4}$$

These weights are used to calculate the similarity between banks under the "formula 2" above.

3. DATA

Lending in Albania is dominated by the banking sector, where approximately 96% of total loans are granted by banks, 3.2% by non-banks financial institutions and 1.1% by saving and credit associations. Lending to the Albanian economy has gone through different development cycles, recording high levels of expansion (booms) and contraction. The intermediation role of the Albanian banking sector became more visible after 2004 as a result of several developments such as: the privatization of the Savings Bank, the largest in the country, in 2004, the entrance of other foreign banks in the market, and supervisory and regulatory framework improvement. Lending during 2001-2004, although with a low basis, marked an average annual growth of 33%, representing an average of 7.4% of Albania's GDP.

During 2004-2008, lending has recorded the highest rates of growth, around 57% on average, representing 24% of the country's GDP. This behaviour was supported by a favourable macroeconomic framework (the relatively high and stable economic growth, low inflation levels within the target range set by the monetary authority). During these years, the households sector saw, although characterized by a low base, the most rapid growth of credit (average 67.2%)-especially mortgage loans as demand for this type of loan increased significantly. Meanwhile, the business sector recorded 45% credit growth, on average. We should emphasize that the loan portfolio quality during this period was quite good, as measured by nonperforming loans to total outstanding loans ratio, averaging 3.6%.

The international financial crisis in the summer of 2007 brought a relatively low exposure of the Albanian banking sector to risks, as a result of low financial development (lack of stock exchange and the so-called toxic securities investments). However, certain financial strength indicators diverged from their historical trend and credit activity started to contract[2]. Lending continued the downward trend in the following years, with the largest decline recorded during the July 2013-July 2014[3] period, mainly as a result of economic slowdown and low performance of credit portfolio (NPL ratio in 2014 recorded 24%, the largest historical level,). All these historical developments of lending behaviour have been associated with regulatory framework improvement and measures to narrow and later expand lending activity.

For our exercise, the database is on quarterly basis from September 2009-December 2014. The selection of the exercise period is not casual as we consider that during these years the financial crisis materialized and they contain more interesting and detailed information about the lending activity (credit crunch and high NPL ratio). However, for comparison reasons, we have developed the exercise for the first concept explained in the methodology above, for December 2008, as e pre-crisis period. We have selected 16 categories, which represent lending to businesses by sector

[2] *After the year 2008 until early 2011, lending activity grew at single digits for the first time in its history. The lowest growth rate was recorded in October 2010, 7.5%.*

[3] *In April 2014, the largest negative growth rate level of loans was (-3.4%) on annual basis.*

(NACE classification –including 11 industries), to households (consumer and mortgage loans), to governmental institutions, other financial institutions and non-resident transactions (table 1).

Table 1. Descriptive statistics for banking credit (as of the end of 2014).

	Credit provided	Share on total	Concentration within sector HHI
	(in mln ALL)	(in %)	Average over 2009-2014
Non-financial corporations			
i) Agriculture, Hunting and Forestry	6,738.01	1.13	0.24
ii) Fishing	348.14	0.06	0.28
iii) Extracting industry	7,982.74	1.34	0.31
iv) Processing industry	59,258.83	9.95	0.13
v) Electricity, gas and water supply	52,908.33	8.89	0.25
vi) Construction	52,759.06	8.86	0.12
vii) Whoolsale and retail trade; repair of motor vehicles and motorcycles	139,048.19	23.35	0.15
viii) Hotels and restaurants	15,229.08	2.56	0.12
ix) Transporting, storage and telecomunication	12,181.93	2.05	0.14
x) Real estate and renting	2,219.09	0.37	0.16
xi) Other	55,557.89	9.33	0.13
Households			
i) Housing loans	102,823.31	17.27	0.12
ii) Consumer loans	41,771.02	7.02	0.18
Loans to banks, credit institutions and other financial institutions	14,264.08	2.40	0.27
Albanian Government and Public Administration	2,040.86	0.34	0.57
Non-resident transactions	30,312.83	5.09	0.53
Total	595,443.38	100.00	0.12

Source: Bank of Albania

In table 1, trade sector and households sector (mortgage loans category) recorded the highest share in total credit provided by the banking sector, at 23.4% and 17.3%, respectively. The highest concentration in terms of Herfindahl Index is calculated for Albanian Government and Public Administration (0.57), credit to non-residents (0.53) and extractive industry (0.31). This is due to the fact that a small number of banks invest in these sectors of the economy. The Albanian banking sector is characterized by a moderate concentration level, which ranges 0.15-0.25.

4. RESULTS

4.1 BALANCE SHEET SIMILARITY (EXCLUDING THE CREDIT RISK PERFORMANCE)

Matrix 1 shows the results based on the methodology explained above in the case of similarity of banks' loan portfolio, regardless of the credit risk:

Matrix 1. Balance sheet similarity (December 2014)

	G3	G1	G1	G3	G3	G1	G3	G2	G1	G2	G2	G1	G3	G2	G2
G3	1	0.84	0.75	0.77	0.81	0.73	0.85	0.86	0.81	0.49	0.65	0.82	0.88	0.85	0.73
G1	0.84	1	0.64	0.54	0.62	0.59	0.52	0.84	0.72	0.31	0.54	0.71	0.93	0.76	0.59
G1	0.75	0.64	1	0.67	0.83	0.65	0.82	0.79	0.76	0.51	0.58	0.80	0.83	0.74	0.80
G3	0.77	0.54	0.67	1	0.83	0.76	0.77	0.64	0.83	0.81	0.84	0.81	0.69	0.82	0.79
G3	0.81	0.62	0.83	0.83	1	0.76	0.84	0.83	0.87	0.80	0.85	0.87	0.74	0.93	0.84
G1	0.73	0.59	0.65	0.76	0.76	1	0.63	0.68	0.81	0.75	0.82	0.84	0.67	0.79	0.94
G3	0.85	0.52	0.82	0.77	0.84	0.63	1	0.71	0.79	0.57	0.63	0.82	0.68	0.77	0.74
G2	0.86	0.84	0.79	0.64	0.83	0.68	0.71	1	0.82	0.50	0.65	0.83	0.89	0.88	0.73
G1	0.81	0.72	0.76	0.83	0.87	0.81	0.79	0.82	1	0.81	0.91	0.97	0.81	0.95	0.87
G2	0.49	0.31	0.51	0.81	0.80	0.75	0.57	0.50	0.81	1	0.94	0.76	0.41	0.34	0.77
G2	0.65	0.54	0.58	0.84	0.85	0.82	0.63	0.65	0.91	0.94	1	0.86	0.61	0.88	0.83
G1	0.82	0.71	0.80	0.81	0.87	0.84	0.82	0.83	0.97	0.76	0.86	1	0.82	0.92	0.93
G3	0.88	0.93	0.83	0.69	0.74	0.67	0.68	0.89	0.81	0.41	0.61	0.82	1	0.81	0.74
G2	0.85	0.76	0.74	0.82	0.93	0.79	0.77	0.88	0.95	0.34	0.88	0.92	0.81	1	0.83
G2	0.73	0.59	0.80	0.79	0.84	0.94	0.74	0.73	0.87	0.77	0.83	0.93	0.74	0.83	1
Pairs	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0

Source: Authors' calculations

In matrix 1, columns and rows represent individual banks by group size[4] under the same order. Each cell represents the similarity between the two banks of the column and the respective row. The darker is the cell, the higher is the similarity between the two banks. Matrix painting is defined by the percentile distribution.

- Light blue colour represents pairs of banks with low similarity. We have defined this level in the 10th percentile, at 0.59
- Blue colour represents pairs of banks with relatively high similarity. We have defined this level in the 50th percentile, at 0.81
- Dark blue colour represents pairs of banks with the highest similarity, which lies in the 90th percentile, at 0.94. We highlight that only 10% of the banks' pairs value have a similarity higher than 0.94 (close to the value 1), indicating that banks are very similar and therefore are similarly exposed to the same potential risks.

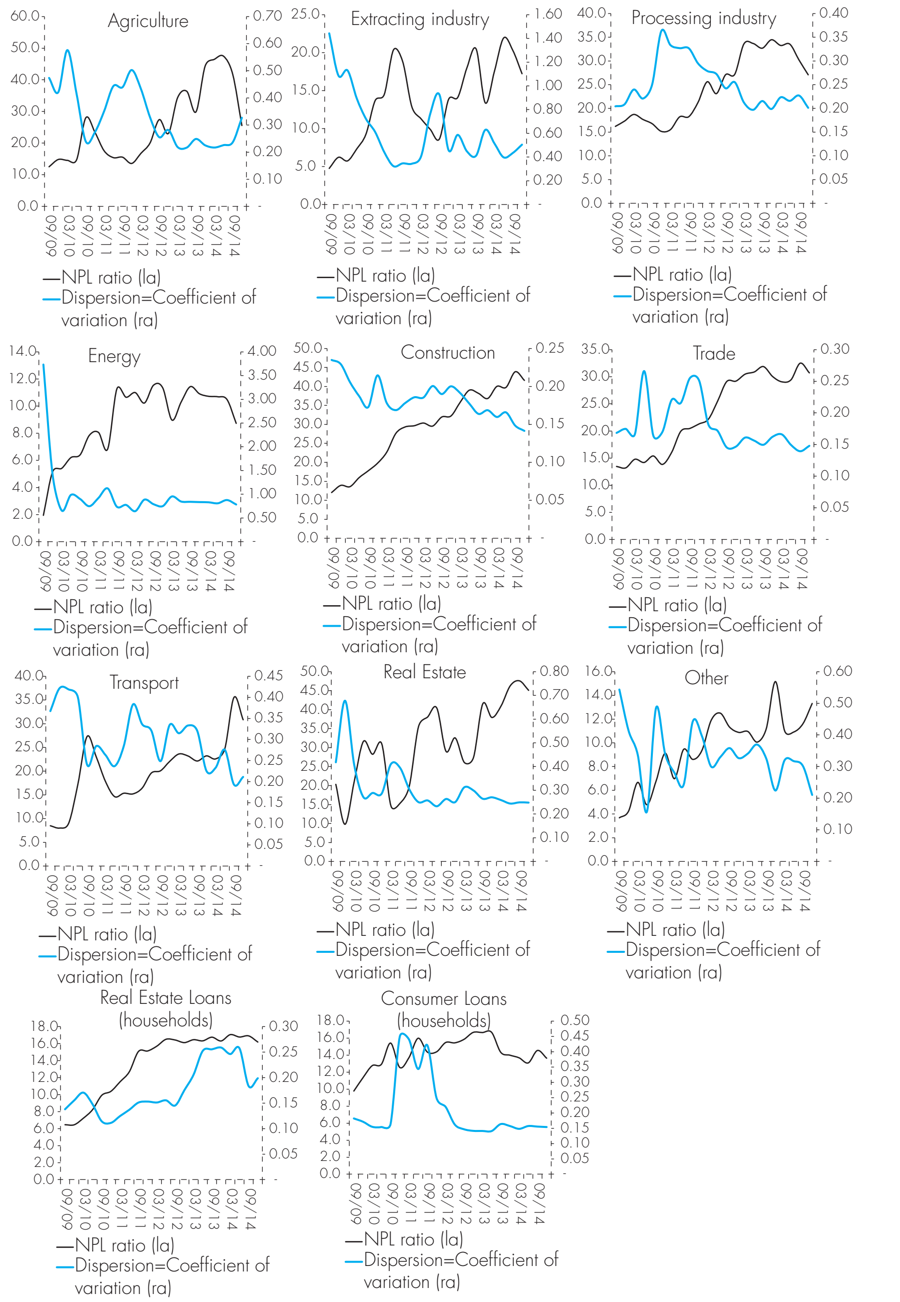
Diagonal white stripe of the matrix is excluded as it shows the similarity of the bank with itself, which is equal to 1. In total, there are 105 pairs of banks. We expect that big banks have high similarity between their loan portfolios, as well as smaller banks with each other. Indeed from the obtained results it appears that despite their size, the combination of a large bank with a small one shows a high level of similarity. This is due to the concentration of lending in the same sectors. For example, the level of similarity between one bank in G3 group and another one in G1 group is 0.93. In aggregate, banks' loan portfolios composition is focused in trade, mortgage, construction and consumer loans. Banks that have granted loans to these sectors show high similarity in their loan portfolios (matrix 1). Under this method, the overall similarity of the banking sector is 0.76.

[4] *Banks, whose total assets constitute less than 2% of the total assets of the banking sector, are part of G1 group. Banks, whose total assets lie to the range 2%-7% of the total assets of the banking sector, are part of G2 group. Banks, whose total assets constitute more than 7% of the total assets of the banking sector, are part of G3 group.*

4.2 BALANCE SHEET SIMILARITY (INCLUDING CREDIT RISK)

In order to include the assets performance in our application, it would be valid to adjust the similarity measurement of portfolio risk characteristics, so that assets with higher risk get higher weight[5]. We consider the impact of credit quality on the similarity of credit portfolio, by defining the weighted coefficients as an interaction between non-performing loans ratio and coefficient of variation. Since high levels of coefficient of variation indicate low similarity, we use the inverse of this to derive weights as follows:

Figure 1. Non-performing loans and coefficient of variation for the main economic sectors.



Source: Bank of Albania, Authors' calculations

5 *Based on the methodology treated in the above sections.*

Figure 1 shows the development of non-performing loans and coefficient of variation by economy sectors.

The most exposed sectors to credit risk are trade, construction, manufacturing, transport and consumer loans, which were characterized by a low level of coefficient of variation. As a result of the symbiotic relation between NPL and the coefficient of variation, these sectors result in a higher level of NPL ratio. Following this reasoning, similarity among pairs of banks for these sectors, considering credit risk, remains high.

The derived results, based on the methodology applied by the study of the Czech National Bank, for the similarity case of the loan portfolio in the Albanian banks considering credit risk, are presented in matrix 2 as follows:

Matrix 2. Balance sheet similarity including credit risk (December 2014)

	G3	G1	G1	G3	G3	G1	G3	G2	G1	G2	G2	G1	G3	G2	G2
G3	1	0.96	0.75	0.83	0.84	0.81	0.81	0.95	0.90	0.57	0.80	0.86	0.95	0.93	0.81
G1	0.96	1	0.68	0.71	0.72	0.72	0.71	0.92	0.86	0.43	0.71	0.81	0.96	0.87	0.71
G1	0.75	0.68	1	0.78	0.87	0.60	0.94	0.78	0.82	0.58	0.71	0.85	0.85	0.73	0.84
G3	0.83	0.71	0.78	1	0.93	0.85	0.87	0.81	0.94	0.92	0.97	0.90	0.79	0.92	0.91
G3	0.84	0.72	0.87	0.93	1	0.74	0.94	0.87	0.89	0.81	0.88	0.88	0.82	0.91	0.87
G1	0.81	0.72	0.60	0.85	0.74	1	0.68	0.73	0.81	0.74	0.84	0.80	0.73	0.81	0.90
G3	0.81	0.71	0.94	0.87	0.94	0.68	1	0.84	0.89	0.69	0.82	0.93	0.85	0.84	0.89
G2	0.95	0.92	0.78	0.81	0.87	0.73	0.84	1	0.89	0.57	0.76	0.87	0.93	0.94	0.78
G1	0.90	0.86	0.82	0.94	0.89	0.81	0.89	0.89	1	0.78	0.94	0.97	0.92	0.94	0.90
G2	0.57	0.43	0.58	0.92	0.81	0.74	0.69	0.57	0.78	1	0.92	0.73	0.51	0.30	0.78
G2	0.80	0.71	0.71	0.97	0.88	0.84	0.82	0.76	0.94	0.92	1	0.89	0.76	0.89	0.89
G1	0.86	0.81	0.85	0.90	0.88	0.80	0.93	0.87	0.97	0.73	0.89	1	0.90	0.90	0.94
G3	0.95	0.96	0.85	0.79	0.82	0.73	0.85	0.93	0.92	0.51	0.76	0.90	1	0.88	0.82
G2	0.93	0.87	0.73	0.92	0.91	0.81	0.84	0.94	0.94	0.30	0.89	0.90	0.88	1	0.84
G2	0.81	0.71	0.84	0.91	0.87	0.90	0.89	0.78	0.90	0.78	0.89	0.94	0.82	0.84	1
Pairs	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0

Source: Authors' calculations

Similarity by balance sheet, considering credit risk as well (represented by the NPL ratio) calculated by formula 2 in the methodology section, is higher for all bank pairs, thus showing higher level of exposure towards credit risk. More specifically, similarity values by pairs, expressed in terms of percentile fluctuate:

- 0.71 for the 10th percentile (which means that only 10% of the bank pairs show similarity up to the value of 0.71 and 90% of the pairs remain above the 0.71 level);
- 0.85 for the 50th percentile;
- 0.96 for the 90th percentile.

The overall similarity of the banking sector in this method scored 0.84, being considered a high similarity of the loan portfolio.

Applying the exercise for the period before the materialization of the international crisis effect (December 2008), gives us a similar overview with the current period, where the main weight of the loan portfolio is composed by loans for trade, mortgage, manufacturing and construction. Similarity among bank pairs remains high, except for some specific banks' combinations, where similarity levels appear low, shown in light-blue colour columns (Matrix 3). This comes as a result of lending to different sectors from the rest of the banking sector.

Matrix 3. Balance sheet similarity excluding credit risk (December 2008).

	G3	G1	G1	G3	G3	G1	G3	G2	G1	G2	G2	G1	G3	G2	G2
G3	1	0.85	0.72	0.70	0.68	0.59	0.82	0.75	0.70	0.43	0.60	0.78	0.15	0.82	0.69
G1	0.85	1	0.86	0.77	0.82	0.51	0.88	0.46	0.81	0.45	0.68	0.82	0.26	0.96	0.74
G1	0.72	0.86	1	0.83	0.85	0.56	0.88	0.49	0.76	0.61	0.73	0.71	0.26	0.83	0.74
G3	0.70	0.77	0.83	1	0.92	0.86	0.95	0.53	0.93	0.87	0.95	0.85	0.20	0.84	0.90
G3	0.68	0.82	0.85	0.92	1	0.78	0.92	0.48	0.94	0.84	0.91	0.87	0.24	0.86	0.96
G1	0.59	0.51	0.56	0.86	0.78	1	0.75	0.72	0.76	0.92	0.84	0.76	0.10	0.63	0.89
G3	0.82	0.88	0.88	0.95	0.92	0.75	1	0.53	0.91	0.74	0.86	0.86	0.26	0.93	0.87
G2	0.75	0.46	0.49	0.53	0.48	0.72	0.53	1	0.43	0.51	0.50	0.66	0.04	0.47	0.64
G1	0.70	0.81	0.76	0.93	0.94	0.76	0.91	0.43	1	0.83	0.96	0.88	0.20	0.82	0.91
G2	0.43	0.45	0.61	0.87	0.84	0.92	0.74	0.51	0.83	1	0.92	0.71	0.09	0.54	0.89
G2	0.60	0.68	0.73	0.95	0.91	0.84	0.86	0.50	0.96	0.92	1	0.86	0.61	0.88	0.83
G1	0.78	0.82	0.71	0.85	0.87	0.76	0.86	0.66	0.88	0.71	0.86	1	0.32	0.85	0.91
G3	0.15	0.26	0.26	0.20	0.24	0.10	0.26	0.04	0.20	0.09	0.61	0.32	1	0.33	0.22
G2	0.82	0.96	0.83	0.84	0.86	0.63	0.93	0.47	0.82	0.54	0.88	0.85	0.33	1	0.79
G2	0.69	0.74	0.74	0.90	0.96	0.89	0.87	0.64	0.91	0.89	0.83	0.91	0.22	0.79	1
Pairs	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0

Source: Authors' calculations

The overall similarity of the banking sector before the crisis scored 0.70, lower than after the crisis (December 2014), which scored 0.76. This shows that the banking sector is currently exposed to potential risks, given the high similarity of the banks' pairs for their loan portfolio.

5. CONCLUSIONS

This work presented several simple tools to fill some of the gaps in the empirical assessment and risk monitoring toolkit for macroprudential authorities. The exercise showed that the concept of "size" is not significant according to loan portfolio similarity in the case of the Albanian banking sector, as a high level of similarity does not stand only between two big banks but also between a small and a big one. This is due to the concentration of lending in the same economic sectors. The methodology applied showed that banks in Albania have made their investments in the same sectors, which makes them similar.

The level of similarity results even higher when, in the exercise, we include a risk factor, represented by the ratio of non-performing loans. Low diversification of the Albanian banking sector exposes the system to potential shocks that could affect financial stability.
Given the high similarity level that characterizes the Albanian banking sector, we suggest careful monitoring of the risk investments undertaken in the same sectors.

The application of the methodology for the pre-crisis period (December 2008) presents a lower level of similarity, consequently lower exposure to potential risks due to the diversification of the loan portfolio in two banks of the Albanian banking sector (one in G3 group and the other in G2 group). These banks have oriented their investments in different economic sectors from the rest of the banking sector.

This methodology may also help to improve the stress testing exercise, providing supervisory authorities a clearer picture of credit risk concentration.

In our study, we applied the presented method with the focus on credit risk of the asset side of banks' balance sheets. Nevertheless, the method is general enough to be applied on any other banks' characteristics such as risk-weighted assets, structure of liabilities, liquidity mismatch, capital structure, and trading activity. This could provide the authorities with a practical tool for classification of banks by their business models and risk management practices.

REFERENCES

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson (2010): "Measuring systemic risk." Working Paper 1002, Federal Reserve Bank of Cleveland;

Acharya, V. V. and T. Yorulmazer (2007): "Too many to fail–An analysis of time inconsistency in bank closure policies."

Cai, J., A. Saunders, and S. Steffen (2014): "Syndication, Interconnectedness, and Systemic Risk."

Elsinger, H., A. Lehar, and M. Summer (2006): "Risk Assessment for Banking Systems"

Hausenblas, V., I. Kubicova, and J. Lesanovska (2012): "Contagion Risk in the Czech Financial System: A Network Analysis and Simulation Approach";

Josef Brechler (2014): "Similarity and Clustering of Banks"- the Application on the Credit Exposures of the Czech Banking Sector (Czech National Bank).

Irini Kalluci (2012): "Credit behaviour in Albania: a sign of convergence or a deviation from its long-term trend?" ;

Blocher, J. (2011): "Contagious capital: A network analysis of interconnected intermediaries".
"Financial Stability Report- 2013 H2", page 67 (May 2014), Bank of Albania

Thomson, J. B. (2009): "On Systemically Important Financial Institutions and Progressive Systemic Mitigation."

ON THE EXISTENCE OF BANKING LENDING CHANNEL IN THE TRANSMISSION MECHANISM IN ALBANIA

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ABSTRACT

The bank lending channel has gained importance in the last decades, in particular after the 2008 global financial crisis. The question that has brought up to the researches was to understand/ determine the handicaps that have risen and hindered the proper functioning of monetary policy mechanism, in an environment of low interest rate. This paper aims at assessing the role of banks' characteristics, such as their liquidity and size, in the transmission of monetary policy measures, through the application of GMM method in the individual data by banks. The results of empirical data confirm the existence of credit channel to banks with high liquidity. On the other hand, the size of the bank does not result statistically important, except of when the bank had high liquidity. The findings in this paper are in line with the conclusions in other researches for the determinant of credit and the functioning of credit channel in the monetary transmission mechanism.

1. INTRODUCTION

Unlike the neoclassic channels, bank lending channel examines the possibility of imperfections in the financial markets. During the last decades it has drawn particular attention in the monetary policy literature to better understand the monetary policy transmission mechanism to economy. In case of Albania, there are some researches that address bank lending, hence the aim of this brief analysis is to make an "inventory" of the empirical findings in the Bank of Albania's research work in this regard, and draw conclusions on their relevance in the current monetary policy analyses. This article briefly presents the concept of lending channel and the empirical research done at the central bank. It then replicates the findings by Vika (2009), and tries to shed some light on the existence of bank lending channel in Albania.

Under the assumption that markets are efficient, the neoclassical view on monetary transmission mechanism focused on the modelling of aggregate demand components. Yet, government interventions and private market imperfections due to the asymmetric information or market segmentation may lead to an inefficient functioning of markets. The literature on monetary transmission mechanism through the "non-neoclassic" channels looks at the impact of government interventions in financial markets; the bank lending

[1] *The views expressed herein are solely of the authors and do not necessarily reflect those of the Bank of Albania.*

channel; and the households and firms balance sheet channel (Boivin, Kiley dhe Mishkin, 2010). The first channel pays attention to the government policies that may impact bank lending, as it was the case of government guarantees in Finland in the 1990s. The second channel emphasises the role of banks in the transmission of monetary policy. If they have different characteristics and financial powers, the credit supply of each bank may react differently against the monetary policy shocks. That means, the structure of the banking system may be important in in the supply of loans by individual banks. Bank characteristics, such as size, liquidity and capital are broadly used in the literature as proxies for information asymmetry, which may help to understand how strong the effects among banks are. On the other hand, the third channel examines the financial statements of households and business.

The literature review identifies certain research works that address lending in Albania. Some of them have aimed at understanding bank lending behaviour at the macro level or its determining factors (for example Kalluci (2012); Suljoti & Note (2013); Shijaku & Kalluci (2014); Tanku, Dushku & Ceca (2015); Rama (2015); etc.] or have been undertaken for the purpose of financial stability (for example Ceca & Shijaku (2011); Dushku & Kota (2014); etc.], but only Luçi & Vika (2005) and Vika (2009) have tried to test more directly on the existence of bank lending channel in the monetary transmission mechanism. The latter works are based on banks' individual data: the first one uses quarterly data from 2001 to 2003, while the second from 2004 to 2006. Although the theoretical framework of both materials remains the same, there are important differences between them, starting with the enlargement of the sample (by including the largest bank that was previously excluded for objective reasons[2]), and then with the estimation of parameters by employing the GMM method (according to Arellano and Bond), which is widely used in the literature as a more statistically reliable method than the OLS in addressing the endogenous problems that arise from the model specification. For this reason we have proceeded by replicating the second material, "The Role of Banks in the Monetary Policy Transmission in Albania" by Vika (2009), in search of the reliability and usefulness of those findings in the current period.

In what follows, we will initially describe some characteristics of the financial system structure in Albania, that may help to form an idea on the existence of the bank lending channel of monetary transmission as discussed above. Then, we discuss some methodological aspects of the analysis and the empirical results.

2. ECONOMIC DEVELOPMENTS AND CHARACTERISTICS OF THE BANKING SECTOR

Similar to other countries in Southeastern Europe, Albania had a high and sustainable growth in the last decade. In 2000-2008, the economic growth averaging around 6% per year was sustained by the fast expansion of private

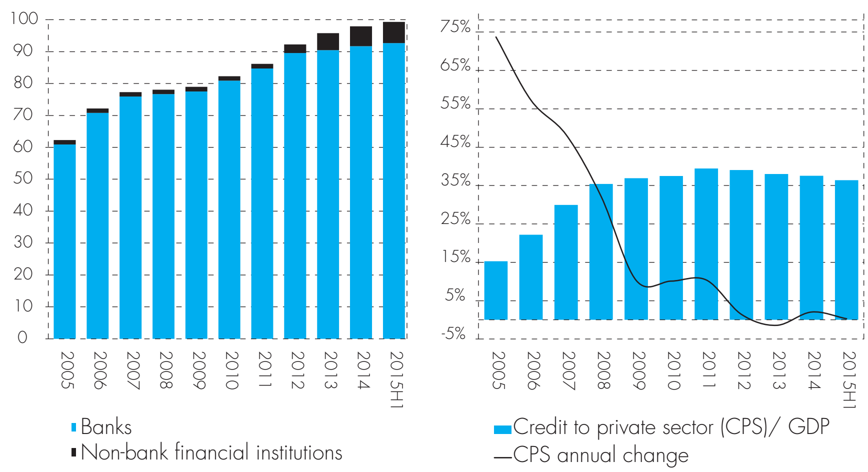
2 *Previously, this bank was not included in the sample, because was not allowed to lend by Supervisory Authorities..*

consumption and increase in productivity, supported by an active role of the banking sector. The financial crisis in 2008 shocked the economic growth, in particular the domestic demand through the consumption and investments. Both components of the aggregate demand were more strongly shocked by the crisis in Europe as well, the fall of remittances and the worsening of confidence. Economic expansion for the period 2009-2014 averaged down to 2.3%.

Albania, in the two last decades, was characterised by a low inflation rate of consumer prices. In particular, after 2008, inflation rate positioned at moderate levels by reflecting the weak aggregate demand, the deflationary external environment and the under potential performance of the economy. Inflation rate, in 2014-2015, averaged 1.7%, below the Bank of Albania's target of 3%. Meanwhile, the performance of exchange rate was stable. Following a considerable depreciation in 2009s (around 15%), the Lek exchange rate against the main currencies was stabilised at a new level. In a sluggish economic environment, the monetary policy of the Bank of Albania was broadly on the easing side. Bank of Albania, since autumn 2011, has continuously cut the key interest rate. The last cut of the policy rate took place in November 2015, driving the key interest rate at the lowest historic level of 1.75%.

The financial system in Albania has experienced important changes in the last 10 years. Financial intermediation is deepened and many new instruments are introduced. Banking system represents the most developed segment of the financial system, sharing around 90% of total assets. Out of the total 16 banks, 14 are foreign owned and conduct their activity in the market. The participation of foreign banks has helped to the increase of competitiveness and efficiency in the system. All banks in the system are universal/commercial banks. The ratio of banks' assets to GDP has increased by 30 percentage points in the last 10 years, posing at 93% in 2015. During this period, banks increased considerably the financial intermediation to economy. Credit ratio

Chart 2.1 Banking sector and credit



Source: Bank of Albania.

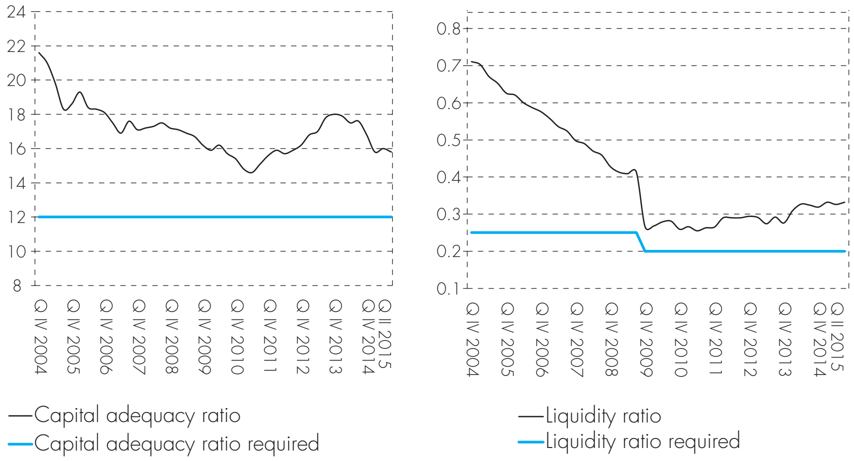
to deposits was 14.4% at the end of 2002, and in the last years is stabilised close to 55%. Notwithstanding the ample number of banks in the system, the latter is dominated by the group of large banks, consisting in three banks, which share more than 50% of the system's assets. Although this indicator has been falling, it continues to show the high concentration of the large banks in the banking activity (Bank of Albania's Annual Supervision Report, 2014).

Lending to private sector, which increased rapidly after 2004, is one of the main activities of banks. Hence, with an annual growth of portfolio, averagely 50%, in the period 2004-2008, the credit ratio to GDP increased quickly, from 7.5% in 2003 to 35.4% in 2008. The acceleration of credit growth pace to private sector was supported by the high demand for financing and the increased supply of banks for crediting, encouraged by the entry into market of the large European banks. The fast expansion of the economic activity, the considerable needs for investment and their financing supported by the positive developments in the banking system were the main determinants of the accelerated lending growth in Albania. Also, the employment of financial leverage from businesses during those years was another important factor to this growth.

The ratio of private sector credit to GDP recorded the highest historical level 40% in 2011. Since the middle of 2012, this ratio has been falling and is stabilised around the level 37% in the last two years, 2014-2015. For the period after the crisis, crediting growth averaged 5% per year, meanwhile it contracted in the last years. The worsening of credit activity in the last years reflects the fall in the demand for financing from private sector and the tight credit standards from banks. The slowdown of the economic activity drove to the incomplete use of producing capacities, and consequently the lower need for investments and lower demand for financing. In parallel, the increased uncertainty for the developments in the future, the confidence fall of both businesses and households, and overall, the weaken income affected the fall of the demand for credit at banks. Also, credit supply shrank considerably and banks became selective, manifesting a risk adverse behaviour after the global crises. Credit risk increased notably after 2008. At the end of 2008, non-performing loans ratio was around 4%. This indicator was included in an upward trend until September 2014, when it recorded the highest level of 25%. The rapid increase of non-performing loans pushed banks to implement conservative crediting policies. These policies were further tightened upon the deleveraging process of western banks from the South Eastern European countries and the interruption of the financing to branches in the region.

Notwithstanding the worsening of the credit portfolio, banking system during this period is characterised by well capital and liquidity levels. After 2008, the capital adequacy ratio, stands at averagely 16.3%, above the required regulatory level of 12%. Liquidity indicators show a gradual fall upon the development and deepening of banks' intermediation role. Before 2008, this indicator varied averagely 65%, while in the period 2008-2015, it fluctuated averagely 30%. Notwithstanding the fluctuations, this indicator was always above the minimum of the regulatory requirement. Nevertheless, the ratio of liquidity the capital adequacy of banks varies considerably from one bank to the other.

Chart 2.2 Indicators of liquidity and capital of the banking sector

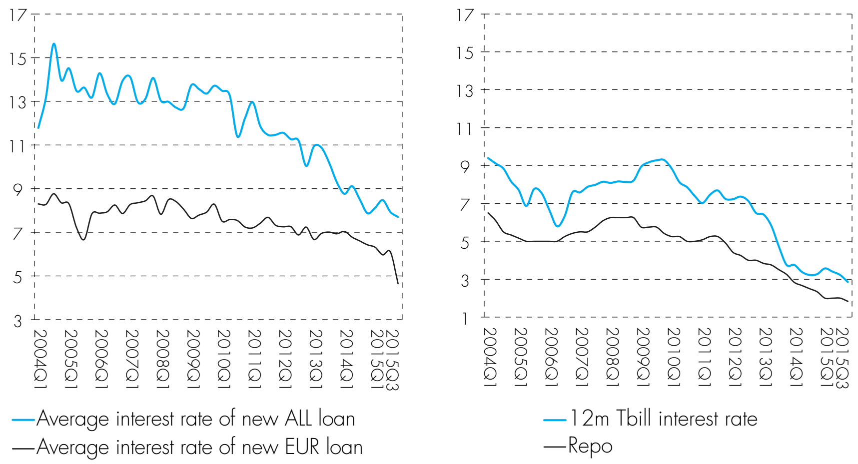


Source: Bank of Albania.

Credit portfolio in banks is dominated by the credit to businesses, around 70% of it. This ratio was higher prior to 2004. During 2004-2008 banks focused to the loans to households as well. Credit to households reached the highest share in credit portfolio at 37% during 2007. After 2008, banks withdrawn from the financing to households, and turned back to this segment only recently. At the end of 2015, credit to businesses accounted for 65% of credit portfolio, credit to households 28% and credit to state-owned enterprises accounted for 7% of total portfolio. Also, credit portfolio was dominated from the foreign currency credit, mainly in euro. Credit ratio in foreign currency recorded the maximum of 80% in 2004, and after 2008 pursued a falling trend. At the end of November 2015, credit in foreign currency accounted for 57% of credit portfolio. In particular, after the crisis of 2008, banks and businesses are oriented more to lending in lek, supporting as such the fall of the high euroisation of the credit portfolio.

Lending cost in lek has followed the performance of the monetary policy key rate. In November 2015, average interest of lek credit recorded the historical minimum of 7.4%, from 14% in 2008. Credit interest rates in euro have been falling as well, but at a more moderate pace in the last ten years. The spread of credit interest rates in lek to euro is narrowed considerably, supporting as such the shift of portfolio toward lek lending. Although the lowering of credit cost, credit remains weak and banks have used non price credit standards to tighten the supply. The shortening of credit maturity, the increase of collateral requirements and the increase of the income to instalment ratio were the core elements that they have used to tighten the supply.

Chart 2.3 Interest rates in the banking sector



Source: Bank of Albania

3. EMPIRICAL ANALYSIS

3.1 DATA

The empirical analysis is based on the GMM methodology and includes quarterly data of individual banks from 2004 to 2014, unadjusted for seasonality. The panel data is unbalanced and consists of 12 out of 16 commercial banks that operate in Albania[3]. Bank credit includes lending to households and non-bank private sector, excluding the non-performing loans. The size and liquidity indicators were employed as proxies for banks' characteristics. Other economic indicators like the effective exchange rate and real GDP were also included in the model. The data for the banking sector, the key interest rate and the exchange rate are taken from the BoA, while gross domestic production is published by INSTAT.

3.2 METHODOLOGICAL ASPECTS

The model specification remains the same as in Vika (2009). The credit volume kit of each bank i at time t is explained by its own developments in the past, the monetary policy indicator approximated to the weekly repo interest rate r_t, the bank characteristics Z_{it} (like the size and liquidity) and by two economic variables, the effective exchange rate EERt and domestic production GDP_t, which try to capture the demand-side effects, apart from the monetary policy changes:

$$\Delta \ln k_{it} = a_i + \sum_{j=1}^{l} b_j \Delta \ln k_{it-j} + \sum_{j=1}^{l} c_j \Delta r_{t-j} + \sum_{j=1}^{l} d_j Z_{it-j} \Delta r_{t-j} + \sum_{j=1}^{l} e Z_{it-j} + \\ + \sum_{j=1}^{l} f_j \Delta \ln EER_{t-j} + \sum_{j=1}^{l} g_j \Delta \ln PBB_{t-j} + u_{it} \quad (1)$$

3 Four banks are omitted from the analysis due to their low share in the total banking sector loans, below 1%.

where Δ indicates the variable is firstdifferenced; l_n is the natural logarithm; and u_{it} is the term of error. Coefficient *c* in front of the monetary policy instrument shows its average impact on bank lending growth. Whereas coefficient *d* before the interaction term evidences how important are the characteristics of each bank in its response to monetary policy actions. If *d* results positive and statistically significant it could lend support to the idea that larger and more liquid banks are less sensitive to the monetary policy shocks.

The size (M_{it}) of a bank is measured by the logarithm of total assets (A_{it}) of bank *i* at time *t* and then centred in relation to the average of each period. Liquidity (Lq_{it}) is calculated by dividing liquid assets to total; in this analysis, liquid assets (L_{it}) consist of reserves, repurchasing agreements, foreign assets, government's bonds and treasury bills.

$$M_{it} = \log A_{it} - \frac{\sum_i \log A_{it}}{N_t}$$

$$Lq_{it} = \frac{L_{it}}{Ait} - \left[\sum_t \frac{\sum_i L_{it} / A_{it}}{N_t} \right] / T$$

3.3 EMPIRICAL RESULTS

The assessment of the role of banks in the transmission mechanism of monetary policy is broadly similar to the findings in Vika (2009), where monetary policy has the ability to influence the bank credit supply in local currency. The relationship between them maintains the magnitude and the negative sign found previously, where a bank is assessed to have decreased its lending by around 0.4% in response to the tightening of the monetary policy by 1 percentage point (please see coefficient in Table 1, column (2), which satisfies the significance level). The interaction of the monetary policy with two characteristics of banks, size and liquidity suggest differing conclusions. According to the common interpretation in the literature, a positive coefficient of their interaction with repo suggests that banks have an active role in the monetary policy transmission (Ehrmann et al, 2001). The results in Table 1 show that the size of banks does not play an important role in bank lending (as the coefficient before Repo*Size has a negative sign), implying that smaller banks do not seem to reduce crediting to economy more than the larger banks during a tightening monetary policy. On the other hand, the situation of banks' liquid assets influences their reaction to the monetary policy. The interaction coefficient of liquidity with repo rate is continuously positive – albeit statistically significant – thereby showing signs for the existence of the credit channel, where banks with higher liquidity are less sensitive than the others against monetary policy actions.

Table 1 Results from the GMM Estimation (long-term coefficients)#)

	Core Eq (1)		Size (2)		Liquidity (3)		Size & Liquidity (4)		Size*Liquidity (5)	
	Dependent variable: local currency loans									
Real GDP	0.71	*0.00*	0.59	*0.00*	0.70	*0.03*	0.56	*0.00*	0.64	*0.00*
Exchange rate	-4.33	*0.00*	-5.01	*0.06*	-4.18	*0.12*	-4.45	*0.46*	-1.90	*0.71*
Repo	-0.32	*0.12*	-0.39	*0.09*	-0.71	*0.32*	-0.40	*0.46*	-0.33	*0.43*
Size			-0.23	*0.06*			-1.29	*0.16*	-0.48	*0.57*
Repo*Size			-0.15	*0.17*			-0.47	*0.67*	-0.31	*0.69*
Liquidity					1.07	*0.30*	3.80	*0.16*	0.76	*0.73*
Repo*Liquidity					3.61	*0.23*	0.57	*0.92*	1.17	*0.79*
Repo*Size*Liquidity									-0.61	*0.67*
S.E. of regression	0.37		0.36		0.44		0.36		0.33	
J-test, p-value	0.67		0.77		0.51		0.34		0.22	
No. of banks, obs.	472		462		472		442		442	
	Dependent variable: Total loans (local plus foreign currency)									
	Core Eq (1)		Size (2)		Liquidity (3)		Size & Liquidity (4)		Size*Liquidity (5)	
Real GDP	0.23	*0.00*	0.11	*0.03*	0.20	*0.00*	0.29	*0.05*	-0.16	*0.74*
Exchange rate	1.84	*0.01*	-1.92	*0.27*	-1.23	*0.51*	0.89	*0.60*	1.84	*0.37*
Repo	-0.06	*0.00*	-0.31	*0.01*	-0.23	*0.12*	-0.12	*0.42*	0.11	*0.69*
Size			-0.29	*0.04*			-0.02	*0.96*	0.06	*0.73*
Repo*Size			-0.06	*0.17*			-0.44	*0.16*	-0.25	*0.04*
Liquidity					0.40	*0.18*	1.32	*0.33*	1.59	*0.01*
Repo*Liquidity					0.23	*0.71*	3.17	*0.09*	0.99	*0.12*
Repo*Size*Liquidity									0.55	*0.02*
S.E. of regression	0.11		0.12		0.11		0.16		0.12	
J-test, p-value	0.46		0.64		0.81		0.47		0.93	
No. of banks, obs.	473		463		463		443		473	

#) Long-term coefficients are calculated as the sum of coefficients of time lags, divided by one minus the sum of the coefficients of the lagged depended variable. Note: Numbers in italics indicate theestimated probability values (p-values).

Besides the response of bank loans in domestic currency, Table 1 displays the sensitivity of total loans (i.e. including foreign currency loans). The results are broadly similar to the first analysis. However, the relatively low coefficient before repo in these equations implies the difficulties encountered by the monetary policy to influence the total credit, owing to the large ratio of foreign currency loans in the total portfolio. Also, if we argue from the statistical importance of coefficients before the banking characteristics, it can be said that banks' role in this case is more evidenced. Their liquid situation seems to help them to resist against shocks of repo. Meanwhile, banks' size does not result to be more important, except in cases when they enjoy simultaneously high liquidity.

Regarding the other explanatory factors in the model, the credit demand proxied by the performance of real economic activity appears to positively affect the banks willingness to lend. However, this relationship appears inelastic to both lek lending and total lending (the long-term coefficient before real GDP is around 0.6 and 0.2, respectively). This may imply that bank lending has been considerably affected also the supply-side factors or the structure of banking sector, in addition to those of the demand-side. On the other hand, the exchange rate appears to have a considerable impact, where the periods of lek depreciations may lead to considerable slowdown in bank lending. The weakening of lek may be considered as an indicator of rising economic uncertainties; also, given the high euroisation of bank loans, a depreciating currency could make it harder for firms and households to pay their liabilities in foreign currency. Nevertheless, the sign of exchange rate coefficients is not stable, thus arousing doubts on the reliability of the link between exchange rate and bank lending.

4. CONCLUSIONS

In Albania, similar to other countries in the region, bank lending has manifested important changes in the last ten years. Based on a macroeconomic environment that has changed from the period prior to 2008, the study of bank credit channel has gained a particular importance. This study serves not only to identify the existence of lending channel in Albania, but also to understand the problems that hamper its well-functioning. Changes in the macroeconomic environment and the shocks from abroad have conditioned a different behaviour of banks after 2008. These changes in addition to the specific characteristics of the banking sector help to the comprehensive elaboration of bank credit channel. An important point of this study is the finding of the newly emerged factors that affect this channel, which may help to better understand the functioning of monetary transmission in Albania in the last years.

It seems that imperfections in the banking market in the form of asymmetric behaviour of bank lending may be identified in the case of banks that have high liquidity. The size of banks does not appear to exercise any impact, except when these banks are well-positioned in the liquid assets ratio. Nevertheless, the size of banks as used here might not be an adequate approximation to assess the allocation of monetary policy effects to banks, as long as banks (including small banks) benefit from the flows of funds sent by parent banks. According to Ehrmann et al. (2001), "…small banks should have the necessary sources to maintain their credit portfolio even in the periods of contractionary policies. This may be achieved either through the higher level of liquidity, as in Italy or France, through liquidity provisioning within the bank's network for example in Germany, and/or thanks to the better capitalisation as in France, Italy and Spain." Owing to the lack of some of these relevant characteristics of banks in Albania in the previous studies, it might be important the deepening of study in this regard to answer to the functioning of credit channel in the monetary policy transmission. Similar to the regional countries, Suljoti and Note (2013) conclude that the factors which have acquired importance and have determined the developments in crediting in Albania in the post-crisis period are: the credit risk, crediting lines from the parent bank, banks' capitalisation and uncertainty. These indicators are not directly included in our analysis; hence the commitment of a further study should consider the inclusion of these indicators, in a certain way, aiming at specifying the model for the functioning of the bank credit channel.

REFERENCES:

Boivin, J. & M. T. Kiley, F. S. Mishkin (2010). "How has the monetary transmission mechanism evolved over time?" NBER Working Paper 15879.

Ceca, Kliti & Hilda Shijaku (2011). "A credit risk model for Albania," Bank of Greece, Special Conference Paper (February, 2011).

Dushku, Elona & Vasilika Kota (2014). "The financial model for Albania: A panel data approach," Bank of Albania, Working paper.

Ehrmann, M. & L. Gambacorta, J. Martinez-Pages, P. Sevestre, A. Worms (2001). "Financial systems and the role of banks in monetary policy transmission in the Euro Area," European Central Bank working paper no. 105.

Kalluci, Irini (2012). "Credit behaviour in Albania: a sign of convergence or a deviation from its long-term trend?" Bank of Albania, Working paper.

Luçi, Erjon & Ilir Vika (2005). "The Bank Lending Channel in Albania: Evidence from micro-level data." Workshop" Monetary Policy Issues and Inflation Forecasting", organised by the Bank of Albania, January 26-27, 2005.

Rama, Arlind (2015). "Investigating financial development – economic growth nexus: a SEE perspective," the 9th Regional workshop " Economic Research in Southeaster Europe" on "Rethinking Economic Policies and Central Banks Methodologies, organised by the Bank of Albania in Tirana, December 3-4, 2015.

Shijaku, Gerti & Irini Kalluci (2014). "Determinants of bank credit to the private sector: The case of Albania" , Bank of Albania, Working paper.

Suljoti, Erjona & Sofika Note (2013). "Assessment of banks' lending determinants in CESEE countries,"the 7th Regional workshop " Economic Research in Southeaster Europe", organised by the Bank of Albania in Tirana, December 4-5, 2013.

Tanku, Altin & Elona Dushku, Kliti Ceca (2015). "The efficiency of credit allocation: an application of Kernel density estimation on Albanian banking system data", the 9th Regional workshop " Economic Research in Southeaster Europe" on "Rethinking Economic Policies and Central Banks Methodologies, organised by the Bank of Albania in Tirana, December 3-4, 2015.

Vika (2009). "Role of Banks in the Monetary Policy Trasnmission in ALbania", Bank of Albania, Working paper.

DO BANKING SYSTEM CONFIDENCE INDICES HAVE SIGNALING POWER FOR DEVELOPMENTS IN CREDIT AND REAL MACROECONOMIC VARIABLES IN ALBANIA?

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INTRODUCTION

All economic agents base their decision-making on data and information about current economic conditions and their expectations on future developments. Sources of providing such expectations are surveys of enterprises, households, banking actors, etc. The measures obtained from these surveys help to shape the decision-making by proving reliable, accurate and timely statistics on market expectations and public confidence, thus addressing the information gap caused by the delay in official data and the inaccuracy in the preliminary data.

The importance of confidence measures for the economy re-emerged after the recent crisis, given that more rigorous and conventional models (which did not include these measures) were not very useful in detecting the turning points in an economy.

Bank of Albania, similar to other central banks, incorporates in its decision-making analysis both the quantitative and qualitative information about current and future economic developments. More specifically, Bank of Albania conducts quarterly business and consumers surveys since 2002. Also, given the importance of the financial sector developments for the economy, the Department of Monetary Policy at Bank of Albania conducts a quarterly bank lending survey (since the second half of 2007), whose main focus is bank experts' perceptions on lending standards. Another survey about banking activity is conducted by the Research Department of the Bank of Albania, aiming to collect opinions and perceptions of banks' CEOs about the current and future development of the banking activity.

There are different reasons why a central bank is interested in information obtained from banks' experts regarding the current and expected banking activity. First, these expectations enable central banks' economists and forecasters to cross-check their own macroeconomic and financial projections, given that banks' experts may possess valuable information that might not be yet reflected in aggregate economic variables. Second, CEOs of banks have the will and the power to take decisions on future banking activity, based on their judgments about current condition and their expectations on future developments. In this way, they provide insights on the future banking activity. Early work on confidence dates back to 1940, with the first consumers' confidence measure designed by Professor George Katona at the University of Michigan. Early studies, Klein and Lansing (1995) and Mueller (1963) found supporting evidence on the predictive ability of consumers' surveys for consumer spending. Households' surveys were later complemented with business surveys, which provide a direct measure of investors' expectations. Klein and Ozmucur (2002; and 2004) demonstrate that models incorporating information from surveys of consumers, producers, and managers perform significantly better than models which do not.

With regard to the predictive content of bank lending surveys (widely used by central banks), most of studies conclude on their usefulness in the forecasting of credit growth and GDP (Lown et al., 2000; Cunningham, 2006; Mottiar and Monks, 2007; De Bondt et al., 2010).

There has been considerable controversy regarding the causality between confidence measures and macroeconomic variables. At one extreme, confidence measures are shown to have both a predictive power and a role in understanding business cycle fluctuations. At the other extreme, some research concludes that the concept of confidence does not play any valuable role. Many economists think that the confidence measure is endogenous and a reflection of current macroeconomic conditions, whereas others argue that psychological factors that are not captured by economic variables can influence confidence measures.

In the case of Albania, there is no previous study attempting to measure the informational content of the banking surveys. Similarly to the existing literature on the usefulness of confidence survey in various countries, this study will explore how the banking confidence survey carried out by Research Department performs in signaling future developments in loan growth and various macroeconomic measures.

The rest of the article will provide a brief description of the banking confidence surveys and list some of its main stylized facts. Next, the article will outline the methodological approach employed and present some results regarding the ability of confidence indices in signalling the future performance of loans and those of the main macroeconomic variables.

OVERVIEW ON THE BOA'S SURVEY: "ANALYSIS ON THE BANKING SYSTEM'S ACTIVITY AND EXPECTATIONS"

In conducting its monetary policy, Bank of Albania considers not only quantitative but also qualitative information about current economic conditions. Since 2006, the Bank of Albania conducts a quarterly survey in order to assess the banks' perceptions and expectations regarding the banking activity, especially lending. The results of such survey are not publicly available, and are mostly used for internal analysis within the Bank.

The survey was composed by the Research Department of the Bank of Albania, and was first launched in the first quarter of 2006. Since then, the survey is carried out at regular quarterly intervals. In the first quarter of 2011, detailed questions were added to the survey regarding the expected demand for loans issued to businesses and loans issued for mortgage purposes.

The questions of the survey are designed in such a way that the answers to them are of qualitative nature. The analysis employed in this material is based on aggregate answers received from a sample of 16 banks over the period 2006Q1: 2015Q2. The response rate of the survey has been 100% for all rounds of interviews. The respondents of the survey (banks' CEOs) are asked to assess the development of their respective bank's activity in the current quarter in comparison with the previous one, and to form expectations for the forthcoming quarter's banking activity compared with the current one.

The survey's questions can be divided into 2 sets. The first set of questions relate to the assessment of the actual developments in the current quarter compared to the previous one, regarding the actual activity, the number of bank employees; the amount of net income realized; the credit risk; employees' skills and the actual physical space where banking services occur.

The second set of questions regard the evaluation of the expected activity for the next quarter compared to that of the current quarter. In addition to the questions of the first set, the second one comprises questions related to expected level of bank's liquidity and capitalization. The rest of questions attempt to extract information on banks' perception on expected demand for total credit demand and its subcategories: businesses' credit (SME and corporations), mortgage credit (issued to businesses or households), and consumers' credit. Lastly, the survey asks the respondents to state their expectations regarding the development of the nonperforming loans in the forthcoming quarter.

The survey asks participants to note the direction of changes in their evaluations or expectations, such as: "better", "worse," or "remain the same", but not the magnitude of such changes.

The net balance statistic is the most commonly used method of calculating confidence indices. A confidence index is constructed by calculating the difference between the percentage of positive responses and the percentage of negative responses. The percentage of positive (negative) responses is calculated as the ratio of share of banks (based on their assets' share) who responded positively/negatively to the share of total banks (based on their assets' share), which participated in the survey, while disregarding the "neutral" (remain the same) responses. In such way, an increase in the value of the index should be interpreted as an improvement in banks' expectations, and vice versa.

In the following chart (Chart 1), the graph on the left plots the change in total assets of the banking system versus the performance of the current banking activity index. Any concern about how knowledgeable and serious the survey's respondents are in their answering is not materialized. The current banking activity confidence index shows us three weeks prior to the release of the data how the banking activity for the current quarter will perform. A drop in the value of the index mostly during the crisis (2008- 2012) seems to be associated with a fall in total assets.

The graph on the right plots the expected total credit demand index against the quarterly growth rate of credit. The graph clearly suggests that movements in the index precede those in total credit.

Chart 1. Current banking activity index versus quarterly change in total banking assets (graph on the left); Expected total credit demand index versus realized quarterly growth rate of total credit (graph on the right)

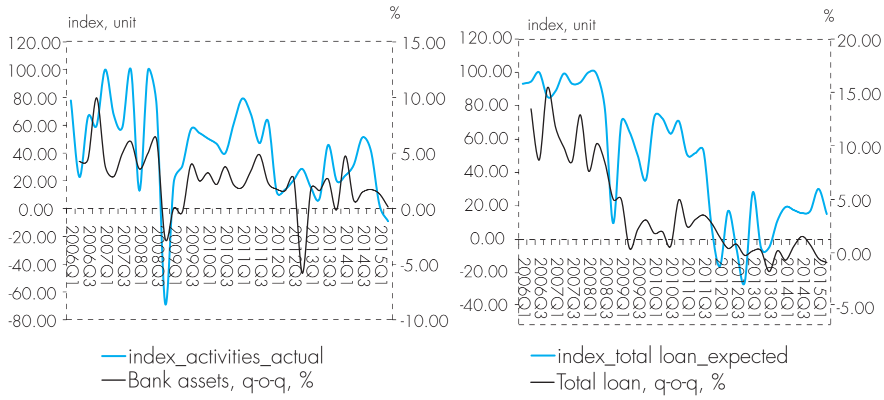
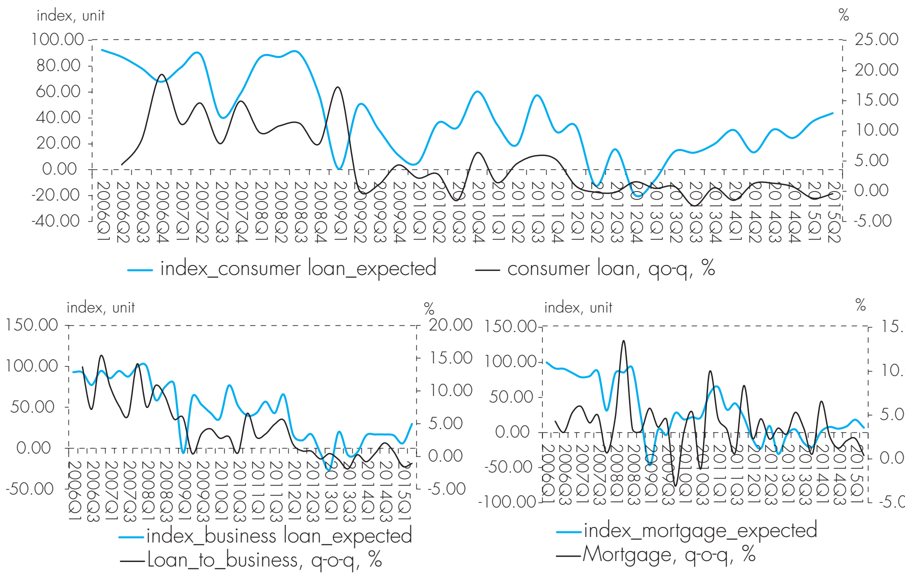


Chart 2 plots the relationship between expected credit demand indices by various categories (issued to businesses, for consumption purposes and for mortgage purposes) with the realized values of the respective credit. The co-movement with the realized values is clear for the first two indices: expected

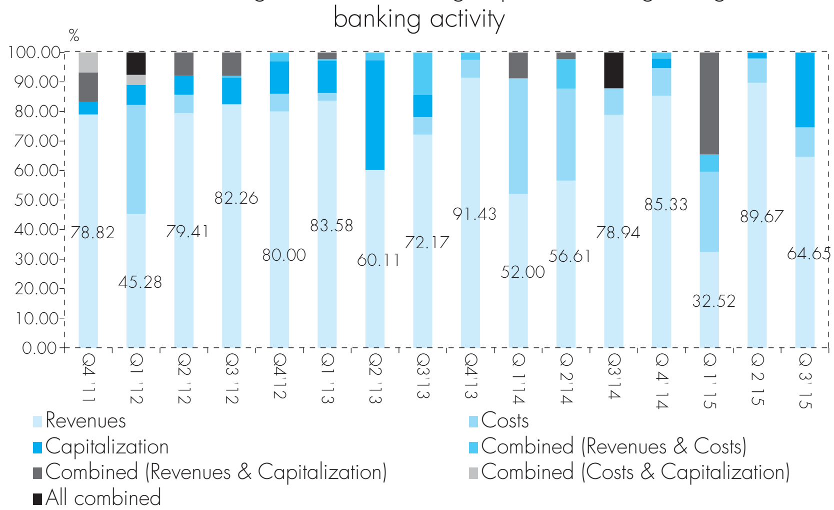
Chart 2. Expected consumption credit demand index versus realized quarterly growth rate of consumption credit (graph on the top); Expected business credit demand index versus realized quarterly growth rate of business credit (graph on the left bottom); Expected mortgage credit demand index versus realized quarterly growth rate of mortgage credit (graph on the right bottom)



consumption credit demand index and expected business credit demand index. The expected mortgage credit demand index does not seem to provide any hints about the future developments in realized mortgage credit. The realized time series of the mortgage credit is quite more volatile that the index would indicate.

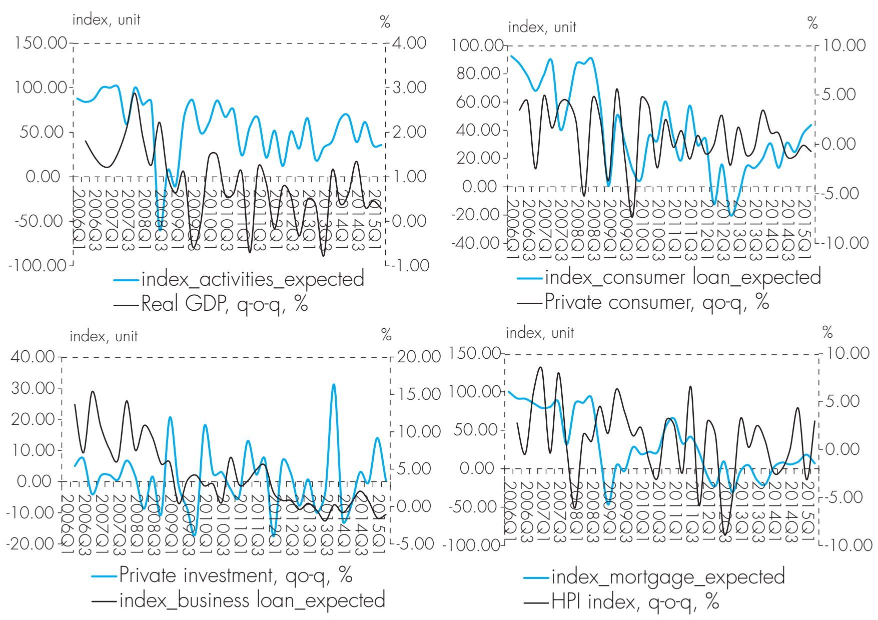
The survey comprises detailed questions which help to understand which the driving forces, which influence the expectations of the surveys' respondents regarding the banking activity in the forthcoming or the current quarter. The respondents are given the option to choose from the following factors: the expected performance of income; the expected performance of costs; the expected liquidity situation; or any combination of them. The chart clearly shows that changes in expectations regarding income developments drive the changes in the expected banking activity index (almost 80% of respondents take into account such factor). The effect of other factors (costs, level of bank capitalization, or a combination of the three factors) is quite volatile and sometimes negligible.

Chart 3. The driving forces influencing expectations regarding future banking activity



A visual inspection between macroeconomic variables and surveys' indices show that the expected banking activity index and the expected consumption credit demand index co-move with the realized real GDP growth rate and private consumption growth rate, respectively. The co-movement between the expected credit demand index and the private investment growth rate is not very clear, and seems to break after mid-2008. The expected mortgage credit demand index does not seem to precede the behavior of the house prices index for the whole period.

Chart 4. Surveys' indices vs. macroeconomic variables



METHODOLOGY AND RESULTS

The study attempts to address two main questions. First, does the survey provide reliable information on the bank lending growth? Second, does the survey have predictive information in terms of macroeconomic variables?

The strategy employed is quite straightforward. It consists in a series of causation regressions of the following form:

$$\Delta\ log(X) = \alpha_0 + \beta * indeksi\ i\ pyet\ddot{e}sorit_{t-1} + \Delta\ log\ (X_{t-1}) + \varepsilon_t \qquad (1)$$

where X represents either one of the variables characterizing the banking system indicators (various types of loans or banks' assets), or one of the macroeconomic variable (real Gross Domestic Product, private consumption, private investment, retail trade index, or house prices index).

In a second step, the former specification is augmented with a vector of control variables (Z), which will be represented by a measure of changes in the shape of the yield curve (measured by the difference between 12-month and 3-month T-bills' rate).

$$\Delta\ log(X) = \alpha_0 + \beta * indeksi\ i\ pyet\ddot{e}sorit_{t-1} + \Delta\ log\ (X_{t-1}) + \gamma * Z_{t-1} + \varepsilon_t \qquad (2)$$

Prior to estimating the above regressions (1 &2), we test for the stationarity properties of the time series using Augmented Dickey Fuller (ADF) test. Results show that all the indices obtained from the survey are I(0) in levels, while the indicators of the banking system, macroeconomic variables and the yield spread are found to be stationary in first difference. All series used in the study are seasonally adjusted using Tramo Seats, when seasonality is present.[1]

Table 1 attempt to answer to the first research question: Does the survey provide reliable information in signalling future changes in total loans and its subcategories?

Here it is clear that the survey respondents know something about the future lending performance. Results show that survey indices related to expected demand for loans are statistically significant in their signalling usefulness and of correct sign. The expected demand index for consumption loans shows the highest signalling ability; a 10-unit increase in this index would translate in an increase of 0.3% in the loans issued for consumption purposes. It is noteworthy to mention that expected credit demand indices are quite volatile, with a standard deviation estimated at [31: 40]. The current and the expected banking activity indices are also good predictors of current or next period's performance of the banks' assets.

Table 1 Informational content of the survey in terms of lending growth[2]

		α	expected lending index	current banking activity index	expected bank activity index	lagged value of the realized lending growth rate	Adj. R-squared
Dependent var., qoq, %	total bank assets	0.004854	-	0.000447***	-	0.044295	0.345275
	total bank assets	0.002073	-	-	0.000405***	0.011693	0.244391
	total loans	-0.003532	0.000342**	-	-	0.579200***	0.763838
	loans to businesses	-0.003549	0.000595***	-	-	0.350637**	0.735557
	loans for consumption	-0.006654	0.000795***	-	-	0.441767**	0.653824
	mortgage loans	0.039326***	0.000253**	-	-	-0.284989	0.150883

*Note. *denotes significance at 10% level of confidence; ** denotes significance at 5% level of confidence; and *** denotes significance at 1% level of confidence.*

We repeat the process, but with a control variable (yield spread) added in each of the regression specification. What the regressions show, is that results are quite robust. The expected credit demand indices show the same informational content in terms of signalling future developments in the respective lending growth rate.[3] The control variable added (yield spread) is found to be statistically insignificant in all specifications, but the one having mortgage credit growth rate, as an independent variable. This might indicate that the banks' loan market is not very sensitive to movements in interest rates, which over the last six years can be justified on the ground of sufficient liquidity in the banking system, with deposits accounting for more than 100% of loans. Also, choosing the yield spread (T-bills in ALL) as a control variable might not be a very good proxy selection to capture market expectations, given that more than 50% of credit is issued in foreign currency.

[1] *Results of unit root tests are available from the authors upon request.*

[2] *Due to how regressions (1) and (2) are specified, the coefficient before the survey's index is a semi-elasticity, and therefore a unit increase in the index is translated into *100) % in the dependent variable.*

[3] *Results when the control variable is added are available from the authors upon request.*

The model fit remains the same, even when accounting for the control variable. In both specifications, with and without the control variable, the worst model is the one with the mortgage lending growth rate, as the dependent variable. Another observation derived is that the time series of loans (total loans, loans issued to businesses, loans issued for consumption purposes, and those for real estate purchases) are quite persistent, given the high and statistically significant coefficient before the lagged value of lending growth rate. The finding that the persistence of loans performance is quite strong might indicate that banks' lending behavior is rather adaptive than rational when deciding to lend.

The following table (2) addresses the second research question: Does the survey have signalling power in terms of macroeconomic variables? Using regressions (1) and (2), we have checked whether the first three surveys' indices (the current banking activity index, the expected banking activity index and the expected demand for total credit index) do a good job in signalling future development in real GDP. The latter is found to be more useful.

An increase by 10 units in the index of expected demand for total credit translates into an improvement of 0.13% in real GDP. Such usefulness of the expected total credit demand index in signalling real GDP is mostly due to its good signalling performance in terms of private consumption, given also the considerable share of private consumption to GDP. Private consumption is expected to increase about 0.24% for a 10- unit increase in the index. In terms of private investment, the expected total credit demand index is not found to have any signalling power, with the coefficient before the index having the incorrect sign and being statistically insignificant.

Next, we test for the relationship between the index of expected demand for total credit issued to businesses with real GDP and its two components (real consumption and real private investment) and with the retail trade index. The index does not provide any reliable information in terms of forecasting any of these macroeconomic variables. In the four regressions, the coefficient of the expected demand for credit issued to businesses is either of incorrect sign, of negligible magnitude, or statistically insignificant. The failure of this index in forecasting macroeconomic variables might be due to the way the question in the survey is raised. The survey asks the respondents to estimate how they expect the demand for credit issued to enterprises (specified as Small Medium Enterprises and Corporations) to change in the forthcoming quarter compared to the current one. The questions does not specify whether the credit issued to businesses would be for consumption or investment purposes, which might confuse the respondents and mislead them in their answering.

The expected demand index for mortgage loans is positively correlated with the next period' house price index, though the relationship is not statistically significant.

The lagged dependent variable (macroeconomic variable) is significant and of considerable magnitude in most of the regressions, confirming the persistence in the behavior of macroeconomic variables.

Table 2 Predictive content of the survey in terms of macroeconomic variables

		α	curr_activity_index	exp_activity_index	exp_totcredit_index	exp_crbiznes_index	exp_crkonsum_index	exp_crmortgage_index	lagged value of the dependent variable	Adj. R-squared
Dependent var., q-o-q, %	Real GDP	0.002637	0.000073*	-	-	-	-	-	0.295212*	0.221862
	Real GDP	0.000728	-	0.000089**	-	-	-	-	0.312317**	0.258939
	Real GDP	0.003619*	-	-	-	0.000071	-	-	0.174121	0.203082
	Real GDP	0.002443	-	-	0.000129***	-	-	-	-0.030639	0.355591
	private cons	-0.003258	-	-	-	-	0.000335**	-	-0.319541*	0.170081
	private cons	0.005937	-	-	-	0.000067	-	-	-0.281600	0.071226
	private cons	-0.001665	-	-	0.000236*	-	-	-	-0.292273*	0.153185
	private inv	0.010055	-	-	-	-0.0000933	-	-	-0.284528	0.081728
	private inv	0.008541	-	-	-0.0000563	-	-	-	-0.27728	0.080999
	retail_index	0.011348	-	-	-	0.000103	-	-	-0.145078	0.026252
	HPI	0.004355	-	-	-	-	-	0.000179	-0.050052	0.030774

*Note. *denotes significance at 10% level of confidence; ** denotes significance at 5% level of confidence; and *** denotes significance at 1% level of confidence*

We repeat the above process[4] while taking into account the effect of the control variable, as measured by the yield spread. Results do not change almost at all compared to the specifications where the control variable is not included. However, the yield spread turns out to be insignificant in almost all regressions. It is essential that such results are taken with much caution, given the quite short sample size.

CONCLUDING REMARKS

This article showed that the qualitative information collected by the banking sector survey is useful in signalling future developments in loan growth (except the mortgage loans) and some of the main macroeconomic variables (private consumption and real GDP).

It is important to emphasize that results should be taken with caution given the short history of the survey, which limited the choice of the empirical approach to be followed. A more rigorous and systematic analysis will be possible as more data are collected. A VAR analysis would be more appropriate in addressing the research questions of this study, as it would allow us to better control for the feedback between current and past level of macroeconomic variables, credit and survey's indices. It is very important to control for the feedback when dealing with confidence indices, as survey's respondents might change their expectations regarding the future banking activity in response to past or present conditions in the economy. In that case, it is really weak output driving up the change in confidence, and not the other way around.

Another approach to tackle the short time span of the survey is by employing panel data analysis for 16 commercial banks operating in Albania.

4 *Results when the control is added in the specification are available upon request.*

REFERENCES

Cunningham, J. T. 2006. The Predictive Power of the Senior Loan Officer Survey: Do Lending Officers Know Anything Special? Federal Reserve Bank of Atlanta, Working Paper Series, No. 24.

De Bondt, G., A. Maddaloni, J.L. Peydro and S. Scopel. 2010. The Euro Area Bank Lending Survey matters: empirical evidence for credit and output growth. European Central Bank, Working Paper Series, No. 1160.

Klein, L.R. and Lansing, J.B. 1955. Decisions to Purchase Consumer Durable Goods. Journal of Marketing, Vol. XX, pp. 109-132.

Klein, L.R. and S. Ozmucur. 2002. The predictive power of survey results in macroeconomic analysis, in Wladyslaw WElfe (ed.) Macromodels 2001, Chair of Econometric Models and Forecasts, University of Lodz, pp. 181 -97

Klein, L.R. and S. Ozmucur. 2004. Some possibilities for indicator analysis in economic forecasting, in Pami Dua (ed.), Business Cycles and Economic Growth: An analysis Using Leading Indicators, Oxford: Oxford University Press, pp. 243 -57.

Lown, C., D. P. Morgan, and S Rohtagi. 2000. Listening to Loan Officers: the impact of commercial credit standards on lending and output. Federal Reserve Bank of New York, Economic Policy Review, 6, 2, 1-16.

Mottiar, R., and A. Monks. 2007. The Bank Lending Survey for Ireland. Central Bank of Ireland, Quarterly Bulletin 2.

MICRO AND MACROECONOMIC DETERMINANTS OF NET INTEREST MARGIN IN THE ALBANIAN BANKING SYSTEM (2002-2014)

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I. INTRODUCTION

Financial intermediation is crucial for economic growth. The wider and deeper financial markets are, the bigger the benefits of financial intermediation. A sound and stable financial market is able to healthily fund the financial needs of the private and public sector by promoting investment growth. Considered as a good indicator of the level of banking intermediation efficiency, interest margin size helps to perceive asymmetries in the banking market and the costs transmitted to the clients. This indicator is commonly defined as the difference between interest income and interest expense divided by total assets [Ho and Saunders (1981), Wong (1997), Demirguc-Kunt and Huizinga (1999), Maudos and Guevara (2004)]. The higher the inefficiencies and information asymmetry in the market, the higher will be the margin set by the banks (Stiglitz and Weiss, 1981).

This paper aims to identify the main determinants of the net banking margin in the Albanian banking market[2] considering microeconomic as well as macroeconomic variables. The first and only study on this topic for Albania belongs to Kalluci (2010) for the period 2002-2007 and it suggests that the margin's main determinants are the fluctuations of market interest rates[3] (especially in Euro), operational expenses and the opportunity cost of obligatory reserve at the central bank. However, the characteristics of the banking market have significantly changed until 2014 and this study aims to empirically analyze the net margin's determinants not only at the banking and market level, but also introducing variables with macroeconomic character like inflation, exchange rate, economic growth and public debt burden. The results of the paper shed light not only in the context of the efficiency level of the Albanian banking market, but unveil also the significance of macroeconomic stability on the subject.

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2 *Albanian financial sector is dominated by banks, therefore the paper focuses only on the banking sector.*

3 *The market interest rates used from Kalluci (2010) are Euribor 3-monthly for Euro, Libor 3-monthly for Usd and the TBills 3-monthly rate has been used for the domestic currency Lek. These variables have been used as proxies for market risk.*

II. BANKING MARKET DEVELOPMENTS

Despite the dominance of banks in Albanian financial market, its development in terms of products and services offered has been quite scarce compared to other developing European countries. According to Mamatzakis et al (2005), this has been a result of deep market fragmentation and weak macroeconomic policies that in many countries lead to financial and economic crises[4]. After 2004 the Albanian banking market was further developed with the privatization of the largest state-owned bank, with the accession of foreign banks in the domestic financial market or with the merger of two banks into a bigger banking institution. These structural changes deepened the level of competition in the banking market and promoted credit lending. The significant lending growth rate during 2005 has been mainly a result of the aggressive lending strategies applied by banks to credit businesses, especially in foreign currency. The banks main investing area was in treasury bills and return generated from them. The growth of deposits has been more gradual. Following the end of 2005, the lending portfolios for both individuals and businesses contracted by reflecting significantly lower growing rates, falling also to negative levels in the recent years. The new situation in the market was a consequence of alarming increase of non-performing loans (22.8% at the end of 2014), but even from lower exposure of European banking institutions and their more restrictive regulations towards risk. The investments structure of the banks changed gradually, seeking higher rates of return from the assets where the credit portfolio was decreasing, while investments in long-term government bonds were increasing. Provisions expenditure also increased from almost 0% in 2002 to 7% in 2014. During the considered period, the net banking margin has fluctuated around an average value of 3.5%. While it has been reflecting an upward trend until 2007, the financial crises of 2008 marked a downturn which has dominated until the recent years. A straightforward way to interpret the margin’s dynamics is to analyze its main components by considering the main sources of income and costs. The main sources of income are from the loan rates as well as from commissions and fees, while the main cost components are from financing costs, risks costs and operational costs. While the credit boom has supported the margin growth in the first years, the contracting trend that began after 2005 contributed to a decline of income from loan interests that became stronger after 2008. On the other hand, expenses have been increasing steadily mainly due to the rise of credit risk costs for provision expenses. However, in the last two years these costs have been declining due to a slowdown of loan portfolio deterioration, early loan restructuring procedures to hamper transformation into non-performing loans as well as the write-offs of lost loans.

III. METHODOLOGY AND DATA

This section explains the econometric model used to describe the determinants

[4] *Albania and Bulgaria in 1997, Romania in 1998, Macedonia in 1999*

of banking margin's behavior. Following the paper of Nassar, Martinez and Pineda (2014), who study margin determinants in Honduras, using a panel dataset of banks for the period 1998-2013, the model is estimated by using an OLS (Ordinary Least Squares) based Panel Corrected Standard Errors procedure (PCSE).

The estimated equation can be written in the general form:

$$NIM_{i,t} = \alpha_0 + \alpha_1 * NIM_{i,t-1} + \alpha_2 * OVERHEAD_{i,t} + \alpha_3 * CAR_{i,t} + \alpha_4 * CLR_{i,t} + \alpha_5 * NPL_{i,t(-4)} + \alpha_6 * SIZE_{i,t} + \alpha_7 * NII_{i,t} + \alpha_8 * HHI_{i,t} + \alpha_9 * GROWTH_{i,t} + \alpha_{10} * INFLATION_{i,t} + \alpha_{11} * REPO_{i,t} + \alpha_{12} * ALL\_EUR_{i,t} + \alpha_{13} * DEBT\_GDP_{i,t} + \varepsilon_{i,t} \quad (9)$$

Where the indexes i and t refer to bank and year respectively and the term $\varepsilon_{i,t}$ represents the model residuals.

Because of banks profit persistency (Carbó dhe Rodríguez, 2007), in the right hand side of the above equation it is included the first lag of net interest margin. Banks with high profits in the previous period are likely to have high profits even in the current period. The explanatory variables are divided in three categories: bank specific variables, bank industry variables and macroeconomic variables.

In the first category we have included 6 variables: the ratio of administrative expenses to total bank assets (Overhead costs), Capital adequacy ratio (CAR), current liquidity, non-performing loans to total credit ratio[5], bank size and non-interest income equals non-operating income divided by total assets.

Among the variables of the banking industry, we have chosen Herfindahl Hirschman index for total assets, which represents the concentration of assets in the banking sector for the period under consideration. In addition, we have included these macroeconomic variables: real economic growth rates, inflation, changes in the nominal exchange rate, repo rate, and debt to GDP ratio, which correspond respectively to these abbreviations GROWTH, INF, REPO, ALL_EUR and DEBT_GDP.

Information on these variables has been taken by the Bank of Albania (BoA) and Institute of Statistics (INSTAT). The data are quarterly for the period 2002Q1-2014Q2 (50 periods) and include all the commercial banks of Albanian banking system (16 banks). The total number of observations is 374 and the panel is unbalanced.

IV. MAIN FINDINGS

Model results suggest that individual bank characteristics: capital adequacy ratio, overhead costs, liquidity ratio, non-performing loans ratio and non-interest income explain a substantial part of the variation in bank interest

[5] *The variable has been inserted with 4 lags because banks need time to implement measures related to increasing credit risk.*

margins. In line with Kalluci's results (2010), we find that overhead costs have a significant positive impact on the banking margin, which means that banks increase net interest margin when operating expenses increase, in order to cover the additional cost. This finding is also consistent with the theory and with earlier studies on net interest margins. A higher ratio of capital adequacy is associated with lower interest margins. This is inconsistent with the model of Ho and Saunders (1981), which provides a positive correlation between the two variables. Our finding is in line with the hypothesis of Brock and Franken (2003), under which less capitalized banks have reasons to accept more risk (associated with higher margins), in order to obtain higher profits. The coefficient before liquidity ratio has a negative sign because banks with higher levels of liquid assets may receive less interest income than banks with less liquid assets. Credit risk, which is measured by the ratio of nonperforming loans to total loans, has a negative statistically significant impact on the margin. This result suggests that banks may prefer lower profit margins when the financial situation of individuals and businesses deteriorates. The positive effect of non-interest income on the margin implies that even if banks provide higher income from commissions or other non-interest sources, they do not lower interest rates on loans.

Our results provide evidence of the important role that macroeconomic variables play in explaining the variation of interest margins. The significant inverse relationship between the real economic growth and bank margin is based on the argument that the improved financial situation of borrowing firms will improve their crediting performance, thereby reducing non-performing loans and allowing banks to cope with lower interest margins. A similar result was found by Silva et al. (2007) in Brazil. The exchange rate has a significant negative impact on margin, which means that a rate increase is associated with lower margin. This result can be explained by the fact that if the domestic currency depreciates, the loan quality might deteriorate and bank margins will go down. This variable results to be significant as a large share of total bank loans is in euro and, hence it is affected by the exchange rate volatility. The impact of domestic debt to GDP ratio on the dependent variable is positive and statistically significant, implying that government debt accumulation increases the net interest margin, probably due to increased macroeconomic risks and the potential unsustainability.

When looking at the possible manoeuvring space for policymakers' actions that could affect the costs of financial intermediation, and therefore indirectly support economic activity, our results indicate that a stable macroeconomic environment support lower net interest margins. Policymakers should focus their efforts on achieving and maintaining macroeconomic stability, in order to minimize information asymmetries. This will allow banks to assess adequately the risks and to improve resource allocation efficiency. This study can be further developed by expanding the data time series, including other variables, splitting the analysis of net interest margins according to different economic sectors etc.

REFERENCES

Brock, Philip and Franken, Helmut (2003). Measuring the Determinants of Average and Marginal Bank Interest Rate Spreads in Chile, 1994-2001: www.econ.washington.edu/user/plbrock/ChileSpreads091603.pdf.

Da Silva, G.J.C, Oreiro, J.L, De Paula, L.F & Sobreira, R. (2007). Macroeconomic Determinants of Banking Spread in Brazil: An Empirical Evaluation. Retrieved from http:// www.anpec.org.br/encontro2007/artigos/A07A098.pdf.

Demirguc-Kunt, A., and Huizinga, H., (1998), "Determinants of Commercial Bank Interest Margins and Profitability: Some International Evidence", The World Bank Economic Review, Vol.13, No.2, pp 379-408.

Ho, T., dhe Saunders, A., (1981), "The determinants of bank interest margins: Theory and empirical evidence", Journal of Financial and Quantitative Analysis, Vol. 16 , No.4.

Kalluci (2010): "Determinants of net interest margin in the Albanian banking system", BoA discussion paper.

Mamatzakis, E., Staikouras, C., dhe Koutsomanoli-Filipaki, N., (2005), "Competition and Concentration in the banking sector of the South Eastern European region", Emerging Markets Review, No.6, pp. 192-209.

Maudos, J., and de Guevara, F., (2004), "Factors explaining the interest margin in the banking sectors of the European Union", Journal of Banking and Finance, No. 28, pp 2259-2281.

Nassar, Martinez and Pineda (2014): "Determinants of Banks' Net Interest Margins in Honduras", IMF Working Paper.

Stiglitz J.E. and Weiss A. (1981), "Credit Rationing in Markets with Imperfect Information", American Economic Review Vol 71, pp.393-410.

"INVESTIGATING FINANCIAL DEVELOPMENT - ECONOMIC GROWTH NEXUS. A SOUTHEASTERN EUROPE PERSPECTIVE"

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1. INTRODUCTION

This article aims to empirically investigate the causal effect that financial development has in influencing economic growth in a group of ten developing and emerging Southeastern Europe economies in a time horizon from 2002 until 2014. Financial sector development is often described as the process of continuous improvement in "quantitative" and "qualitative" terms of financial services and intermediation activity delivered by financial institutions, mainly those performing intermediary functions in efficiently optimizing financial resources allocation towards higher returns market opportunities and lower risks. This research work seeks to find answers in understanding the extent to which financial sector development is related or plays a role in determining output growth trends for the countries of South-Eastern Europe (SEE) tegion. The main purpose behind paying a dedicated attention to the finance-growth nexus in this context is the effort to fill an existing gap in regional topical related economic literature caused from lack of recent similar studies containing updated, wide and inclusive analysis of this relationship in SEE countries.

In a vacuum of empirical analyses exploring the latest data on finance-growth causal relation in the SEE economies, this research work aims to provide an empirical investigation of whether the financial sector has started to positively influence growth and whether the implementation of legal and financial sector reforms during recent years has played a role in making financial development "matter" in supporting growth in ten regional developing and emerging economies. Applying panel data techniques and building the empirical analyses over the same economic variables used in Levine et. al. (2000), as representative to a wide range of economic studies analyzing the same nexus, and basing on the most recent annual data available for ten countries of the sample, this study tends to investigate the "new stance" of finance and growth relationship.

The aimed contribution of this work consists in creating a continuance of empirical studies on SEE economies, focusing primarily on financial development-economic growth causal relationship and trying to bring the most up-to-date, to the extent of author's knowledge, and inclusive analyses on this region, in a time perspective when no civil conflicts have taken place allowing thus a consistent process of financial development.

2. LITERATURE REVIEW

2.1 THEORETICAL ARGUMENTS IN UNDERSTANDING FINANCIAL DEVELOPMENT– GROWTH NEXUS.

Influential works from Bagehot (1873) and Schumpeter (1912) unveil the early theoretical deductions that development of financial intermediaries in support of entrepreneurial initiatives positively impacts the economic growth by channeling the sources of funding towards the most efficient innovative ideas in the market, destined to succeed and eventually impulse growth in economy. Robinson (1952) focuses his theoretical work on analyzing the importance of capital management for maximizing profits and the utility of production functions for economic agents and economy as a whole, through optimizing determination of production factors. The study concludes that to a certain extent, financial development is a structural consequence of population growth and technical progress. Boyd and Prescott (1985) emphasize the endogeneity in the growth environment of "intermediaries' coalitions". Robert Lucas in his influential work (1988) manifests a skeptical belief on the real importance that financial sector development has in fostering economic growth, "over-stressing" the relevance of financial intermediation in inducing faster pace of growth. For Greenwood and Jovanovic (1990) the economic growth creates the needed stimulus for the "financial superstructure" to maximize profits and further consolidate while in turn, financial development paves the way for further growth.

2.2 EMPIRICAL RESEARCH ON GENERAL GROUPS OF COUNTRIES

Paying a dedicated attention to the empirical analysis of finance-growth relation, Goldsmith (1969) offers significant proof of positive relationship between the financial sector development and economic growth in a wide group of developed and developing economies. King and Levine in their much referred paper of (1993) find a significant positive relationship between the financial sector development and economic growth in the wide sample of developed and developing economies, going further in concluding that in the development of financial sector lays also the key to predict future rates of growth in coming 10 to 30 years given this robust positive relationship. Rajan and Zingales (1996) obtain robust results support the hypothesis that financial development stimulates economic growth through lowering external funding interest rates that are essential for expansion of industries dependent on external funding. From a different perspective, Levine and Zervos (1998) in their empirical investigation of the causal significance of banking and stock market development indicators over the short and long-run economic growth indicators, find a robust correlation between stock market liquidity and banking development with present and future rates of economic growth as well as two other growth related indicators, productivity and capital accumulation.

Levine, Loayza and Beck (2000) in addition to positive relationship on the finance growth nexus emphasize that enforcement of legal and accounting frameworks by implementing "best practices" contributes exogenously in the consolidation of a sound development of financial intermediary sector, favor the creation of a business enabling environment and positively supports economic growth. Loayza and Ranciere (2005) find that, in long run, increased financial depth and further financial sector liberalization contribute in financial development that stands in a positive relationship with economic growth, while in short-run for troubled economies, typically after post crisis, financial intermediation liberalization and depth do not contribute in impacting growth. Greenwood et. al. (2012) conclude in an impressing result that in case the sample countries would implement the "best financial practices" for developing their financial sector, the world output is projected to significantly grow by 53 per cent, under the assumption that financial markets, enhanced by higher productive intermediation channels, would boost economic growth.

2.3 EMPIRICAL STUDIES FOCUSING ON THE SOUTHEASTERN EUROPE

There is an incremental attention on better understanding of financial development and growth paths of the Southeastern Europe economies. And in this context some research works have been exploring the ways how finance and growth representative economic indicators stand to each-other in a causal relationship in the Region.

Mehl, Vespro and Winkler (2005) testing the finance-growth relation focus their study on a sample of nine SEE economies namely Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Macedonia, Moldova, Romania, Serbia and Montenegro for the period from 1993 until 2001, but not finding empirical evidences for a positive relation between financial development and economic growth, explaining it with the poor economic environment consisting in deficiencies Caporale et. al. (2009) analyzing the group of ten newest countries joining European Union, of which Romania and Bulgaria considered in SEE, find a positive causal effect that financial development has on growth but not any sign of vice-versa, despite the still underdeveloped financial sectors in these economies. Haiss et. al. (2007) find empirical evidences that the finance-growth positive causal relation widely seen in developed economies, stands true also for a sample of four SEE countries, namely Bulgaria, Romania, Croatia and Turkey, but an interesting finding of this study is that different scale of economic development in SEE countries determines a different pace of financial market consolidation and as a different result impact on economic growth. Using quarterly data for 11 years for the Albanian economy, Dushku (2009) investigates the causal relationship between financial development and growth in Albania, finding that in long run empirical results confirm a positive relation between the two while in short-run the results remain ambiguous. Koczan (2015) highlights that Western Balkans economies continue to be vulnerable in different sectors because of being depended from the economic development of their neighbor economic and trade partners, while high public deficits and debt levels still remain a public finances challenge for the region.

3. DATA AND METHODOLOGY

3.1 DATA AND METHODOLOGY

This contribution aims to provide a wide inclusive analysis of investigating the finance-growth nexus on a group of ten Southeastern Europe economies for a period of time covering years from 2002 until 2014. Five are the main variables used in this analysis to define financial sector development and intermediaries' position Liquid Liabilities, Domestic Credit to Private Sector, Assets Ratio as Deposit Money Banks assets over the sum of Commercial Banks Assets and Central Bank assets, Bank Deposits to GDP and Private Credit from Banks to GDP. The frequency of data is annual. Please refer to Table 2 of the Appendix for the Data Descriptive Statistics.

The empirical investigation of the financial development and economic growth relation in Southeastern Europe treated in this study is made by utilizing as main econometric tools of panel data techniques. Real per capita growth rate and financial development indicators, together with the conditioning set factors, for the sample of ten economies are regressed by using pooled OLS, fixed and random effects econometric tests. Being dependent on short annual data time series for the sample under study and the limited number of countries, dynamic panel data techniques such as GMM methods are not seen adequate to properly investigate this relation under the present data limitations. Following the economic logic and variables behind the Levine, Loayza and Beck (2000) analysis, the representative regression of the model would be:

$$R.GROWTH_{it} = \alpha + \beta\ FIN.DEV_{it} + \lambda\{CONDITIONING\ SET\}_{it} + \varepsilon_{it}$$

where *i* indexes the cross-section in this case countries and *t* the time

In order to avoid the risk of co-linearity between the financial development indicators, they are included in the equation one by one. In other words, if the dependent variable is the real GDP growth per capita, independent variables are either Liquid Liabilities, Credit, Assets Ratio, Private Credit or Bank Deposits and the conditioning set consisting in explanatory variables commonly used in relation to growth such as Initial per Capita income, Government size, Trade openness, Inflation and Average secondary schooling years. Being conditioned on the availability of data on deposit money-central bank assets ratio, regressions are run over the period 2002-2011 testing for the relationship with per capita growth, while tests for Liquid Liabilities, Private Credit and Banks Credit impact on growth are run over 2002-2014 period. Deposits over GDP as a financial depth indicator enters the analysis for the period 2002-2013. In order to catch the 2009 crises negative impact on SEE economies and the contagion effect of sovereign debt crises in Greece and Italy over the sample economies, two dummy variables are added in the econometric analyses indicating years 2009 and 2012.

4. RESULTS

Empirical results obtained from panel data techniques investigating the relationship between financial and economic development in ten SEE countries for the time horizon 2002-2014 unveil the importance of domestic credit to private sector as an indicator of financial development in positively contributing in the economic growth in these economies. Indicators identifying private credit issued from financial institutions in general and banks in specific are found empirically significant in the analysis as result of econometric tests, while does not happen the same with other variables Liquid liabilities, Assets ratio and Bank deposits over GDP that despite the positive coefficients do not manifest a strong explanatory significance on rate of growth.

See Table 1 in the Appendix for full set of results.

As possible to see the econometric results of tests run assembled in Table 1, domestic credit to private sector from financial institutions indicating the total volume of financing towards private sector from banks, microfinance institutions and other financial institutions, and the other variable indicating solely the commercial banks credit to private sector, manifest a significant empirical positive relationship between private credit and growth in these economies. These referring results have been obtained from fixed effects regressions over 2002-2014.

Hausman test results show that for analyzing the finance-growth nexus in the context of these two finance indicators it is more effective to rely on fixed effects estimation rather than random effects. Hausman test value is significant at 10% confidence interval.

Domestic credit to private sector from financial institutions indicating the total volume of financing towards private sector from banks, microfinance institutions and other financial institutions, and the other variable indicating solely the commercial banks credit to private sector, manifest a significant empirical positive relationship between private credit and growth in these economies. These referring results have been obtained from fixed effects regressions over the 2002-2014 period.

Paying attention to obtained coefficients of policy factors included in the conditioning set is possible to notice that trade openness positively contributes to growth, while government size stands firmly in a negative relation. Inflation and education appears ambiguous in their significance to growth in the contexts of the present empirical set. Dummy variables indicating the 2009 financial and 2012 sovereign debt crises of the main trading partners for SEE countries are significantly important showing for a negative impact that these crises have had on the economic growth of Southeastern Europe economies. However, is needed to be taken in consideration when reading these results the quality and the frequency of data that do not favor a further optimization of econometric analysis.

5. CONCLUSIONS

This paper analyzed the extent and the significance of causal relationship between development of financial system and economic growth in the Southeastern Europe countries in the period from 2002 until 2014. The empirical investigation aim was to test if financial development contributes in the growth of 10 developing and emerging SEE economies that compose the study sample in order to understand the dynamics of finance-growth nexus in this region by comparing results with earlier studies. Conditioned from availability of data, the research was performed using panel data methodologies such as pooled OLS, fixed effects and random effects models. Empirical results obtained show that financial sector size, represented from Liquid liabilities, is not statistically significant in relation to economic growth. The same applies to Assets ratio and Banks deposits indicators that theoretically measure structural functions of intermediaries in financial system to serve in pooling risks and accumulate savings. In contrast with these findings, statistically important in positively affecting growth appears to be the impact of Private credit being measured and included in regressions independently under two indicators, domestic credit to private credit from all financial institutions and private sector financing from banks. Interpreting empirical results in this point is possible to emphasize that financing private sector productive activities is an effective channel via which financial sector contributes in fostering economic growth in short-run SEE economies. Interpreting the obtained empirical results is possible to state that financial sector expansion in Southeastern Europe is not fully reflected in the economic growth process, but despite this fact, signs of a positive relationship between financial development and growth in this region have started to emerge significantly. A representative sign on financial environment improvement is the significant explanatory link between private credit and growth obtained from empirical tests, while the remaining gap in the finance-growth nexus is manifested through the absence of such correlation in the case of Liquid liabilities and Assets ratio.

In conclusion, financial development relationship with economic growth in Southeastern Europe has started to become significant in a positive context, dynamically evolving due to quantitative and qualitative changes in countries' financial systems.

BIBLIOGRAPHY

- *Koczan Z. (2015) - "Fiscal Deficit and Public Debt in the Western Balkans: 15 Years of Economic Transition" –IMF Paper Series*
- *Greenwood J.; Sanchez J and Wang Ch. (2012) – "Quantifying the impact of financial development on economic development" Review of Economic Dynamics, 16 (2013), pp. 194–215*
- *Tanku A. (2012). "The impact of China and Russia on catching up in South-Eastern Europe," Chapters, in: European Integration in a Global Economy, chapter 15, pages 157-176 Edward Elgar.*
- *Sinha A.; Kumar R. And Chandra Dha S. (2011) - "Financial Sector Regulation and economic growth" Paper presented at the CAFRAL-BIS International Conference on Financial Sector Regulation for Growth, Equity and Financial Stability in the post-crisis world, Mumbai,*
- *Hassab K.; Sanchez B. And Yu J. (2011) – "Financial Development and economic growth. New evidence from panel data" Quarterly Review of Economics and Finance 51 , pp 88-104*
- *Seetanaha B.; Sawkut R., Sannasee V. (2010) – "Stock Market Development and Economic Growth in Developing countries: Evidence from Panel VAR framework' CSAE Conference Papers Series*
- *Dushku E. (2009) - "Financial development and economic growth: The Albanian case" , Bank of Albania Working Paper Series*
- *Caporale G. M.; Rault Ch.; Sova R. and Sova A (2009) - "Financial Development and Economic Growth: Evidence from Ten New EU Members" Brunel University Economics and Finance Working Paper Series, Working Paper No. 09-37*
- *Haiss P.; Sumegi K. and Hagmayr B.; (2007) - "Financial Sector development and Economic Growth – Evidence from Southeastern Europe" –University of Vienna Graduate School Working Paper Series*
- *Alici A. and Ozgoker U. (2006) – "Can Financial Regulations Strengthen Financial Stability in Developing Countries? : The Case of Turkey" , Paper to be Presented at the ECPR/CRI conference*
- *Loayza N. Ranciere R. (2005) - "Financial Development, Financial Fragility, and Growth" -; IMF Working Paper Series, WP/05/170*
- *Mehl, A.; C. Vespro and A. Winkler (2005) - "The finance growth nexus and financial sector environment: new evidence from South East Europe", OENB Paper Series, No 09.*
- *Rojas-Suarez L. (2004) – "Domestic Financial Regulations in Developing Countries: Can they Effectively Limit the Impact of Capital Account Volatility? Center for Global Development Paper Series*
- *Levine R.; Loayza N. ; Beck Th. (2000) - "Financial intermediation and growth: Causality and causes." –; Journal of Monetary Economics 46, 77 No. 31*
- *Rousseau P.; Wachtel P. (1998) - "Financial Intermediation and Economic Performance: Historical Evidence from Five Industrialized Countries" –; Journal of Money, Credit and Banking; Volume 30 pg 657-78*
- *Levine R.; Zervos S. (1998) - "Stock Markets, Banks, and Economic Growth" -,The American Economic Review, Vol. 88, No. 3. , pp. 537-558*
- *Raghuram Rajan R. G.and Zingales L. (1996) - "Financial dependence and growth" NBER Working Paper No. w5758*
- *King G. R.; Levine R. (1993) - "Finance and Growth: Schumpeter Might be Right" –,The Quarterly Journal of Economics, Vol. 108, No. 3., pp. 717-737*
- *Greenwood J.; Jovanovic B., (1990) - "Financial development growth and distribution of income" The Journal of Political Economy, Vol. 98, No. 5, Part 1, pp. 1076-1107*

APPENDIX 1

Table 1. Panel data analyses results

Regressors	(1) random	(2) fixed	(3) fixed	(4)fixed	(5) fixed
Constant	2.650	1.020	2.740	2.750	2.470
(p-value)		*0.310*	*0.007*	*0.007*	*0.015*
Logarithm Income per capita	-2.720	-3.410	-4.260	-4.330	-3.030
(p-value)		*0.001*	*0.000*	*0.000*	*0.003*
Government size*	-0.910	-0.760	-1.710	-1.690	-0.360
(p-value)		*0.451*	*0.090*	*0.094*	*0.719*
Trade Openness*	0.880	3.350	1.230	1.350	0.260
(p-value)		*0.001*	*0.222*	*0.180*	*0.011*
Inflation*a		-2.050	0.020	0.030	-1.270
(p-value)		*0.044*	*0.981*	*0.979*	*0.207*
Secondary education years	-0.530	1.270	0.630	0.730	0.940
(p-value)		*0.207*	*0.530*	*0.467*	*0.348*
Liquid Liabilities*	0.890				
(p-value)					
Assets Ratio*		0.280			
(p-value)		*0.780*			
Private Credit in Economy*			2.810		
(p-value)			*0.006*		
Credit by banks*				2.910	
(p-value)				*0.004*	
Banks Deposits*					0.510
(p-value)					*0.610*
Dummy 1	-7.330	-7.240	-7.200	-7.170	-7.210
(p-value)		*0.000*	*0.000*	*0.000*	*0.000*
Dummy 2	-4.690		-4.800	-4.810	-4.970
(p-value)			*0.000*	*0.000*	*0.000*
Hausman Test (p-value)	0.292	0.005	0.067	0.066	0.030

* *variable is included in regression in a log-linear form a inflation enters the regressions as log(3+variable) for linearization purposes*

Table 2. Data Descriptive Statistics

	Liquid Liabilities Broad Money % GDP)	Credit to Private Sector % GDP	Comercial - Central Bank Assets Ratio	Credit from provate banks % GDP	Bank Deposits % GDP
Mean					
Median	48.5	39.6	98.4	38.4	41.2
Maximum	84.7	87.0	100.0	86.9	71.2
Minimum	11.3	3.0	56.3	3.0	11.1
Std. Dev	17.7	19.3	11.4	18.7	14.4
Observations	130	130	100	130	120

HOUSE PRICES IN ALBANIA: DEVIATIONS FROM THE EQUILIBRIUM?

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(2016)

ABSTRACT

This article is a short summary of a working paper written during 2014, but includes the latest available data from 2015. The housing bubble that developed throughout most of the 2000s in the developed world is seen as one the most important causes that led to the global financial crisis. Ever since the start of the crisis, the housing market has become an increasingly important topic for researchers and policy-makers, who regularly track its developments. The Albanian housing sector also experienced a rapid price increase, leading therefore to questions regarding possible overvaluations. Using a theoretical "fundamental house price" model, this article shows that prices have been increasing at a faster pace after 2006. However, from 2012 the market seems to be entering a "correction" phase; however, a statistically significant long-run relationship between actual and "fundamental" prices cannot be established at this point.

Keywords: Housing prices, rents, fundamental prices, calibration, VECM, long-run equilibrium

JEL Classification: C32, C61, D11, D12, G11, G12, R21, R31,

I. INTRODUCTION

Many economists interpreted the global financial crisis of 2008 as the final outcome of an asset bubble that had been developing throughout most of the developed world during the early years of the decade. The key element, which exacerbated the crisis, was an overheated housing market. While fuelled by an expanding economy, housing prices were increasing at a much quicker rate compared to other key economic indicators, such as household income.
House prices play an important role in a household's financial decision. A house represents the largest purchase households will make during their lifetime. Houses are also part of a household's equity, and are used as collateral in order to borrow. Changes in house prices will directly affect other economic decisions by households. Policymakers and researchers alike are very keen to understand the dynamics of the housing market precisely due to this special role. Historically, rent-to-price and income-to-price ratios have been seen as potential indicators that could reveal overheating in the housing market. Current research though, has tried to go beyond those indicators to determine whether price levels are justified.

Housing prices in Albania also experienced a rapid increase during the last decade. While fuelled by some fundamental factors, such as the rapid economic growth and the development of the financial sector, a traditional indicator such as the rent-to-price ratio suggests that there were periods when the actual housing price level showed signs of overheating. This article aims to understand these dynamics by using some of the recent developments in the housing market literature. The results obtained suggest that following 2006, signs of house prices moving away from the levels predicted by the fundamentals exist. The degree by which these prices differ from the actual ones depends mostly on the type of variables one uses to construct the index for fundamental prices. However, in line with theoretical predictions, prices are seen closer to their fundamental level exhibiting signs of a functioning correction mechanism.

II. MODEL AND DATA

The article attempts to create a fundamental house price index, which relies on the imputed rent concept – i.e. the sum of implied costs that arise from owning a house in a given period. Theoretically, these costs should equal the cost of renting per period. To begin with, every homeowner has to bear the cost of the interest rate on a mortgage, . The second factor is the maintenance cost, ρ. On the other hand, homeowners will benefit from future price increases affected by the depreciation rate, . Similar to Poterba (1992), the imputed rent per period, , can be written as:

$$H_t=(r_t+\rho+1)\, P_t-(1-\delta)\, E_t\,(P_{t+1}). \qquad (1)$$

Rearranging in terms of , the price of the house, and through forward iteration equation (1) can be written as:

$$P_t=E_t=\left[\frac{H_t}{R_t}+\frac{(1-\delta)\,H_{t+1}}{R_t\,R_{t+1}}+\frac{(1-\delta)^2\,H_{t+2}}{R_t\,R_{t+1}\,R_{t+2}}+\ldots\right]=E_t\left[\sum_{i=0}^{\infty}\frac{(1-\delta)^i\,H_{t+i}}{\prod_{j=o}^{i}R_{t+j}}\right] \qquad (2)$$

House prices in the present are driven by, predictably in a world with rational expectations and market clearing conditions, expected future imputed rents and expected future user cost. This result is similar to Shiller (1981), equations (2) and (3).

Actual rents might also differ from their fundamental value due to the same factors that cause disruption and volatility for house prices. Following Hott (2009), rents are assumed to be driven by the demand and supply of housing for one period. It is assumed that the market is made up of homogenous agents that derive utility from consumption and housing in any one period. The Cobb-Douglas utility function can be written as:

$$U_t=d_t^{\alpha}\,c_t^{1-\alpha}, \qquad (3)$$

where U_t is the utility at time t for the representative agent; d_t is the amount of housing the agent wishes to occupy; c_t is consumption in period t; and the parameter α is the elasticity of substitution. It is subject to the budget constraint:

$$y_t=H_t\, d_t+c_t, \tag{4}$$

where y_t is the representative agent's income per period t.

Setting up and solving the f.o.c and multiplying for the total population number to obtain to optimal demand across the entire market, the :

$$D_t= \alpha Y_t\, /H_t\, , \tag{5}$$

where Y_t is the total income of the economy, otherwise known as the GDP; D_t is the aggregate housing demand.

Similarly to Hott (2009), the housing supply is given by:

$$S_t(1\text{-}\delta)\, S_{t\text{-}1}+N_{t\text{-}1}=(1\text{-}\delta)^t\, S_0+\sum_{i=1}^{t} (1\text{-}\delta)^{i\text{-}1}\, N_{t\text{-}1}\, , \tag{6}$$

where S_t is the supply of housing per period t; N_t represents the new construction which is approved in the previous period; and δ as mentioned before is the depreciation parameter which affects the existing.

Finally a market clearing condition can be stated by equating the demand function with the supply function of equation:

$$H_t= \frac{\alpha Y_t}{S_t} = \frac{\alpha Y_t}{(1\text{-}\delta)^t\, S_0+\sum_{i=1}^{t} (1\text{-}\delta)^{i\text{-}1}\, N_{t\text{-}1}} \tag{7}$$

The last step for solving the model requires rearranging equation (2) by substituting in equation (7). This yields a fundamental house price value:

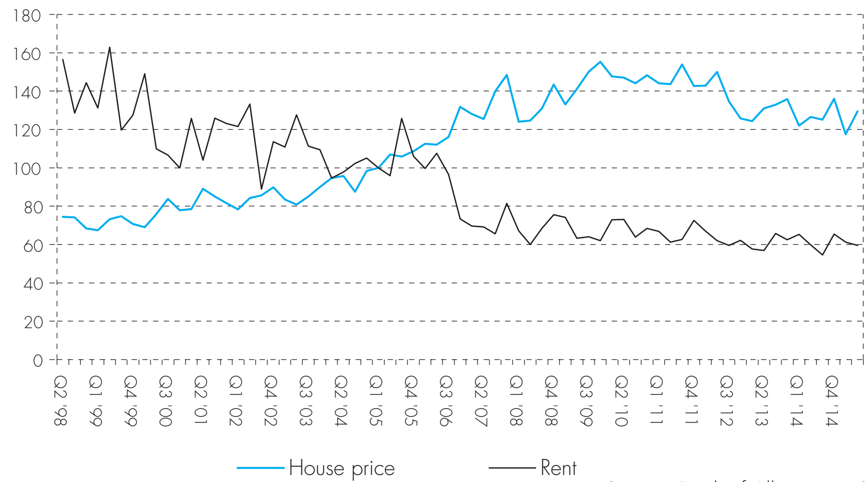
$$P_t=E_t \left[\sum_{i=0}^{\infty} \frac{(1\text{-}\delta)^i\, \alpha Y_{t+i}}{S_{t+1} \prod_{j=o}^{i} R_{t+j}} \right]. \tag{8}$$

Equation (8) is a forward-looking function, which suggests that fundamental house prices are driven by past as well as expected future development of income, user costs and housing supply.

As for the data, indices on house prices and rent are calculated by Bank of Albania's Monetary Policy Department. One noteworthy drawback of the indices is that the data is gathered only for the city of Tirana, the capital of the country. However, it is important to note that most of the Albanian construction boom has been centred on Tirana. The CPI index is also obtainable through Albania's National Statistics Institute, INSTAT. Figure 1 summarizes the developments of the real house price and rent indices.

In a market equilibrium, prices and rents should move in tandem, as reflected by the imputed rent theory. Figure 2 shows how the ratio has evolved. While a constant rise has been associated with the ratio ever since data was collected, it is noticeably more evident beginning in 2004 until around 2011. These developments justify a more thorough examination of the dynamics in the housing market.

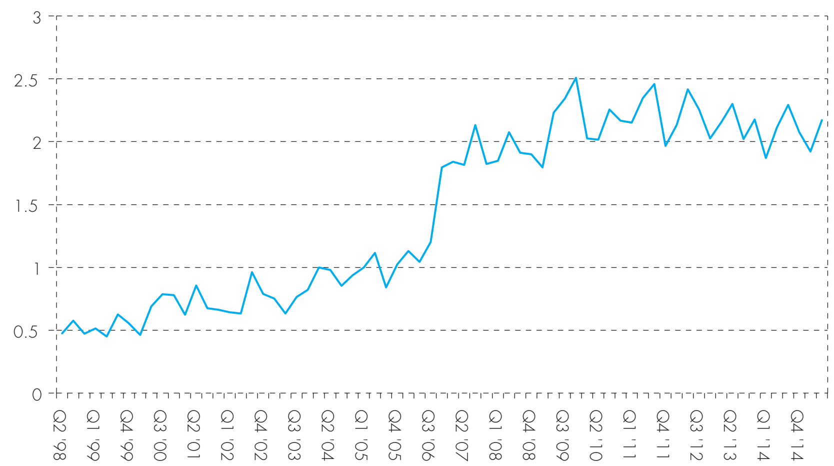
Figure 1. Real House Prices and Rent indices



Source: Bank of Albania, INSTAT

The Albanian 12-month bond yield was used, as in most of Bank of Albania's working paper series, to proxy the economy's interest rate. The use of other interest rates leads to similar results. Quarterly data on nominal and real national

Figure 2. Price-to-Rent Ratio



Source: Author's Calculations

GDP is also available through INSTAT, and some backward interpolation is used to extend the series back in time, given that a new methodology has recently been introduced. INSTAT also publishes data on building permits in the country until 2015.

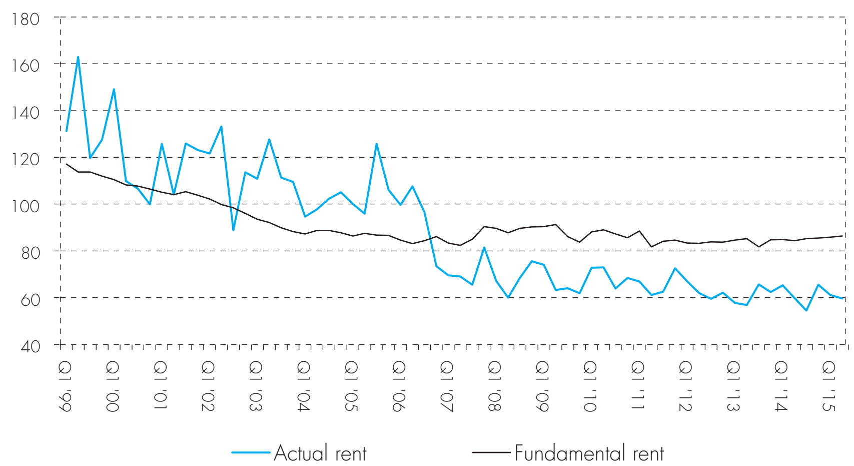
III. EMPIRICAL ESTIMATION

Using the theoretical model obtained in Section II, a calibration is performed to calculate fundamental rents and house price values. Before estimating the values for fundamental house prices, a series for fundamental rent will initially be calibrated. To do so, equation (7) is used. To obtain the fundamental rents the following minimization problem needs to be solved:

$$\min \sum_{t=0}^{T} \left[\frac{\alpha_1 Y_t}{(1-\delta)^t S_0 + \sum_{i=1}^{t} (1-\delta)^{i-1} N_{t-1}} - H_t^{\alpha} \right]^2, \tag{9}$$

where H_t^{α} is the actual rent series. To solve the minimization of equation (9), finding the optimal values for the parameters is required. One possible approach would be to allow the parameters to take on any value. However, economic theory and intuition can restrict said values to a more reasonable range. The minimization problem of equation (9) is therefore solved, subject to the following restrictions: $\alpha_1 \geq 0$; $\delta \geq 0$; $S_0 \geq 0$ with results displayed in Figure (3). Table (1) summarizes the results from the calibration. The values obtained from the parameter calibration compare well to the results obtained from the literature. The initial stock is also similar to results obtained from the literature.

Figure 3. Actual v. Fundamental Rent



Source: Bank of Albania; Author's Calculations

Table 1. Fundamental Rent coefficients

Coefficients	α_1	δ	S_0
	9.12	0.01%	8887

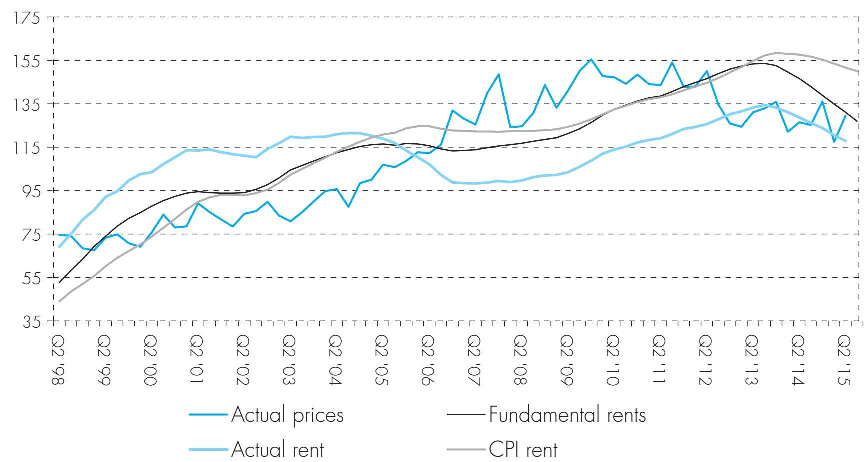
Source: Author's Calculations

To calibrate a fundamental house price index a similar methodological approach is chosen. The minimization problem is based on equations (2) and (8) as follows:

$$\min \sum_{t=0}^{T} \left[\frac{\alpha_2 H^*_t + (1-\delta)P^*_{t+1}}{1+\rho+r_t} - P^{\alpha}_t \right]^2. \qquad (10)$$

There are two further issues to address. First, as can be seen, equation (13) relies on a rent series to perform the minimization. In order to provide more robust results, three different series will be used: the actual rent; the fundamental rent calculated above; and a rent series obtained from the CPI basket. Its evolution since 1998 suggests that it closely resembles the house price index. The second issue to address is the evolution of fundamentals. Underlying the attempt to build a fundamental house price index is the assumption of forward-looking rational agents. For time periods, included in the dataset, this requires replacing expected fundamentals with their actual values. For future developments a simple calculation by forecasting for the fundamentals with an ARIMA model is used. The average value of the forecast for the following 12-month period is then used as a constant growth rate for the rent indicators as well as the mortgage rate. In the *T+1* period rent will be equal to (1+*g*)H, where *g* is the constant growth rate; whereas the future interest rate will be equal to the constant value $\dot{r}$. Again, using economic theory and intuition the constraints for the parameters are: $\delta \geq 0$; $\alpha_2 \geq 0$; $-0.01 \leq \rho \leq 0.09$. The results from the calibrations for all three indicators for rent prices are shown in Figure 4. Table (2) provides a summary of the calibrated coefficients.

Figure 4. Actual v. Calibrated House Prices



Source: Bank of Albania; Author's Calculations

As shown during the calibration of the fundamental rent, this methodology provides indices that are less volatile than actual prices. The use of different rent series has a clear effect on the calibrated fundamental price. Higher rent levels also imply higher fundamental house prices. Table (2) shows that the parameters obtained from the calibration are well within the constraints, except the risk and maintenance cost. Further calibrations showed that in case of a larger range, the parameter would change, but this would be, in turn, countered by shifts from the other parameters. The basic shape and trend of the fundamental house prices was, therefore, not subject to significant changes.

Table 2. Fundamental Price coefficients

Fundamental Price	α_2	δ	ρ	$\bar{g}$	$\dot{r}$
H_t^*	0.091	0.01%	-0.01	-1.5%	5%
H_t^{α}	0.096	0%	-0.01	1%	5%
H_t^{CPI}	0.257	4%	0.09	0.1%	5%

Source: Author's Calculations

As for the development of fundamental prices, all three series seem to suggest that the Albanian housing market has experienced a period of rapid appreciation and that housing prices, just like other financial assets, tend to be volatile even in developing countries. The three series differ regarding the size by which this overpricing has been present and how much of this is currently undergoing a correction. Some of the most recent actual house price data have consisted in slow but constant growth.

Building on the insights provided by the literature, as well as the results obtained in the previous section, one would expect to find a relationship between the actual data and the fundamental price. As Campbell and Shiller (1988) show, given a long enough time frame, asset prices will return to fundamentally justified levels. The econometric methodology that is preferred by the literature to conduct such testing is the vector error correction modelling (VECM). The Johansen co-integration procedure is followed for all three series. The results are shown in Table (3), and, as can be seen a long-term relationship could not be established at this time for each of the three fundamental price series. Different specifications were also tried, namely a shorter time frame; however, the results did not significantly differ. This result is not uncommon in literature. Cambpell and Shiller (1988) warn that long data is often required to establish a relationship between fundamentals and actual asset prices. Egert and Mihaljek (2007) also suggest that countries undergoing a transition period are characterized by large structural changes.

Table 3. Johansen Co-integration test

Fundamental Price	Trace-Statistic	0.05 CV	Prob
H_t^*	8.45	15.49	0.41
H_t^{α}	9.96	15.49	0.28
H_t^{CPI}	9.18	15.49	0.34

Source: Author's Calculations

IV. CONCLUDING REMARKS

This article attempts to shed light on some developments in the Albanian housing market in the last decade and a half. More specifically the article attempts to provide guidance on whether housing prices have been over or even undervalued during this time. To accomplish this goal, an attempt is made to build a "fundamental" housing price index – an index that measures how house prices should evolve, according to some fundamental variables. Using Poterba's (1984 and 1992) imputed rent definition and a methodology presented by Hott and Monin (2006), a simple two-step model for estimating fundamental house prices is employed. According to the series obtained from the model, house prices in Albania have been overvalued during the latter half of the 2000s; but, there are signs the market has been undergoing a correction in the most recent years. Lastly, an attempt to find a long-run relationship through a VECM model is made. However empirical tests suggest that, as of right now, such relationship does not exist and should be the focus of further research.

There might be various reasons for this result. Firstly, the quality of the local data could be improved on. The model could benefit from the addition of other data. Which theoretical model is correct is an open-ended question in the literature. The findings of many empirical studies suggest that other variables tend to play an important role in explaining house price fluctuation, but they are yet to be included in theoretical models. As for the policy implications, the recent development of house prices would suggest that the risk of a housing bubble burst is reduced, since they are mostly at levels predicted by the fundamentals.

REFERENCES

Ayuso, Juan, Jorge Martinez, Luis Maza and Fernando Restoy, 2003. "House prices in Spain", Economic Bulletin, Banco de España, October 2003.

Bollano, Elona and Kristo, Ermelinda "House Price Index -Methodology and Use," Bank of Albania Economic Bulletin 2012 H1

Campbell, John Y. and Robert J. Shiller, 1988. "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors," Review of Financial Studies, Society for Financial Studies, Society for Financial Studies, vol. 1(3), pages 195-228.

Case, Karl E. and Robert J. Shiller, 2003. "Is There a Bubble in the Housing Market?," Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution, vol. 34(2), pages 299-362.

Ciarlone, Alessio, 2012. "House price cycles in emerging economies," Temi di discussione (Economic working papers), Bank of Italy, Economic Research and International Relations Area 863, Bank of Italy, Economic Research and International Relations Area.

Égert, Balázs and Mihaljek Dubravko , 2007. "Determinants of House Prices in Central and Eastern Europe," BIS Working Paper No. 236.

Glaeser, Edward L., Joshua D. Gottlieb and Joseph Gyourko, 2010. "Can Cheap Credit Explain the Housing Boom?," NBER Working Papers 16230, National Bureau of Economic Research, Inc.

Glaeser, Edward L., Joseph Gyourko and Albert Saiz, 2008. "Housing Supply and Housing Bubbles," NBER Working Papers 14193, National Bureau of Economic Research, Inc.

Glaeser, Edward L., Joseph Gyourko and Raven E. Saks, 2006. "Urban growth and housing supply," Journal of Economic Geography, Oxford University Press, Oxford University Press, vol. 6(1), pages 71-89, January.

Glaeser, Edward L. and Joseph Gyourko, 2005."Urban Decline and Durable Housing," Journal of Political Economy, University of Chicago Press, University of Chicago Press, vol. 113(2), pages 345-375, April.

Glaeser, Edward L. and Joseph Gyourko, 2002. "The Impact of Zoning on Housing Affordability," NBER Working Papers 8835, National Bureau of Economic Research, Inc. Granziera, Eleonora and Sharon Kozicki "House Price Dynamics: Fundamentals and Expectations" Bank of Canada Working Paper 2012-12 (English) April 2012.

Gyourko, Joseph, Christopher Mayer and Todd Sinai, 2006. "Superstar Cities," NBER Working Papers 12355, National Bureau of Economic Research, Inc.

Hashorva, Gent and Erjona Suljoti, 2012. "House prices and mortgage loan - Empirical evidence for Tirana" Suljoti, Bank of Albania Economic Bulletin 2012 H1.

Himmelberg, Charles, Christopher Mayer and Todd Sinai, 2005. "Assessing High House Prices: Bubbles, Fundamentals and Misperceptions," Journal of Economic Perspectives, American Economic Association, American Economic Association, vol. 19(4), pages 67-92, Fall.

Hott, Christian and Terhi Jokipii, 2012. "Housing Bubbles and Interest Rates," Swiss National Bank Working Papers 2012-07.

Hott, Christian, 2009. "Banks and Real Estate Prices," Swiss National Bank Working Papers 2009-08.

Hott, Christian, 2009. "Explaining House Price Fluctuations," Swiss National Bank Working Papers 2009-05.

Hott, Christian and Pierre Monin, 2006. " Fundamental Real Estate Prices: An empirical Estimation with International Data," Finrisk Working Paper Series No. 356.

Hwang Smith, Margaret and Gary Smith, 2006. "Bubble, Bubble, Where's the Housing Bubble?," Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution, vol. 37(1), pages 1-68.

Johansen, Soren, 1991. "Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models," Econometrica, Econometric Society, Econometric Society, vol. 59(6), pages 1551-80, November.

McCarthy, Jonathan and Richard W. Peach, 2004. "Are home prices the next "bubble"?," Economic Policy Review, Federal Reserve Bank of New York, Federal Reserve Bank of New York, issue Dec, pages 1-17.

McCarthy, Jonathan and Richard W. Peach, 2002. "Monetary policy transmission to residential investment," Economic Policy Review, Federal Reserve Bank of New York, Federal Reserve Bank of New York, issue May, pages 139-158.

Poterba, James M, 1992. "Taxation and Housing: Old Questions, New Answers," American Economic Review, American Economic Association, American Economic Association, vol. 82(2), pages 237-42, May.

Poterba, James M, 1984. "Tax Subsidies to Owner-occupied Housing: An Asset-Market Approach," The Quarterly Journal of Economics, MIT Press, MIT Press, vol. 99(4), pages 729-52, November.

S&P Case-Shiller Price Index, 2015. http://us.spindices.com/indices/real-estate/sp-case-shiller-us-national-home-price-index

Shiller, Robert J., 2014. Personal website. http://www.econ.yale.edu/~shiller/data.htm

Shiller, Robert J., 2007. "Understanding Recent Trends in House Prices and Home Ownership," NBER Working Papers 13553, National Bureau of Economic Research, Inc.
Shiller, Robert J., (2005). Irrational Exuberance, 2nd Edition, Princeton: Princeton University Press.

Shiller, Robert J., 1981. "Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?," American Economic Review, American Economic Association, American Economic Association, vol. 71(3), pages 421-36, June.

Sinai, Todd and Nicholas S. Souleles, 2005. "Owner-Occupied Housing as a Hedge Against Rent Risk," The Quarterly Journal of Economics, MIT Press, MIT Press, vol. 120(2), pages 763-789, May.