WORKING PAPER

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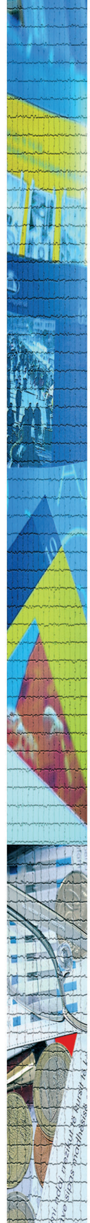

BANK OF ALBANIA

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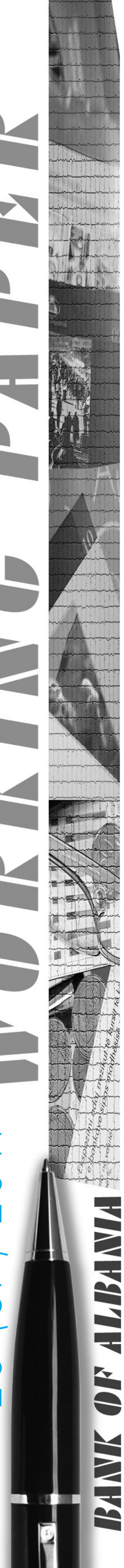


BANK OF ALBANIA

Altin Tanku*
Research Department, Bank of Albania, email: atanku@bankofalbania.org

Elona Dushku
Research Department, Bank of Albania, email: edushku@bankofalbania.org

Kliti Ceca
Research Department, Bank of Albania, email: kceca@bankofalbania.org

Note: The authors would like to emphasize that the ideas and comment expressed in this paper are responsibility of the authors only and not those of the Bank of Albania.

**/Corresponding author: atanku@bankofalbania.org*

C O N T E N T

ABSTRACT

This study investigates the efficiency of credit allocation in Albania, with a particular focus on the use of kernel density estimation as an alternative estimation methodology for pooled and panel data sets. We focus on the allocation of banks credit portfolio (credit to business) to investigate whether sectorial distribution of credit after 2008 reflects the trends of sector developments (in terms of expansion), performance of credit portfolio and banks own characteristics. Empiric analysis is based on the adoption of kernel density estimation, for the panel datasets. Conclusions are based on the estimation and interpretation of multidimensional joint densities.

JEL: C5; C14; C23, G21

Key words: Panel Data Estimation, Kernel Density Estimation, Credit Allocation

1. INTRODUCTION

Financial intermediation and credit growth in particular, are important factors for economic growth. They have played a significant supporting role for the Albanian economy since 2004, contributing to what is randomly called absorption lead growth model. That model collapsed following the global 2008 financial crisis. The fast credit growth before 2009 "failed" to produce sustainable growth and employment. It did not even produce enough to sustain itself, leading to a sharp increase of nonperforming loans (NPL) from 4 to 25 %. Credit and financial intermediation reduced sharply after 2009 following the global and domestic developments, and have been a hindrance to investment and growth from that point on. This reduction generated a symbiosis in the performance of NPL and the economic activity leading to the deterioration of the balance-sheets of the business and the banking system, making it more and more difficult to support credit expansion and economic growth. Banks constrain new credit not only fearing new bad loans but also because NPL deteriorates their financial soundness indicators, imposing capital and liquidity constrains on further credit expansion. Under these circumstances, it is important that credit growth is distributed efficiently to the most productive use.

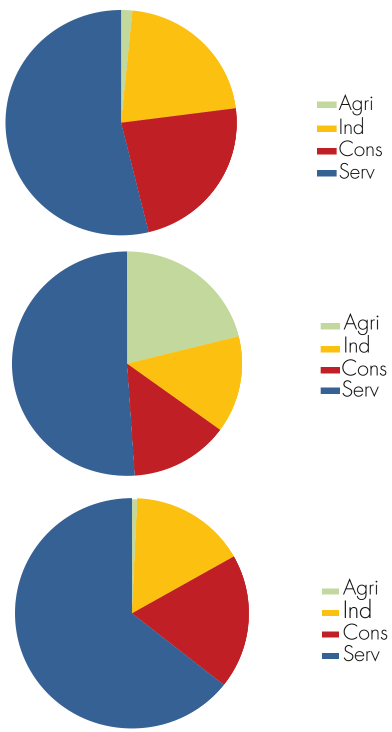
This study focuses on the sectorial allocation of banks' credit portfolio of business loans in response to sector specific economic, and risk developments and bank specific characteristics observed after 2008. Our focus is to investigate whether and how banks' business credit portfolio is responding to changes in real economic activity, credit risk indicators and developments in the banking system itself as a measure of credit efficiency. We do so by analyzing a panel of banks using kernel estimation methodology and the cross-section method proposed by Tanku and Ceca (2013; 2014). The advantage of this method is that among others, the analysis does not suffer from the endogeneity and autocorrelation problems that impair traditional panel data analysis. The adoption and application of the method itself in panel data sets is a second important objective of this research.

Stagnation of new credit in Albanian economy is somehow hard to explain for several reasons. First, the banking system is well capitalized and the overall liquidity of the system is abundant. Second despite its slow rate, economy has been growing. At the same time, the composition of growth has changed in favour of tradable sectors. These sectors could benefit from new credit and contribute to faster growth and eventually to reduction of NPL. Third, credit is stagnating in spite of several expansionary monetary policy and macro prudential measures taken by the central bank. Starting from 2008, Bank of Albania has reduced its policy rate by 4.5 %. The reduction of monetary policy rate has been followed by a substantial reduction in credit interest rates meanwhile inflation is low and Albanian Lek has been stable. Monetary policy is supported by the introduction of macro prudential expansionary measures. Yet despite all that, credit has not recovered. Financial institutions have failed to respond to the significant decrease in interest rates or to stimulating macro-prudential measures undertaken by the Bank of Albania. New credit has developed in favour of domestic currency but remains anaemic and has failed to produce significant growth. Most importantly, several important sectorial and macroeconomic imbalances that preceded the crisis are still present and there is no sign of significant adjustment in relative prices that would lead to their reduction. As a result, the transmission mechanism of monetary policy seems to be broken and Albanian economy remains in stuck in low gear for more than 5 years. This is all documented in the Bank of Albania analyses and research discussed in its Annual, Monetary Policy and Financial Stability reports published between 2008 and 2014.The reasons behind this prolonged bad underperformance is very important from the Bank of Albania's point of view.

Existing research indicates that such poor performance could relate to inefficient credit allocation. Peek and Rosengren (2003) observe that following periods of economic and financial stress, banks do not distribute credit to economy to the most productive sectors. This is also confirmed by the works of Ahearne and Shinada (2005), and Caballero, Takeo and Kashyap (2006). They find that banks have short term incentives to credit the underperforming sectors, insulating "zombie firms" from market forces that would otherwise force the restructuring or bankruptcy of those otherwise insolvent firms. Banks tend to stick to their bad decisions of the past, and continue to support the same companies by restructuring or trading existing bad loans. Thus restricting investments and growth in the most productive sectors and affecting the growth potential of the economy. This study investigates whether traces of this behaviour are currently present in the Albanian banking system by investigating the efficiency of credit allocation (with regard to business loans).

Albanian banking system data shows that, current distribution of outstanding stock of credit among sectors is disproportional to the sectors contribution in economy (fig.1). This composition reflects first and foremost the characteristics of the fast financial intermediation process and those of the absorption lead growth model that dominated economic activity before 2008.

Figure 1 Sectorial share of Value Added and Credit



However, as it is mentioned above, credit expansion stopped after 2009 despite the fact that bank liabilities are mainly supported by domestic sources. Due to this anaemic growth the composition of credit flows have not produced significant change in the sectorial composition of the outstanding credit stock. The important question is whether the banks have adopted their behaviour to support the fastest growing sectors while simultaneously reflecting the risk proportionally? We would also like to investigate whether bank specific factors have contributed to the speed and amount of adjustment.

Using data on loans from individual banks for the period 2008-20014, we find evidence which shows that banks do not respond appropriately to changes in economic development and credit risk in all sectors. Not surprisingly in some cases this response goes in the opposite direction. We find evidence that banks tend to shield some sectors from negative developments and do not respond with the same intensity to support positive developments in other sectors. Capital ratios do not seem to play a significant role in credit allocation. In general we find that banks behaviour is not unique across sectors and explanatory variables, confirming the hypothesis that credit allocation is not efficient.

The rest of this study is organized as follows: next section discusses the strategy of research, section III and IV, discuss the methodology; section IV describes variables, the dataset and its sources. Results are summarized in section V, which is followed by conclusions.

2. PLAN & METHODOLOGY OF RESEARCH

This paper investigates whether changes in outstanding credit stock to domestic sectors is responding to development in domestic sectorial growth and other financial and bank based indicators.

The efficiency of credit allocation is an important issue and has been discussed previously in literature. Mankiw (1986) defines a theoretic model for credit allocation which explains the bank's decision to lend on two important elements: first, the expected return in the industry that borrows money, and second, the firm's probability of default. These two characteristics of the firm are important to the bank in the light of the probability of repayment. They are however both unknown to the bank. Therefore, the bank must form a judgment or expectation with regard to the indicators which serve as proxy of these two elements. Assuming that the idiosyncratic return and risk preference are distributed normally amongst firms in the industry with the mean equal to the industry average allows researcher to use of overall industry profitability and default figures. This leaves the bank and us with one problem: figure out the best figure for the profitability and risk of the industry relative to the rest of the economy. This direct relationship can be altered by three different and opposing forces.

First the relationship between sectorial growth and sectorial credit allocation will be affected by the banks' past exposure to a particular industry because more concentrated portfolios are less protected or incorporate higher risks.[1] Banks can control their risk exposure by reducing or containing new credit to this sector, discouraging new loans to the sector or encouraging additional loans to alternative sectors. The problem would be even more evident once the sectorial breakdown of bad loans is taken into account. A larger exposure to a sector with higher or rapidly increasing share in non-performing loans, could force the bank to discourage new loans to this sector either by imposing growth targets or higher interest rate.

[1] Concentration measured as share of sector to total business loans.

This adjustment might be altered by the "legacy" related costs associated with the outstanding stock of debt at the beginning of the period of study relative to the rest of the sectors. In this ***second case***, inherited credit allocation becomes a burden to portfolio adjustment. Like Peek and Rosengren (2003) have found, once banks inherit a given distribution among industries it might not be easy for them to adjust to new expanding sectors considering their commitment to the old ones. Especially in times of difficulty when, due to hard economic conditions banks will restructure bad credit, and support struggling client companies to contain NPL-s in their balance sheets. Therefore, when considering efficient credit risk allocation, it is important to account for bank exposure to the sector relative to the rest of the economy. As such, it would make sense to include some relative perspective in the sectorial credit allocation and NPL, expressing both variables in terms of the outstanding obligations.[2]

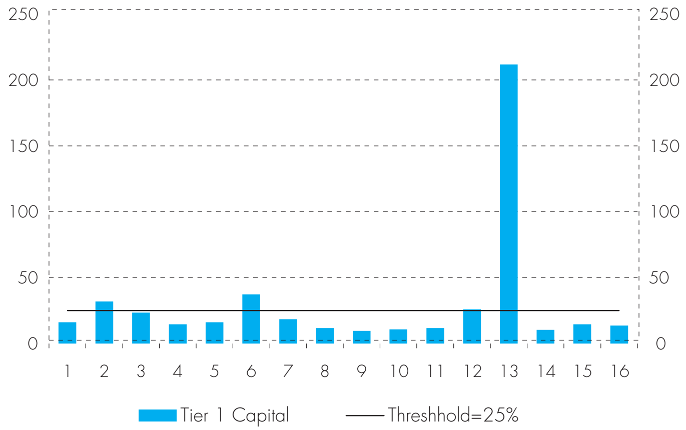
Third, the reorientation of credit toward new sectors would depend on the bank's ability or necessity to adjust its portfolio quickly. Kishan and Opiela (2000) find that the ability of banks to maintain loan growth depends on the bank's own characteristics, like capital and asset size. It is common to assume that larger and better capitalized institutions with larger network and deposit base would be able to maintain their preferred portfolio allocation much easier than smaller and financially constrained institutions. This is acknowledged by other studies, which have included individual bank characteristics into the regression equation. We intend to do the same by adopting capital adequacy ratio in the analysis.

Capital adequacy ratio is an important indicator of bank behavior in Albania. Figure 2 depicts the average capital adequacy ratios (CAR) for the period of the study (2008 – 2014). Banking supervision regulation requires that banks maintain a capital adequacy ratio of 12 %. However, the level shown in the figure is substantially higher than level for several banks. The larger CAR ratios, which correspond primary to smaller banks, indicate particular "forced" episodes of compliance with banking regulation, due to the

[2] This is discussed in more details in the variable description and data construction section.

injection of new capital or immediate disappearance of the large (relative to the bank size) loans for particular sectors form the banks' credit portfolio. Capital situation is important in the banks' decision making process; especially so for the smaller institutions.

Figure 2 Banking System Capitalization



Empiric studies on the topic, including Peek and Rosengren (2003), Buch, Schertler and Westernhagen (2006), Bebczuk and Galindo (2005), etc., have relied on the general narrative above to investigate the efficiency of credit allocation. These studies are conducted on panel datasets of individual banks or enterprise records, and the empiric model is traditionally estimated by linear regression methods. Most of these studies have investigated credit allocation in response to sectorial growth, sectorial risk, institutional factors and bank specific indicators. The model takes the form below:

$$\Delta l = \alpha + \beta \Delta l_{t-1} + \theta X + \varepsilon \tag{0}$$

Where:

l represents lending.

X represents the vector of sector specific or institutional and the bank specific explanatory variables.

β and θ represent the vector of estimated elasticities that corresponds to lagged value of lending and the set variables in X.

Finally, ε represents the errors of the estimated model

However, the implementation of this framework is not trouble-free, given the structure of the model and the endogeneity status of the variables. They have potential implications on the estimated coefficients, and therefore in the conclusion. We try to deal with these problems by adapting to an alternative methodology based on the kernel estimation technique as discussed by Tanku and Ceca (2013, 2014). The following section discusses both methods.

3. THE GENERAL DESCRIPTION OF THE ESTIMATION OF THE OLS AND KERNEL ESTIMATION MULTIDIMENSIONAL DENSITY ANALYSIS

Economic developments have the characteristics of random events. The outcomes are generated and governed by the data generating process (DGP), which is defined by Ericsson, Hendry and Mizon (1998), in the form of a probability space [Ω, F, $\mathcal{P}$]. This DGP is in *general unknown to the researcher.* Due to this limited knowledge, it is most likely that the choice of the variables involved in empirical investigation process represent only a subspace of the true GDP, defined as the Local DGP or LDGP.

The focus of empiric analysis is the identification of the functional form of this LDGP and the estimation of its unknown parameters. The estimation of parameters in pooled and panel data analysis is traditionally based on the linear regression methodology or alternative techniques which build upon linear regression by dealing with potential violations of the general assumptions in OLS.

$$\{X_t^k\} = \begin{pmatrix} x_1^1 & \cdots & x_1^d \\ \vdots & \ddots & \vdots \\ x_T^1 & \cdots & x_T^d \end{pmatrix} \tag{1}$$

where $t, k \in N$ such that $t = 1, \ldots, T$ and $k = 1, \ldots, d$, represent the number of observations and the number of variables in the dataset, respectively.

Given any observed dataset specified in expression (1), the linear regression technique singles out one of the variables (let us call it the dependent or the response variable) and tries to express it as a function of the other d-1 variables (which we will call predictor variables or regresses). In general, linear regression assumes that that the conditional mean of the response variable $\underline{X}^k$ is a linear function of the predictor variables X^{d-1}, multiplied by a vector of unknown parameters β, formulated by expression 2 below:

$$E\left(\underline{X^k}\middle|\underline{X^{d-1}},\beta\right) = E\left(\underline{\hat{X}^k}\middle|\underline{X^{d-1}},\hat{\beta}\right) \qquad (2)$$

where:

$\underline{X^k}$ and $\underline{\hat{X}^k}$ represent the observed and estimated *T x 1* vectors of response variable respectively,

$\underline{X^{d-1}}$ represents *d -1* vectors of predictor variables or alternatively a (d -1) x *T* matrix of repressors,

β and $\hat{\beta}$ represent the true and estimated coefficients respectively.

In addition, linear regression assumes that that the conditional variance of the error made in prediction of the response variable (conditioned on $\hat{\beta}$ and X^{d-1}), defined as twhe error term of the model, has a known matrix variance Ω. This definition of the linear regression is usually written in the form below:

$$X^k = X^{d-1}\hat{\beta} + \varepsilon \qquad (3)$$

where $\underline{\varepsilon} = \underline{\hat{X}^d} - (\underline{X^{d-1}\hat{\beta}})$, *and* $E(\varepsilon|X^{d-1}) = 0,\ Var(\varepsilon|X^{d-1}) = \Omega$

Equation 3 is one way to represent the LDGP (where LDGP ∈ R^d) as a linear combination of the reduced space R^{d-1} spanned by the vectors of the regressors. It represents a projection of vector $\underline{X^k}$ along the basis of X^{d-1}, with the *vector of coefficients* $\hat{\beta}$, *being the factor that achieves this decomposition.*[3] *The estimation of this model is justified by a set of additional assumptions, including exogenous covariates* $Cov(\varepsilon,\ X^{d-1}) = 0$ *and uncorrelated errors* $Cov(\varepsilon_t,\ \varepsilon_{t+m}) = 0$*which guaranty consistent unbiased and efficient estimators.*

This framework is adapted in the context of panel estimation leading to the following representation:

[3] Vector $\hat{\beta}$ is estimated by means of minimizing the sum of the squared residuals.

In a typical panel dataset eq.(1) transforms into:

$$\{X_{i,t}^{k}\} = \begin{pmatrix} x_{i,1}^{1} & \cdots & x_{i,1}^{d} \\ \vdots & \ddots & \vdots \\ x_{i,T}^{1} & \cdots & x_{i,T}^{d} \end{pmatrix} \tag{4}$$

where $i, t, k \in N$ such that $i = 1, 2, \dots, k$ represent the number of observed cross-sections in the dataset *and* t *and* p *preserve the same definition as in (1) above, transforming equation 3 in the following form:*

$$X_i^k = X_i^{d-1}\hat{\beta} + \varepsilon_i \tag{5}$$

here however, $\underline{\varepsilon_i} = u_i + \vartheta_{i,t}$, with u_i & $\vartheta_{i,t}$ representing the cross-section *specific unobserved variable and the residual respectively; and* $E(u_i|X_i^{d-1}) = 0$, $E(\vartheta_{i,t}|X_i^{d-1}) = 0$, $Var(\vartheta_{i,t}|X_i^{d-1}) = \Omega$ *in addition* $Cov(\vartheta_{i,t}, X_i^{d-1}) = 0$ *for all i must be satisfied.*

The problem with the panel estimation of linear regression models is the assumption regarding the nature and the violation of the linear regression assumptions across cross-sectional or periods in the pooled data due to lack of knowledge of the true DGP.

The relationship among credit and growth, credit and risk or credit and capital adequacy ratio are typical examples of endogeneity and autocorrelation problems. The simultaneity of such events and/or potential loops of causality generate a symbiosis among credit growth and sectorial growth. These represent a significant problem in the empiric investigation analysis and the estimation of the coefficients. Any traditional econometric analysis textbook, like Greene (2005), will provide a full discussion of the related problems; additional arguments are provided in Hendry and Johansen (2013).

The violation of the above mentioned assumptions is problematic and must be addressed by the choice of the estimation methodology. Depending on the specific violation, the problem is solved by the adoption of alternative methods of linear regression referring here to

GMM, GLS, 2SLS, Weighted OLS, non-linear OLS etc.

The solutions discussed above are not a panacea either. The "tweaks", augmentations and substitutions of the error variance matrix represent arbitrary interventions which control and/or change the information to satisfy the assumption. The identification of instrumental variables is a problem in itself. Given the difficulty and subjectivity in above mentioned methods, several studies have resorted to the use of panel VAR methodology. However, this too is subject to correct model identification. Erickson, Hendy and Mizon (1998) describe the endogeneity problem in detail and identify the correct conditions under which the estimation of the conditional part of the "empiric" model is justified. Therefore, the correct inference on all these particular elements will bare significant impact on the results, and their interpretation. In general autocorrelation, endogeneity, linearity, normal distribution of errors, etc., are frequently present and hard to eliminate and justify in panel data. They remain important obstacles in the estimation of econometric model.

Against these potential problems we propose the density estimation techniques as an alternative to linear regression estimation. We follow Tanku and Ceca (2013), based on the approximation of the joint density function using kernel density estimation technique. Kernel density estimation allows the representation of the data generating process in terms of the joint density function of any d-dimensional space spanned by the variables of interest, yielding to the following general representation of the DGP:

$$D_{X^k}(X^k \mid f(.)) = D_{x^k}\left(x^k \middle| \hat{f}(.)\right) \tag{7}$$

where:

D_{X^k} represents the density function of the LDGP

$k \in \{1, \dots, d\}$ *represent the dimensions of the LDGP which density function is estimated (the variable or the set of variables of interest to the researcher*

and

$\hat{f}(.)$ *represents the estimated d-dimensional joint density function.*

Alternatively, the data generating process could be expressed as a conditional probability of the joint density function of our d-dimensional space by the variables of interest in the following general form:

$$D_{X^k}\left(X^k \middle| X^j, f(.)\right) = D_{x^k}\left(x^k \middle| x^j, \hat{f}(.)\right) \qquad (7.1)$$

where

$j = (1, 2, \dots k-1, k+1, \dots, d)$ *represent the conditioning dimensions variables and the rest of the notations preserve the same references as above.*[4]

The focus of density estimation is the joint density of the LDGP rather than the vector $\boldsymbol{\beta}$. The estimation of the density function given in 7 & 7.1 builds upon the density estimation technics discussed in Silverman B.W., (1986). Tanku and Ceca (2013) calculate and show the estimated densities of any *d-dimensional* space of economic variables, using Gaussian Kernel takes the form below:[5]

$$\hat{f}(\underline{l}) = \frac{1}{Th^d (2\pi)^{d/2}} \cdot \sum_{t=1}^{T} exp\left\{-\frac{1}{2h^2}\left[(l_1 - x_t^1)^2 + (l_2 - x_t^2)^2 + \cdots + \left(l_d - x_t^d\right)^2\right]\right\}, \quad (8)$$

where:

$\underline{l} \in R^d$ is the variable of the estimated density $\hat{f}(\underline{l})$ and h is the smoothing parameter.

Equation 8, provides the model that defines and expresses DGP in its alternative interpretation defined by equation 7 and 7.1. Tanku and Ceca (2013) point to the fact that this representation allows the definition of economy as an expanding sequence of spaces in leading to the interpretation of each m dimensional LDGP as a projection of the original DGP in the R^m subspace (*where m < d*).

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[4] The reader must not confuse the condition of equation 7.1 with the condition of equation 2. As it will be explained below condition in 2 defines the set of regressors, while the meaning of condition in equation 7.1, is for particular values or intervals along the variables in LDGP. The equivalent of condition in equation 2 will be presented in eq. 9, in the following section.

[5] In addition Tanku and Ceca (2013) also provide the functional form of the estimated density in the case of Epanechnikov kernel.

Density estimation provides several benefits compared to traditional linear regression methods. First, unlike linear regression methods, density estimation provides a method to project DGP in itself, without loss of dimensions. At first glance, equations *7 – 8* seem to provide a "similar" representation the LDGP as equation 2; however, there is a fundamental difference. Equation 8, express LDGP as a joint density function of LDGP in R^d space as opposed to R^{d-1} space spanned only by the vectors of the regressors in the case of linear regressions.

Second, under this alternative representation, the object of investigation shifts from estimation of β to the estimation of joint density function of the DGP. The focus of the investigation is the resulting density function D_x distribution which contains the fullest information with regard to variable X. This provides a significant improvement upon equation 2, which focuses exclusively on the expected value of the dependent variable.

Third, there is no need to discuss the linear independence among regressors since the "solution" is not found in the decomposition of the LDGP among the orthogonal bases of the subspace R^{d-1} spaned by the regressors. Therefore, the assumption of endogeneity becomes redundant, for it does not affect the calculation of equation 8. This is to say that the relationship among any two or more variables is given once and for all by their uniquely defined joint density. One must be careful, as the estimation indices simultaneity and might not exclude both variables reacting to a third and unknown cause. However, the important thing is that it does not affect the calculation of the density function.

Tanku and Ceca (2013) rely on the graphical representation of the estimated densities to interpret and analyse the information contained in the multidimensional density functions. In this respect, the analysis of estimated multi-dimensional densities is limited by our inability to perceive beyond three dimensional spaces. This limitation constrains the analysis to the estimation of two dimensional joint density functions. Therefore, the analysis of the LDGP is carried by the estimation of equation 8 and the interpretation of the resulting graphical presentations representing the projection of the LDGP onto R^2. This two-dimensional mapping has become a traditional approach in the study of density estimation and other forms of multi-dimensional data computation, analysis and visualization methods. In addition, Tanku and Ceca[6] (2014, pp. 5) introduce the "cross section method" to ease the readability, interpretation and comparison of the resulting d-dimensional estimated densities, based in the first moment and its standard deviation. This cross-section is defined as: Generalized definition of conditional distribution of a continuous random variable – the case when the condition is a set to be a single value. The method estimates the continuous density function of the dependent variable for any potential value of the regressor, based on the expression given in eq. 9 below.[7]

$$\hat{f}\left(\underline{l} / l_{k+1}, \dots, l_{k+m}\right) = \frac{1}{h^{d-m}(2\pi)^{\frac{d-m}{2}}} \cdot \frac{\sum_{t=1}^{T} exp\left\{-\frac{1}{2h^2}\overbrace{\left[(l_1 - x_t^1)^2 + \dots + (l_d - x_t^d)^2\right]}^{d\ monomials}\right\}}{\sum_{t=1}^{T} exp\left\{-\frac{1}{2h^2}\underbrace{\left[(l_{k+1} - x_t^{k+1})^2 + \dots + (l_{k+m} - x_t^{k+m})^2\right]}_{m\ monomials}\right\}} \quad (9)$$

$\hat{f}\left(\underline{l} / l_{k+1}, \dots, l_{k+m}\right)$ *represents the conditional density estimates with m dimensional condition, for density estimates given as the ratio of the d-dimensional density estimates* $\hat{f}(\underline{l})$ *with the marginal ones* $\hat{f}_{\{k+1,\dots,k+m\}}(l_{k+1}, \dots, l_{k+m})$ *using the Gaussian kernel. The rest of the notations follow the same interpretation as above.*[8]

Eq. 9 represents the analytical expression of the continuous density functions of the variable of interest for all potential values of other m "explanatory" variables *where* $(m,d \in N \mid m < d)$. It simultaneously serves as the tool of investigation and as the metric of interpretation of the relationships among our variables of interest. The numeric characteristics of the resulting density can be used to describe and interpret the density function and provide comparison

[6] Forthcoming in Bank of Albania Working Paper Series. The paper is available by authors upon request.

[7] The derivation is provided by Tanku and Ceca (2014), forthcoming Bank of Albania working paper series. Manuscript available by the authors.

[8] The expression of the calculated conditional density in the case of 1 and multidimensional conditions for the Gaussian and Epanechnikov kernels are available in Tanku and Ceca (2014).

with the traditional linear regression method. In the exercise below we have calculated and shown the continuous first moment as well as its standard deviation of the resulting two-dimensional densities for all potential values of the explanatory variable.

The shape and position of such “maps” of estimated densities (eq. 8) and conditional expectations (eq. 9) contain and reveal information on the relationship between the variables in the graph.

4. ADAPTION OF DENSITY ESTIMATE AND MULTIDIMENSIONAL DENSITY ANALYSIS TO PANEL DATA.

Given that the informative structure of panel data and the benefits of kernel density estimation with regard to endogeneity and autocorrelation problems, we would like to adopt density estimation as a tool of investigation for the panel data approach. The focus is the estimation of multidimensional density probabilities of DGP using the kernel density estimation technique. We start by rewriting DGP in its vector form as a process of dimensions along all cross-sections and time observations, as below:

$$\begin{aligned} X^1 &= \left(x_{i,1}^1, x_{i,2}^1, \dots, x_{i,T}^1\right)' \\ X^2 &= \left(x_{i,1}^2, x_{i,2}^2, \dots, x_{i,T}^2\right)' \\ X^3 &= \left(x_{i,1}^3, x_{i,2}^3, \dots, x_{i,T}^3\right)' \\ \dots & \qquad \dots \qquad \dots \\ X^d &= \left(x_{i,1}^d, x_{i,2}^d, \dots, x_{i,T}^d\right)' \end{aligned} \tag{10}$$

for i = (1, 2, …,p) where p represents the number of cross-sections in the panel

The representation of panel data structure in the form of the joint density function of our d-dimensional space in the form of any d-dimensional density, using Gaussian Kernel requires rewriting eq. 7:[9]

$$\hat{f}(\underline{l}) = \frac{1}{(Tp)h^d(2\pi)^{d/2}} \cdot \sum_{t=1;i=1}^{T;p} exp\left\{-\frac{1}{2h^2}\left[\left(l_1 - x_{t,i}^1\right)^2 + \left(l_2 - x_{t,i}^2\right)^2 + \dots + \left(l_d - x_{t,i}^d\right)^2\right]\right\} \tag{11}$$

where:

$\underline{l} \in R$ is the variable of the estimated density $\hat{f}(\underline{l})$ and h is the smoothing parameter.

[9] In addition Tanku and Ceca (2013) provide also the functional form of the estimated density in the case of Epanechnikov kernel.

This leads to the transformation of equation 9 into the following general representation:

$$\hat{f}\left({}^{l}\!/\!_{l_{k+1},\dots,l_{k+m}} \right) = \frac{1}{h^{d-m}(2\pi)^{\frac{d-m}{2}}} \cdot \frac{\sum_{t=1;i=1}^{T;p} exp\left\{ -\frac{1}{2h^2} \overbrace{\left[\left(l_1 - x_{t,i}^{1}\right)^2 + \dots + \left(l_d - x_{t,i}^{d}\right)^2 \right]}^{d\ monomials} \right\}}{\sum_{t=1;p=1}^{T;p} exp\left\{ -\frac{1}{2h^2} \underbrace{\left[\left(l_{k+1} - x_{t,i}^{k+1}\right)^2 + \dots + \left(l_{k+m} - x_{t,i}^{k+m}\right)^2 \right]}_{m\ monomials} \right\}}$$

(11)

Eq. 11 represents the estimated continuous density of the dependent variable for all potential values of the independent variable (preserving simultaneity across cross-sections and time period). So the evolution of density (or its numerical characteristics) provides all the information for the behaviour of the dependent variable in response to changes in the independent (regressor) variable.

The above mentioned advantages of kernel density estimation methodology relative to linear regression, transfer nicely to the study of panel data sets freeing the estimation from potential implications of the cross-section (in our case bank) specific errors and other endogeneity and autocorrelation problems. Therefore there is no need to test and compensate for the presence of such problems in the data or, have prior knowledge of the true DGP. There is no miss-specification of the functional form as there is no need to assume a functional form for the DGP.

Our exercise has simply projected the expected value and its standard deviation. However analysis can continue with the remaining numerical characteristics of the distribution. The variables and other characteristics of the database are discussed in the following section.

5 VARIABLE DESCRIPTION AND DATA CONSTRUCTION

The purpose of this study is to investigate whether credit allocation is responding to sectorial developments in terms of growth and risk performance, and banks own financial situation. We plan to investigate this topic using kernel density estimation and the cross section method as proposed by Tanku and Ceca (2013; 2014). We use a panel of 16 banks and quarterly observations over the period of 2008Q4 – 2014Q4. Following theoretic models and previous empiric research, we will examine the behaviour of credit for four different sectors in response to value added by the sector, the behaviour of nonperforming loans in the sector, and the banks financial situation. Specifically we will use the value added by sector, nonperforming loans by sector and capital adequacy ratios.

The dependent variable is represented by the first difference of the sectors share in the stock of outstanding credit to business at the end of each period. The share of credit for each sector represents the total outstanding debt allocated to the sector, expressed as a %age of total outstanding stock allocated to business at the end of the reference period.

Following Buch, Schertler and Westernhagen (2006), we will use sectorial value added as a proxy of return in the respective industry, and an explanatory variable for credit allocation among sectors. This is reasonable under the assumption that the fastest growing industries are also the most profitable ones. Therefore, the banks' evaluation for the industry specific allocation in our model will depend on their expectations for the value added by the industry relative to the rest of the economy.

Traditional studies have regressed change in loans to value added by sectors. However this might not be an accurate measure in the case when sectors' contributions to DGP are substantially and persistently different. Faster growth in a relatively small sector would absorb much smaller share of credit as opposed to a larger sector which is growing at a substantial slower peace. In this respect it is necessary to introduce a sense of relativity in the sector's value added indicators. We subject the value-added variable to this effect by calculating for each sector, its value added, as the share (in % age) of the total value added during the reference period. In addition, given the high seasonality of the value added indicator, each sector's value added is represented in its annualized form (calculated as the rolling sum of 4 quarters). This indicator is lagged one quarter to account for the fact that the information can affect banks' decision only after it becomes available.

The individual probability of default is also unknown to the bank, but can be approximated by the probability of the sector. Sectorial probability of default is not available either; therefore, we rely on the relative share of sectorial NPL as a proxy indicator of the ability of the sector to repay back loans. This is based on the assumption that the idiosyncratic risk in the industry is distributed normally with the mean equal to sector's NPL. The nonperforming loan indicator represents the first difference of sectors' outstanding stock of NPL, expressed as a % of total outstanding stock of NPL for each bank at the end of the reference period. Like in the case of value added above, this indicator is lagged one quarter to account for the fact that the knowledge of NPL situation at the end of a period can affect banks' decision in the following one.

Banks' own indicators are defined by capital adequacy ratio. This indicator varies substantially among cross-sections (and for some particular banks, across the time dimension). Figure 2 shows the average CAR indicator for the period for each bank. The Albanian banking supervision regulation requires that CAR equals 12 %; however, figure 2 shows that this indication has been substantially higher. While this is in itself a sign of financial inefficiency, it seems to be a rule rather than exception in the banking system. The figure is, however, extremely high for three particular banks. Not surprisingly, it corresponds to the banks that are very inactive in credit activity. Their situation represents an exception rather than reflection of their business strategies, so they are considered outliers and are dropped from the sample, reducing the number of cross-sections to 13 from the original 16. In addition, four more observations are lost in each cross-section, three due to the calculation of the rolling sum, plus one for the first difference in credit variable. After these adjustments are made, the number of observations in our balanced panel dropped to a total of 286 from the original 400. Table 1 below summarizes the dataset and its sources.

Credit indicators and bank specific data comes from Bank of Albania reporting system, value added data come from INSTAT (Albania Institute of Statistics). More specific information is provided below:

Table 1

Variable name*	Variable description	Source	Sector	Time period
AgriDk IndDk ConsDk ServDk	Credit variable: first difference of respective sector's outstanding credit calculated as %age of total outstanding credit to business. Expressed in basis points.	BoA	Agriculture Industry Construction Services	Q4,2008-Q4,2014
AgrirkDL1 IndrkDL1 ConsrkDL1 ServrkDL1	Credit risk variable: first difference of respective sector's NPL calculated as %age of total outstanding stock of NPL in economy.	BoA	Agriculture Industry Construction Services	Q4,2008-Q4,2014
AgrivaAL1 IndvaAL1 ConsvaAL1 ServvaAL1	Value added variable: annualized (rolling sum of last 4 quarters) of quarterly, not seasonally adjusted observations.	INSTAT	Agriculture Industry Construction Services	Q4,2008-Q4,2014
Tier 1	Capital adequacy ratio	BoA	Banks	Q4,2008-Q4,2014

*/ D indicates the first difference, A indicates annualized data, and L1 indicates lagged 1 period.

6. RESULTS

This section presents and discusses the results of our empiric investigation. Analysis is based in the interpretation of graphs (figures 3.1 through 6.3), which represent the result of density estimation in R2. Graphs depict the joint density and the conditional mean of the dependent variable (change in credit for each sector) and each of the independent variables value added, credit risk and capital adequacy ratio separately. The discussion is focused on the shape and position of the isobars (of the density function resulting from equation 10) and the calculated conditional mean (of the density function resulting from equation 11). The analysis can easily extend to include other moments or numerical characteristics for a more detailed discussion of the estimated conditional densities calculated by the cross section method. The exercise is repeated for each sector.[10]

The graphs read as follows: the vertical axis shows the value of the dependent variable, while the horizontal one the value of the regressed. The colour of isobars depicts the probability weight, with the scale shown on the right hand side of the graph. In general, stronger red colours indicate events with high probability, and light blue colours indicate the opposite. The behaviour of the dependent variable is described by the shape and position of the isobars and the conditional mean in the graph, as the repressor's value moves from its min to its max value. As a general rule, estimating regular concentric circles and/or oval shaped isobars positioned perpendicularly to one of the axes in graph a, would indicate independence of the response variable from the regressed. If that is the case, the resulting conditional mean in graph b will be horizontal, confirming that the expected value of the response variable does not respond to changes in the observed value of the regressed.

[10] The resulting estimated density functions are subject to the choice of the smoothing parameter h in the eq. 10 and 11 above controlling the smoothness of the density function. The choice of the variable h is made so that we retrieve meaningful maps. In general we tried to keep the value of this parameter between 0.5 and 3. For further details in the selection of optimal h please see Tanku and Ceca (2013).

Alternatively, the estimation of a density function whose main axes are positioned at an angle to the main axes of the graph would indicate that the response variable reacts to changes in the observed value of the regressor, and the inclined position of the estimated conditional mean should confirm this, with the angle indicating the speed of response. Sections of graphs with higher elevation depict episodes with higher frequency, indicating that events in the corresponding range have a higher probability of occurrence. Therefore they deserve more attention in the interpretation of normal market developments. Events with lower elevation (especially the ones in the tails of the distribution) indicate rare events, and deserve more attention in the discussion and understanding of stress episodes. The following analysis discusses credit developments in each sector separately.

We start our discussion by analysing the behaviour of credit in the agriculture sector. In general, based on economic interpretation, we would expect to observe a direct relationship between economic activity (value added) and sectorial developments in credit. The relationship between credit risk and credit could go in both directions, but a negative relationship would indicate that banks are behaving responsibly by reducing exposure to one sector when its credit risk increases. Finally, we would expect some reaction in credit as the CAR ratio moves away from its required level of 12 %. The size and direction would depend on the size of the bank and accessibility to funds. We would look to identify those particular patterns in the density and cross-section graphs.

Fig 3.1a and 3.1.b respectively show the estimated densities and conditional mean of the credit to agriculture in response to value added. Graph a shows that credit to the agriculture sector is mainly located around 0, with two other frequent locations (dominant locations) located symmetrically on both sides of the main elevation at a distance of around 50 basis points. All three frequent locations on the graph are positioned horizontally, indicating that credit to the agriculture sector does not respond to changes in value added in this sector. This is also confirmed by the conditional mean in graph 3.1.b, which lays almost horizontally, responding only by a few basis points to the increase of value added in the agriculture sector vis-à-vis the rest of the economy.

Figure 3.1

a. *b.*

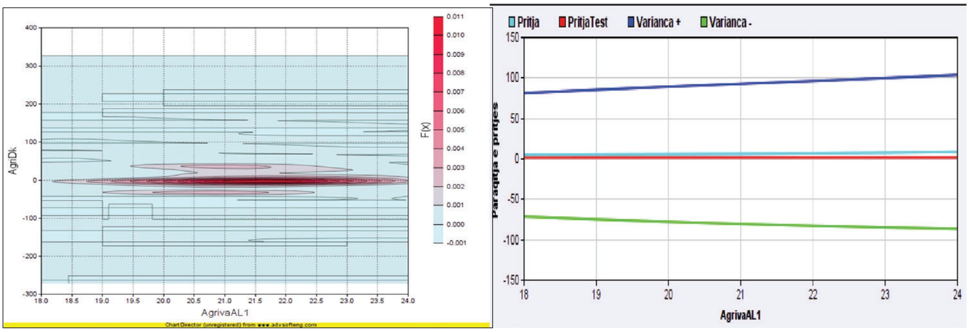


Figure 3.2

a. *b.*

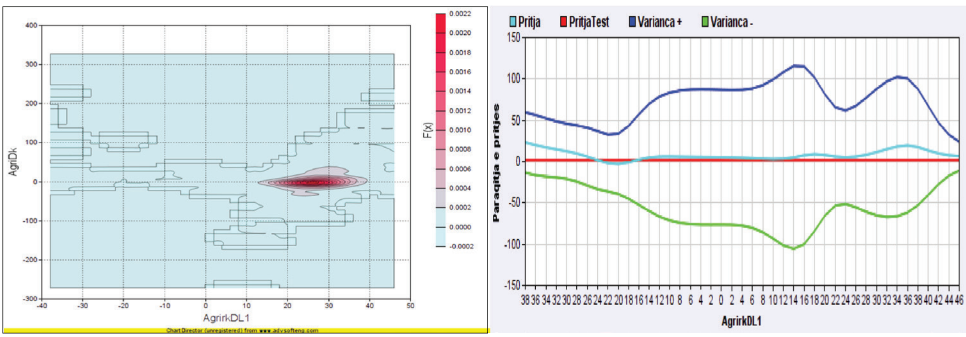


Figure 3.3

a. *b.*

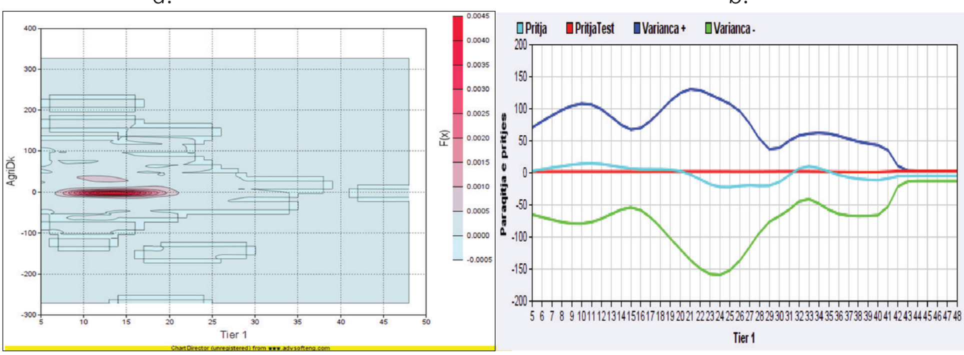


Figure 3.2 shows the response of credit to the agriculture sector to changes in the credit risk. The estimated density depicted in panel a, shows that the density is dominated by a single rise, located horizontally around 0, with the tails extending in the direction of the main diagonal. We interpret this as an indication that an increase in the credit risk is matched by an increase in credit growth. This is confirmed by the behaviour estimated conditional mean in panel b of the same figure, which shows that as the credit risk indicator increases between 24 and 36, credit increases by almost 20 basis points. In principle this observation shows bank support for the sector while its credit risk increases and indicates an inefficient allocation of credit. The effect is marginal however, and credit growth is almost horizontal around 0 in the majority of the observed credit risk interval. A marginal increase in the expected value of credit is observed also as the credit risk indicator decreases faster than 24 units, indicating that a drop in credit risk is accompanied by an increased credit to the agriculture sector, as one would normally expect. In addition to its marginal effect, the observation is based on events with very low probability, and therefore might not be considered representative behaviour.

Finally, the density estimation of the credit growth and capital indicator, in figure 3.3.a, and the estimated conditional mean in figure 3.3.b indicate a marginal response of credit to changes in capital adequacy ratio. Again the density map is dominated by a single rise concentrated almost horizontally around 0, with few concentrated observations distributed above it. This is just enough to demonstrate a slight increase in credit as CAR approaches 10-12 % in fig. b. The conditional expected value of credit to agriculture sector drops marginally in the CAR interval 22-30 %. This later effect is almost twice as strong but of a less importance due to its low probability of occurrence, as shown by the density map in panel a.

In summary, we observe a marginal response to credit risk and to capital situation developments. It seems that extreme values of relative credit risk influence credit in the opposite direction. Despite this, large changes in explanatory variables are met by only marginal increase in credit. We interpret this as a sign that credit to the agriculture sector develops independently of the developments in real economic activity and credit risk banking indicator.

Credit to industry sector is depicted in figures 4.1 to 4.3. In this case, the estimated densities are dominated by the presence of a larger number of bell shaped rises, in particular in the case of development in value added and capital, all while being dominated by a single node in the case of credit risk.

The many nodes in the case of value added are spread out and positioned horizontally parallel to each other. Even when considered all together, they produce a trivial general upward trend, indicating a direct but trivial relationship between credit and value added. This is confirmed by the response of the estimated expected value of the conditional density in figure 4.1.b. The graph shows that as the relative share of value added in construction increases from 10 to 14 %, credit to this sector increases almost 50 basis points and becomes horizontal after that. This reaction is very small and indicates that banks are marginally more attentive to bad performance of the industry sector.

Figure 4.1

a. *b.*

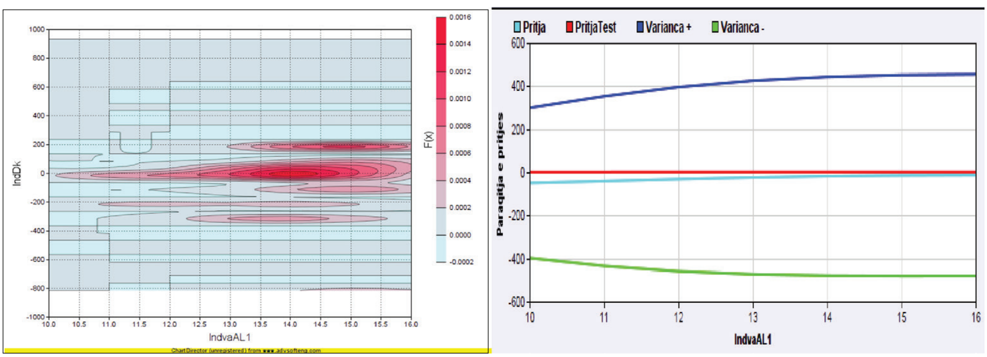


Figure 4.2

a. b.

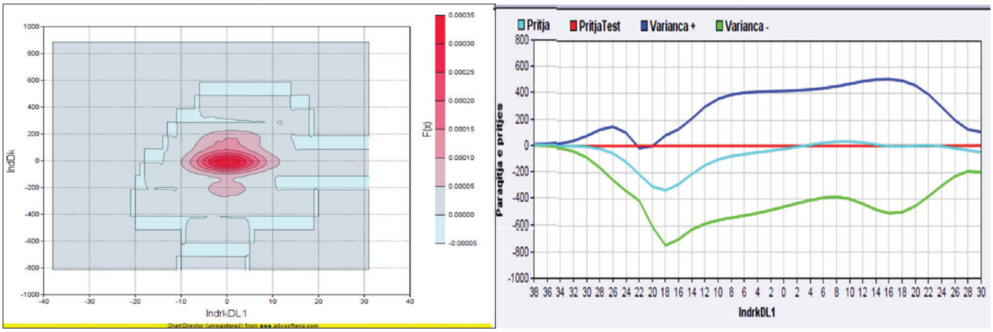
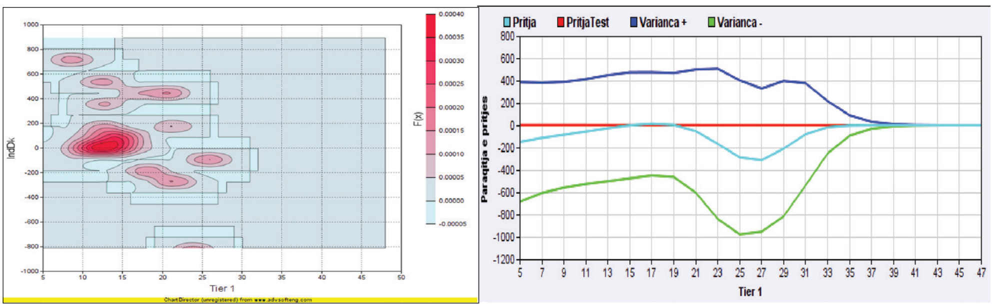


Figure 4.3

a. b.



Like in the case of value added above, credit to industry sector does not respond significantly to changes in relative credit risk (figure 4.2). The density is dominated by a single oval bell with its main axes seemingly parallel to the main axes in the graph. The most important observation here is the fact that as the relative credit risk increases we do not observe a strong adjustment in credit to this sector. The expected value of the conditional density in panel b. rises slightly by 100 basis points in response to changes in credit risk from -10 to 2. In principal, this indicates that a reduction in the relative share of NPL of the industry sector to the rest of the economy is accompanied by a reduction of credit in this sector. Banks credit reduces significantly as credit risk drops in the interval -10 to -18. These developments are against our expectation and difficult to explain. The expected value of credit increases only as the credit risk indicator falls below -18, which is what we would normally expect. However, both these changes are observed in events with low probability and do not indicate significant developments.

Finally, the behaviour in response to banks own capital is non-linear (figure 4.3). The estimated density is dominated by the presence of many "bells", which all together produce a non-linear expected value for the conditional density. The response of credit to industry sector to the CAR indicator is direct in the intervals 5-15, indicating that a reduction of CAR below the optimum level results in a reduction of credit to this sector. This credit drops significantly in the CAR interval 21-31, first falling and then rising again as CAR increases beyond 27 %. We find these non-linear patterns difficult to interpret, but one can say that at as CAR indicator reaches the 21-31 % banks tend to allocate less credit to the industry sector.

In summary, credit to industry responds to developments in real economic activity and banks' own indicators. Like in the case of the agriculture sector, the relationship is direct but trivial in the most significant interval (referring to the interval with high elevation in the density graph 4.2.a). On the other hand, the relationship between CAR and credit in the industry sector is not direct. In general, credit to industry drops as CAR approaches its extreme values.

Developments in the **construction** sector are of particular interest because this sector has suffered the most prominent loss in its value added and increase in NPL during the period of observation. As such, it would be interesting to see how banks have adjusted to these negative developments. The results of the analysis are reported in figures 5.1 to 5.3., we start with the discussion of value added. Graphs show that the estimated densities are dominated by the general presence of multimodal distributions which individually do not show much to changes in explanatory variables.

Figure 5.1

a. b.

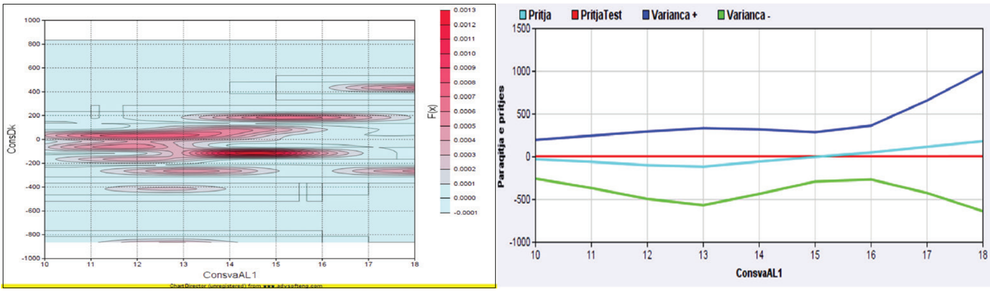


Figure 5.2

a. b.

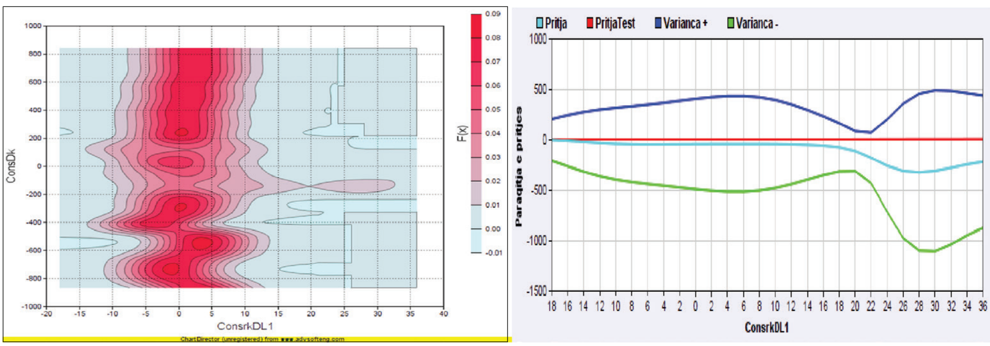
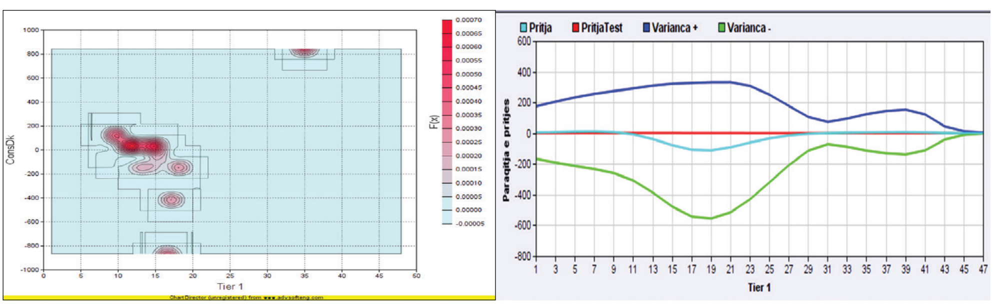


Figure 5.3

a. b.



Yet, when considered all together they produce a general upward trend indicating a direct relationship between increases in value added and increase in credit. This is confirmed by the response of the estimated expected value of the conditional density in figure 5.1.b. The graph shows that as the relative share of value added in construction increases from 13 to 18 %, credit to this sector increases almost 300 basis points. It is however, interesting to observe, that the reduction of value added indicator below 13 % does not coincide with the reduction of credit to this sector. Instead, the graph shows a marginal increase in the expected value of credit to construction below this point. We interpret this episode as a sign of "unnatural selection", since banks continue to support this sector even when its value added underperforms relative to the rest of the economy.

Credit in the construction sector is almost independent to changes in credit risk during most of the credit risk range. However, it reduces by almost 300 basis points as the relative credit risk falls in the interval of 20 to 28 %. The general explanation that emerges from the graph is that banks react by reducing credit to construction industry only in response to extreme values in credit risk, precisely as the NPL of this sector approaches almost 1/3 of total NPL. The relationship of credit indicator with CAR is multimodal, dominated by several almost regular bell shaped peaks which do not contribute in a significant reduction to the expected value of credit to this sector. Figure 5.3.b, shows that credit to construction reduces to its minimal value as CAR approaches 19 %; however, this is a marginal effect, depicting an almost horizontal relationship.

We conclude that the banking system has responded to the reduction of construction share in economic activity. Banks, however, seem to have adopted a protective behaviour toward the sector, shielding it from large reductions of value added and responding only to extreme values of NPL in the construction sector relative to the rest of the economy.

Figure 6.1

a. b.

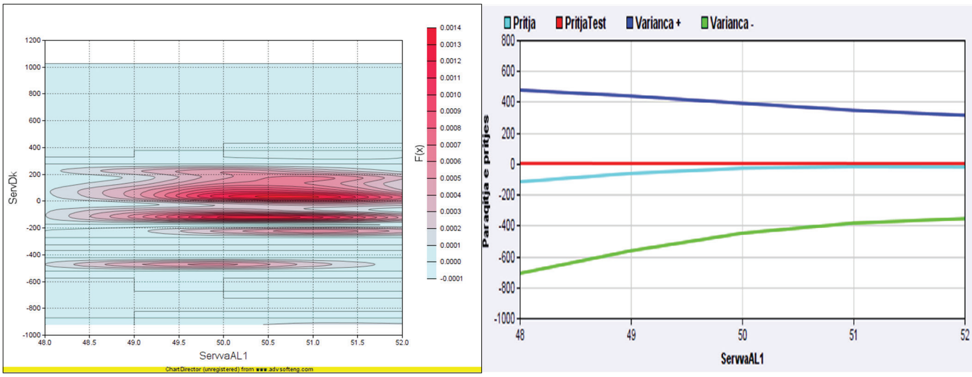


Figure 6.2

a. b.

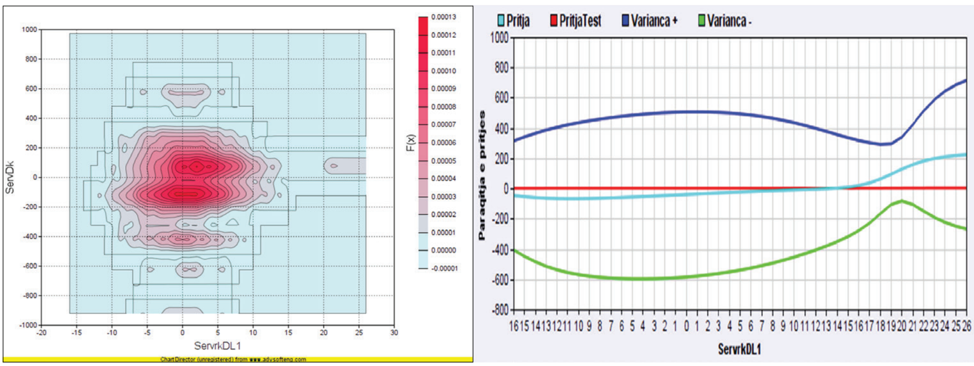
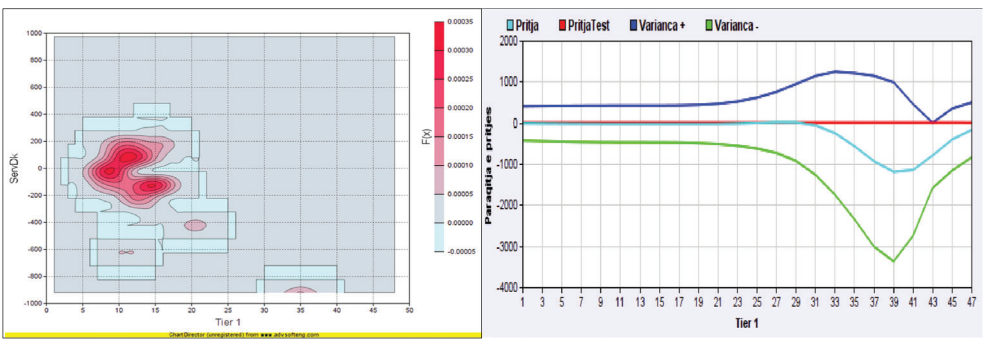


Figure 6.3

a. b.



Densities estimated for the service sector, depicted in panel a, figures 6.1 to 6.3, are dominated by parallel multimodal nodes, which yield almost horizontal expected values for conditional densities (panel b, figures 6.1 to 6.3). Credit to services sector seems to respond relatively well only when the share of services to value added drops below 50 % and remains unchanged above this point. The rest of the graphs indicate little or no response to changes in explanatory variables. Like in the case of the construction sector, the response is stronger in the tails of distributions. In particular, we observe a relatively strong increase in credit to this sector as the credit risk increases beyond 17 %, and a strong decrease in credit only as the capital adequacy ratio increases beyond 39 %. Our interpretation is that credit to services sector adjusts to reflect the relative slowdown of the sector, during which the demand for funds probably drops. However, banks try to keep the flow of credit to this particular sector constant, despite developments in the sectors' NPL, and might even increase credit when the NPL situation aggravates to keep underperforming firms of the sector floating. This evidence of inefficiency of allocation is to be expected. The services sector is very important for banks. It represents more than 50 % of total credit to business and the legacy costs are very high.

It is difficult to put these results in perspective due to the absence of previous studies in this important topic for the Albanian economy. Comparison of our results with existing literature, indicates that credit response to changes in economic activity for construction and services sectors, is of comparable range with estimated elasticities in the case of Germany, Korea and Japan. Whether this is reasonable can't be stated with credible accuracy since credit response depends on the characteristic of each economy and on the choice of the variables. In addition, our results indicate that the response is non-linear and banks' reaction might differ depending on the particular value of the relative value added, credit risk and capital adequacy ratio.

7. CONCLUSIONS

This study investigates the efficiency of banks' credit portfolio allocation in response to changes in the composition of economic activity, credit risk and banking system indicators in Albanian economy. The study introduces the application kernel density estimation and the cross-section method Tanku and Ceca (2013 & 2014) as a tool of empirical analysis on panel data. In this respect our results show for the first time density estimates for credit broken down by its sectorial allocation and its behaviour in response to changes in the above explanatory variables.

We find that the response of credit activity, meaning the incidence of reaction, its direction and magnitude, differs among sectors and among explanatory variables. Moreover, this response is not linear. In some occasions credit behaviour reverses directions in response to "extreme negative" developments (tail developments) in the explanatory variables, in particular in response to increase in credit risk indicator; in other occasion credit behaviour response is trivial having no real impact in convergence of credit to the size of sectors' contribution in Economic activity. Banks seem to shield preferred and/or suffering sectors from really bad economic performance and credit risk. A stronger protection against credit risk is reserved for the services sector (which owns the largest share in total outstanding debt) and smaller one for the agriculture (owning the smallest share) indicating that the banks' exposure to the sector might have a role in the persistence and extend of such protection.

Banks behaviour seems to provide protection for troubled sectors against market forces which could lead a better distribution of resources end economic restructuring. In this respect the misallocation of credit inhibits the efficiency of monetary and financial policies of the central bank and imposes a burden on economic recovery.

The response of credit to CAR is more or less similar across sectors but puzzling. It could reflect the structure of the financial market (dominated by large banks) with the observed tail events dominated by small less active banks. It requires further investigation and research in the future.

The presence of multimodal densities in our results could indicate the presence of bank specific factors. Therefore future research can focus its investigation on sub samples of the dataset into groups of banks with similar characteristics.

Our interpretation of the results leads to two important conclusions: first, we find evidence which indicates inefficiency in credit allocation, reflecting a general problem with the banks' incentives; and second, we find that kernel density estimation and cross section method are useful tools in the empiric investigation and visualization of panel data sets. Density estimation proves a useful alternative method to traditional panel data analysis. This kind of empiric analysis represents an alternative to traditional linear regression methods. Most importantly, its application and results are not constrained by the knowledge of the DGP, its functional form, the stochastic behaviour of the error term and endogeneity and autocorrelation status among variables, cross-section specific random effects and residuals.

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