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Anastasiya Ivanova
National Bank of Ukraine

Alona Shmygel
National Bank of Ukraine

Ihor Lubchuk
National Bank of Ukraine

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Chemin Eugène-Rigot 2
P.O. Box 136
CH - 1211 Geneva 21
Switzerland

THE GROWTH-AT-RISK (GaR) FRAMEWORK: IMPLICATION FOR UKRAINE

Anastasiya Ivanova, Alona Shmygel, Ihor Lubchuk

Abstract

Using data for the Ukrainian economy, we applied and adapted the growth-at-risk (GaR) framework to examine the association between financial conditions, credit and sectors' activity, and external conditions and the probability distribution of GDP growth in Ukraine. We applied CSA and PCA approaches to construct indices of these partitions. We further derived GDP growth distributions and explored their behavior under different scenarios. Results from the model with PCA indices suggest that the relationships between financial conditions as well as external conditions indices and economic activity are inverse regardless of quantile of GDP distribution. Moreover, we found that the financial conditions index has the largest effect on the GDP growth on the lower quantiles, which could generate significant downside risk to the economy.

Keywords: quantile regression, economic growth, GDP, principal component analysis, GDP growth distribution.

JEL: C31, C53, E17.

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Introduction

In recent years Ukraine has experienced a few major crises that translated into large-scale economic downturns and severely impacted the performance of its national financial system and sectoral output. To prevent such crises, the regulator should have an effective toolkit to monitor systemic risk and prevent its realization. There are plenty of indicators that financial market regulator should monitor to analyze the systemic risk and maintain financial stability. Therefore, it is extremely useful to have a single indicator that would give a broad view of the state of the entire economy and capture its financial conditions, macrofinancial situation, as well as external factors affecting financial stability. The goal of this paper is to develop such an index for Ukraine using the Growth-at-Risk framework.

A stable and efficient financial system resilient to crises is essential for sustainable economic development. Therefore, the National bank of Ukraine (NBU) takes measures to minimize risks to the financial system and helps banks and non-banking institutions withstand systemic risks. The NBU promotes financial stability by implementing macroprudential policy, stress-testing the banking system and the largest banks' borrowers, supporting banks as the lender of last resort, and supervising banks, non-banking financial companies, and payment systems. The ultimate goal is triune: prevent crises and mitigate contagion, enhance the financial system's resilience to crises, and reduce the consequences of crises.

Since the goal of any regulator, including the NBU, is to clearly understand the direction of growth of the economy and prevent crises, the primary scope of systemic risk analysis must be the estimation of the downside risk of the largest economic indicators and the factors, which may contribute to it. The Growth-at-Risk tool serves this purpose: it allows to estimate the scope and consequences of large-scale downturns of GDP under a given probability and time horizon and define indicators of building it up.

Although the Growth-at-risk (GaR) is a relatively new approach, it is becoming a widely used tool in the implementation of macroprudential policy. GaR allows to monitor and quantify the severity of systemic risk and the likelihood of a sharp economic slowdown based on the current level of macrofinancial, financial and external conditions; as well as calibrate macroprudential instruments. As a starting point, we follow Prasad et al. (2019), in which the authors provide practical guidelines on how to construct the GaR framework on a national level and give some insights on how this approach has been applied for a set of countries. GaR framework has also been incorporated into the International Monetary Fund's macrofinancial surveillance procedure. Since the Global Financial Stability Report in 2017, the tail risks to economic growth based on financial conditions are being constantly monitored worldwide. Several countries (e.g., Italy (Busetti et.al, 2020), Canada, Peru, Portugal, and Singapore (Prasad et.al, 2019)) have begun using GaR analysis to enhance macrofinancial analysis and policy discussions.

The growing popularity of the GaR approach is explained by its ability to encompass the entire GDP growth distribution, which, compared to traditional point forecasts, provides a more detailed picture – with all downside and upside risks. It also gives a tool for analyzing the key drivers of future GDP growth and their relative importance, which change across the growth distribution and the forecasting horizon. Another useful quality is GaR's ability to quantify the impact of systemic risks on future GDP growth, making it an important tool in the development of macroprudential policy. GaR also has some limitations. It is not a structural model, and therefore it is not a good way to make conclusions about causality.

This paper links such factors as financial conditions, credit and sectors' activity, and external conditions to the probability distribution of future real GDP growth to estimate the downside risks of GDP growth and explore factors affecting them. As a result, we obtain the quantitative perception of the effects and nature of risks to future growth, which can be used to develop the preventive measures of macroprudential policy. There are no specific variables that reflect the factors mentioned above for Ukraine. Therefore, in the first part of our work, we construct such indices. Specifically, we build three different indices of *financial conditions* summarizing the information on risk (include government and Eurobond yields, interest rate indicators, and capital adequacy ratio); *credit and sectors` activity* indicators that can be a potential source of vulnerabilities (credit-to-GDP gap, sectors' indebtedness, banking performance, etc.); and *external factors* (dollarization level, financial conditions index for the USA, a composite indicator of systemic stress in Euro area, etc.), since Ukraine is a small open economy, significantly impacted by global tendencies.

Our method is similar to Prasad and others (2019). To compute indices based on constructed categories, we employ two approaches. In the first approach, we aggregate variables inside each partition with a simple cross-sectional average (CSA) after standardizing our data. In the second approach, we apply principal component analysis (PCA) to identify the relative importance of each indicator within each partition. After estimating the pool of the quantile models, we derive GDP growth distribution at chosen time horizons. The final step of our research is scenario analysis, where we re-estimate the conditional quantiles with new partitions under the different scenarios that enable us to derive the probability distributions of GDP growth under different macroeconomic conditions. One application of such scenario analysis might be the estimation of the effect of the COVID-19 pandemic on the financial system.

Our calculations for Ukraine confirm the findings (Prasad et.al, 2019) that the dependence of future GDP growth on current financial conditions is stronger for the lower quantiles of the distribution than for the upper ones. So, measuring downside growth vulnerability can help quantify the cost side of the tradeoff for monetary policy between present macroeconomic objectives and risks to objectives in the future.

The evidence of a strong relationship between Ukrainian GDP vulnerability and economic conditions will help improve the macroprudential policymaking of the National Bank of Ukraine, allowing to monitor how risks to real GDP growth may evolve. With the ability to quantify the likelihood of future GDP growth, GaR analysis can help assess the credibility of baseline and alternative scenarios and check whether they are too optimistic or pessimistic. It also serves as an additional early warning indicator and provides a basis for preemptive policies to mitigate downside risks. The likelihood of a severe recession for a given macroeconomic, financial, and external environment produced by GaR approach can be used to design scenario severity for stress testing, calibrate the countercyclical capital buffer, LTV, and LTI ratios. Furthermore, GaR analysis will enable the National bank of Ukraine to better communicate the risks to growth to the public. Finally, in this paper, we applied two approaches to construct the indices of aggregated economic conditions (financial conditions index, credit and sectors' activity index and external conditions index), which extends the toolkit for systemic and macrofinancial risk analysis of the NBU.

The rest of this paper is organized as follows. Section II presents the literature review. In section III, we provide a detailed overview of the methodology. Section IV describes our data, section V presents key results (baseline regression, principal component analysis, forecast, distribution, and scenario analyses), and section VI concludes.

II. Literature Review

The Growth-at-Risk (GaR) concept was first introduced by **Wang and Yao (2001)** as a new measurement of the downside growth risk of the economy. GaR enables one to find the perceived level of downside growth risk and its severity as a particular number and facilitate risk monitoring over different time frames and across countries. The key finding was that more extreme downside growth risk has a strong and negative association with long-term growth. However, the authors did not advise Growth-at-Risk as a predicting tool due to the risk of structural breaks.

One of the first works that explicitly described the vulnerability of GDP growth and how it is affected by financial conditions was Adrian, Boyarchenko, Giannone (2016). The authors measured the extent to which the GDP growth is vulnerable to downside risks as degeneration of the unconditional relative to conditional distribution. They showed that the GDP growth vulnerability is correlated with financial conditions.

The preliminary concept of the Growth-at-Risk framework as a systemic risk analysis tool was introduced in the April 2017 edition of the Global Financial Stability Report by IMF (**GFSR April 2017**). The report focused on variables and indices that depict financial conditions and their predictive power for future economic downturns. This analysis showed that financial conditions indices contain crucial information about future economic development and may be beneficial in determining the downside risks to economic growth. This concept was later developed and further enhanced by more sophisticated analytical underpinnings. in the October 2017 edition Global Financial Stability Report by IMF (**GFSR October 2017**)

The Growth-at-Risk framework became available to a broader audience during the **2018 Peru Financial System Stability Assessment** when it was recommended as a new tool for systemic risk monitoring. The underlying research was based on nearly 30 Peru-specific macroeconomic and financial variables. The groups of variables were used to model the future distribution of GDP at different time horizons. Following the results of the GaR exercise, external conditions, leverage, and price of risk had the most statistically significant effect on the GDP distribution. The analysis suggested that external conditions (measured by the major trading partners' economic growth) were the most important determinant of the economic growth and had major effect on the tails of the distribution.

The complete GaR framework was later described by **Adrian et al. (2018),** where the authors applied quantile regression analysis to examine the empirical relationship between the financial and economic conditions, inflation and credit growth, and the distribution of real GDP growth using the data for 11 advanced economies from 1973 to 2017 and 11 emerging economies from 1996 to 2017. Having generated the term structure of expected GDP growth, the authors further focused on the lower 5th percentile for horizons of up to 12 quarters. The paper's main contribution was to show that financial conditions variables are a precise forecasting tool for the future economic growth distribution. Also, it was proven that the coefficients of the financial conditions reverse from the short-term to medium-term time frames, particularly for the lower tail. One of the key findings, among others, was that the lower tail of the GaR distribution is more responsive to the financial conditions than the median and upper tails.

The concept was further developed by Prasad et al. (2019) who offered practical guidance on constructing the Growth-at-Risk framework bringing some insights from country case studies. The work also discusses an Excel-based GaR tool developed to support the IMF's bilateral surveillance efforts and provides recent and ongoing applications of how the GaR framework can enrich policy discussions. In our research, we mostly follow this paper's methodology.

Further, the framework was enriched by a new branch of the "at-risk" concept: House-prices-at Risk, introduced in the **Global Financial Stability Report (April 2019)**. The chapter "Downside Risks to House Prices" develops a methodology to model house price declines with a given probability and horizon — that is, house prices at risk. The measure of house prices at risk helps forecast downside risks to GDP growth and adds to early-warning models for financial crises. The analysis resulted in findings that the lower house price momentum, overvaluation, excessive credit growth, as well as tighter financial conditions predict significant downside risks to house prices on the horizons up to three years ahead.

Lang and Forletta (2019) take the next step in widening the "at-risk" where authors introduce "Bank capital-at-risk" (BCaR), which focuses on future downside risks to bank capital. The authors modify a standard GaR framework and employ quantile projections to calculate the impact of domestic cyclical systemic risk indicator (d-SRI) on the tails of micro-data (bank-level) ROA-distribution over different time horizons. "Bank capital-at-risk" has three practical innovations for macroprudential policy: usage of bank capital instead of real GDP; it is derived from bank microdata instead of country-level aggregates, which allows considering the bank heterogeneity in a research; and also, it uses the d-SRI – the authors' preferred measure of cyclical systemic risk – as the driver of variations in tail risk.

Also, Hengge (2019) analyzes if macroeconomic uncertainty affects the future GDP growth distributions. To calculate whether the indicators of macroeconomic uncertainty are informative about risks to economic performance, the author estimates a set of quantile regressions and finds that economic movement in the further periods is distinguished by strong and asymmetric nonlinearities both one and four quarters ahead. The author finds that the GDP distribution`s left tail was strongly explained by the uncertainty indicators while the right tail remained stable.

Two other recent papers that informed our research were Gondo (2020) on GaR in Peru and Busseti et al. (2020) on factors affecting GDP growth distribution of the Italian economy. Gondo (2020) used financial data such as leverage variables, domestic asset prices, and foreign financial variables to define the most relevant factor predicting GDP growth under different risk scenarios. Gondo (2020) found that excessive credit and asset price growth rates are good indicators of a downturn in future financial conditions and lower GDP growth under risk scenarios using different forecast horizons. In contrast to Gondo (2020), Busseti et al. (2020) examined the GDP growth distribution of the Italian economy using specific risk indicators that characterize not only financial but also real components of the economy. The authors derived conditional GDP Growth distribution using expectile regressions, proposing a technique similar to the Expected Shortfall framework.

All the aforementioned studies informed our research by contributing to selection of partitions and the indicators to form them.

III. Methodology

Our research is based on the methodology described by Prasad et al. (2019). We are going to conduct GaR analysis in the following four stages.

First, we select the main variables of interest and divide them into three partitions. These groups represent three main factors that influence GDP growth. These factors are *financial conditions, credit and sectors` activity, and external conditions*. Each group of factors consists of groups of indicators relevant to the Ukrainian economy.

After forming the list of indicators, we compute three indices based on constructed partitions using two approaches. In the first approach, we combine variables inside each partition by aggregating them with a simple cross-sectional average (CSA) after standardizing our data. Using the second approach, we construct separate partitions (groups) by applying principal component analysis (PCA), which allows us to identify the relative importance of each indicator among one group of factors. The main goal of the PCA is to reduce the dimensionality of the data by losing the least amount of information. Therefore, after conducting PCA, we obtain three indices that correspond to the partitions.

We further employ the quantile regression approach, which is an extension of the ordinary least squares method. Contrary to standard linear regression, quantile regression has no assumption about the residual distribution. Also, instead of estimating coefficients at the conditional mean of the dependent variable, quantile regression gives estimates at the conditional quantiles (e.g., conditional median). Therefore, estimated coefficients are not constant but are the function of the quantile.

Following Koenker and Bassett (1978b), the distribution function of a random variable Y which is:

$$F(y) = \Pr(Y \leq y),$$

for any $\tau \in (0, 1)$, the τ -th quantile of Y is:

$$Q(\tau) = \inf\{y : F(y) \geq \tau\}.$$

Given that, the coefficients β_τ can be obtained by:

$$\beta_\tau = argminE(\rho_\tau(Y - X\beta))$$

$$\widehat{\beta_\tau} = \sum_{i=1}^{n}(\rho_\tau(Y_i - X_i\beta)),$$

where Xi, i = 1...n, a K × 1 vector of regressors.

The second step in our GaR analysis is quantile regressions to identify the relationships between partitions and GDP growth. It will subsequently allow us to derive the GDP growth distribution. The central concept of quantile regression is to estimate the coefficients for conditional quantile functions. Our set of regressions will take the following form:

$$Q_\tau(Y_{t+q}) = \beta_0(\tau) + \beta_1(\tau)X_{t1} + \beta_2(\tau)X_{t2} + \beta_3(\tau)X_{t3} + Q_\tau(Y_t) + \varepsilon(\tau)_{t+q}, \text{ where} \quad (1)$$

$Q_\tau(Y_{t+q})$ – GDP growth q period ahead (the quarter) at a particular percentile, τ – percentile,

t- time,

q- quarter,

X_{t1}, X_{t2}, X_{t3} – financial conditions partition, credit and sectors' activity, external conditions partition,

$\beta_0, \beta_1, \beta_2, \beta_3$ – sets of parameters associated with the τth percentile,

$Q_\tau(Y_t)$ – GDP growth at the current period at a particular percentile (autoregressive term),

$\varepsilon(\tau)_{t+q}$ – residuals.

To increase the forecasting power of our model in terms of pseudo-R-squared and avoid omitted variable bias, our model controls for GDP growth in a current period (GDP_t).

After estimating the pool of the quantile models, we derive GDP growth distribution a period ahead. Considering that plenty of distributions in finance are skewed, we fit a parametric form of a skewed t-distribution described by four parameters: mean, degrees of freedom, variance, and skewness.

To derive the t-skew distributions, we calculate the necessary parameters by minimizing the distance between the empirical quantiles and the quantiles of a t-skew. After estimating the optimal t-skew parameters, we will derive the fitted t-skew CDF and probability density function (PDF), which will facilitate the GaR analysis.

For this purpose, we use the form of skew t distribution function as in Fernandez and Steel (1998), which has the following density function with df = n degrees of freedom:

$$f(x) = \frac{2}{\Upsilon + \frac{1}{\Upsilon}} f(\Upsilon x) \quad for\ x < 0 \tag{2}$$

and

$$f(x) = \frac{2}{\Upsilon + \frac{1}{\Upsilon}} f\left(\frac{x}{\Upsilon}\right) \quad for\ x \geq 0 \tag{3}$$

where $f(x)$ is the density of the Student- t distribution determined by μ as a location parameter and as a scale parameter, and with df as degrees of freedom;

ϒ – is the shape parameter, which defines skewness

We solve the optimization problem to minimize the sum of squared differences between the estimated quantiles and theoretical quantiles governed by the function stated above. Therefore, the result of the minimization problem takes a form:

$$\{\mu, s, \Upsilon, \mathrm{df}\} = argmin_{\mu,s,\Upsilon,\mathrm{df}}\left[\sum\nolimits_\tau \{\widehat{y^q} - y^{q,f}\ (\mu, s, \Upsilon, \mathrm{df})\}^2\right], \tag{4}$$

where $\mu, s, \Upsilon, \mathrm{df}$ are the optimal parameters, and

$\widehat{y^q}, y^{q,f}$ – are estimated and theoretical quantiles, respectively.

The fourth step of our research is scenario analysis. We use quantile regressions estimates to re-estimate the conditional quantiles with new partitions under the different scenarios (i.e., employing higher interest rates or higher dollarization) by applying different shocks to our explanatory variables: $\widehat{X_{i,t}} = X_{i,t} * (1 + shock)$. This will enable us to derive the probability distributions of GDP growth under different macroeconomic conditions.

IV. Data description

We use quarterly data from 3Q 1996 to 2Q 2020 provided by the National Bank of Ukraine. Our main variables include GDP quarterly growth (yoy, %) and 23 financial variables used to construct three main partitions of the indicators.

The *financial conditions partition* captures the relationship between financial vulnerabilities and country's output and. *Credit and Sectors` activity partition* captures macro-financial imbalances and sectoral balance sheet weaknesses. Deterioration of macro-financial vulnerabilities, such as worsening of households` financial positions or a decline in corporate profitability, can lead to lower economic activity and, as a result, to lower GDP growth. *External factors partition* represents other elements influencing the GDP growth.

We construct each partition using the variables that fit mainly for emerging markets and developing economies. We include classic (e.g., interest rate spread or house price growth) and specific indicators that describe the Ukrainian economy.

Table 1 includes the set of indicators for GaR analysis. All data are publicly available or available within the National Bank of Ukraine.

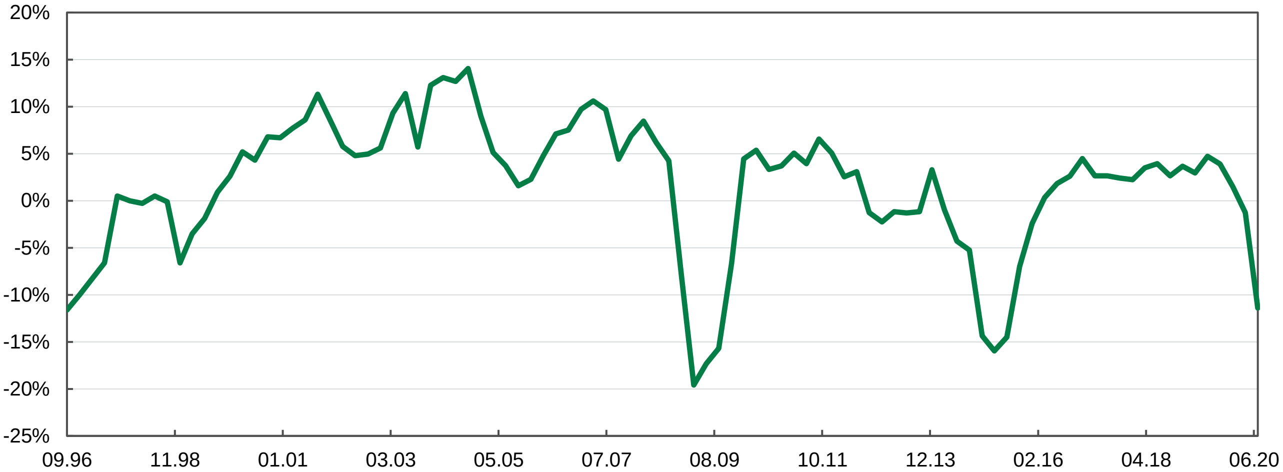
Table 1 – Partitions and indicators included.

Financial Conditions					
Variable		**Mean**	**Standard deviation**	**10th percentile**	**90th percentile**
Bond yields		10.721	8.704	5.768	18.280
Corporate IR spread		11.391	9.171	4.508	26.080
Household IR spread		17.381	7.649	8.343	26.080
Corporate lending IR		21.921	13.629	13.141	43.650
HH lending IR		28.509	11.625	15.312	43.651
RWA to Capital		0.065	0.015	0.050	0.078
Corporate Eurobonds		15.691	12.311	6.6400	36.160
Credit and Sectors Activity					
Credit to GDP Gap		3.21E-18	0.044	-0.056	0.059
Household	House price growth on a primary market, quarterly	0.019	0.090	-0.071	0.137
	House price growth on a secondary market, quarterly	0.018	0.064	-0.037	0.063
	PTR	10.379	1.065	9.252	12.364
	PTI	9.819	2.644	6.204	13.597
	HH debt to GDP	0.112	0.075	0.025	0.229
Corporate	Corporate debt to GDP	0.343	0.117	0.202	0.492
Government	Public debt to GDP	0.424	0.197	0.169	0.752
Banking	Banks` leverage	12.470	1.926	9.990	14.750
	Banks` ROA	-0.618	4.482	-4.420	3.310
	Banks` ROE	-8.252	48.408	-33.710	24.750
External Conditions					
Dollarization	Credit dollarization	0.442	0.068	0.356	0.528
	Deposit dollarization	0.393	0.057	0.314	0.461
FCI US		-0.344	0.529	-0.716	0.079
CISS		0.175	0.162	0.038	0.421
CA Deficit		0.006	0.051	-0.068	0.072
Commodity Prices (Index)		0.000	0.945	-1.164	1.407
GEPU Index		128.073	66.910	63.579	232.586

GDP Growth (yoy, %) is measured quarterly in constant prices and derived from raw data provided by the State Statistics Service of Ukraine. In 1996-2001, GDP is calculated using the definition in the 1993 System of National Accounts (SNA) 1993. In 2002-2013 the SNA 2008 definition is used while the SNA 2014 is used for

2014-2020. It is essential to note the SNA 2014 excludes the temporarily occupied territory of the Autonomous Republic of Crimea, the city of Sevastopol and a part of temporarily occupied territories in the Donetsk and Luhansk regions.

Figure 1 – Ukraine`s GDP quarterly growth, yoy %



Source: State Statistical Service of Ukraine

Financial Conditions. In our work, the variables that reflect the price of risk included in asset prices represent *financial conditions.* The partition consists of corporate and household interest rates on loans and deposits, bond yields, corporate Eurobond YTM, and interest rate spreads. These factors reflect the probability of default of financial institutions. Moreover, we include the inverse ratio of regulatory capital to risk-weighted assets representing the banks` ability to provide loans and absorb shocks. Hence, this partition explains how such factors as financial stress, cost of financing, and funding influence the GDP growth and help forecast its downside risks.

The ratio of the regulatory capital to risk-weighted assets, also known as the regulatory capital adequacy ratio, reflects the ability of the bank to cover its liabilities arising from trade, credit, or other monetary transactions. The higher the value of the indicator, the greater is the share of risk taken by the owners of the bank. Conversely, the lower is the value of the indicator, the higher is the share of risk carried by creditors and depositors of the bank. Currently, the regulatory requirement for this indicator is at 10% for Ukrainian banks. We take an inverse value of capital adequacy ratio because we need all variables to move in the same direction.

Figure 2 – Bond yields, %

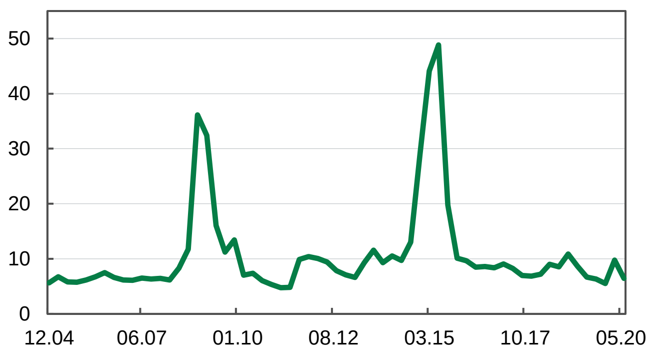
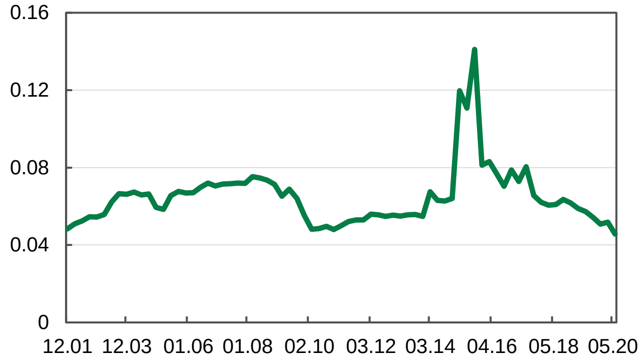


Figure 3 – Inverse ratio of regulatory capital to RWA, %



Note: The movement of two indicators started moving into the same direction after the crisis episode of 2014 due to the reform of banking sector in Ukraine. As a result of it, prudential ratios started to be estimated in a more appropriate manner. Also, it could be explained by the different nature of crises. The one of 2008 was global and represented financial point, while the crisis of 2014 is at nation level and had political origin.

**Credit and Sectors` Activity.** Before constructing the index of credit and sectors` activity conditions, we build four sub-indices representing main sectors of the economy. They are household (comprised of housing market indicators and the level of the debt burden of households), corporate (corporate debt-to-GDP), government (public debt to GDP), and banking (banks` profitability ratios) sectors. Additionally, we include the credit-to-GDP gap, which reflects the conditions of the credit cycle. This partition captures excessive credit growth risk, risk of imbalances on a housing market, and other vulnerabilities stemming from different sectors of the national economy.

Housing market indicators include house prices, price-to-income ratio, and price to rent ratio. House prices on the primary and secondary markets of Kyiv are collected by the five biggest real estate agencies as the average monthly price of housing on the market measured in hryvnias per 1 square meter. The data from these sources is further aggregated by NBU as an arithmetical average of five values. Price-to-income is the ratio of a price of a standardized dwelling in Kyiv (70 square meters) to an average annual disposable income of an average household in Kyiv. Data come from the real estate agencies and the State Statistical Service of Ukraine (SSSU). Calculated monthly by the NBU.

Price-to-rent is the ratio of an average price of a square meter of housing in Kyiv (both on primary and secondary real estate markets) to an average yearly rent of a square meter of multi-dwelling housing in Kyiv. Calculated monthly by the NBU.

Figure 4 –House price quarterly growth, %

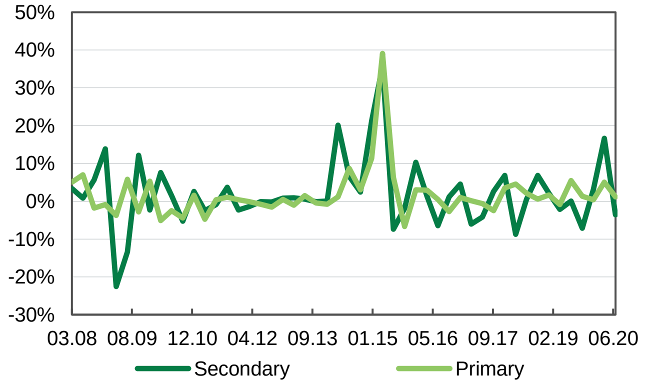
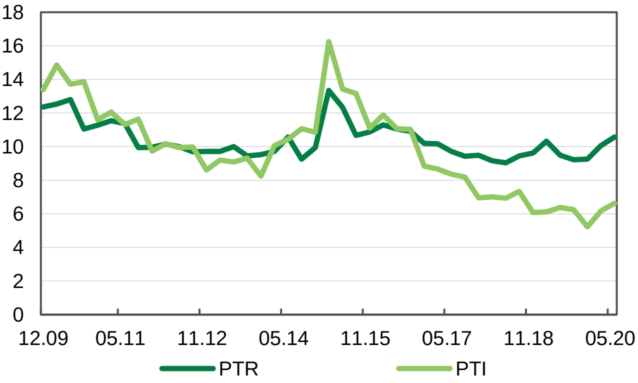


Figure 5 – Price-to-Rent and Price-to-Income



External Conditions. Other factors reflect the main characteristics of the Ukrainian economy that impact the country`s output. Considering that Ukraine is a small open economy significantly impacted by global tendencies, we included the dollarization indicators, which explain the risks of currency depreciation. Dollarization indicator is measured as a simple average of standardized credit and deposit dollarization levels for each period. Considering that significant changes in the price of a currency lead to potential problems of country`s output, central banks pay a lot of attention to the level of dollarization and measures for reducing it. After a crisis in 2008, Ukraine prohibited retail lending in foreign currency and imposed some regulatory requirements to limits an open currency position. Although these actions have helped reduce the level of dollarization, it remains fairly high.

We also incorporated such indicators as the financial conditions index of the USA (FCI US) and the Composite Indicator of Systemic Stress for the Euro Area (CISS), which demonstrate the state of the world economy. In addition, Global Economic Policy Uncertainty Index and commodity prices are included in the index.

Another indicator is the current account deficit that summarizes transactions between residents and non-residents during a period. It consists of the balance of trade, net primary income, and net secondary income. The NBU compiles the indicator based on the BPM6 (the sixth edition of the IMF's Balance of Payments and International Investment Position Manual, 2009).

Figure 6 – Dollarization level, %

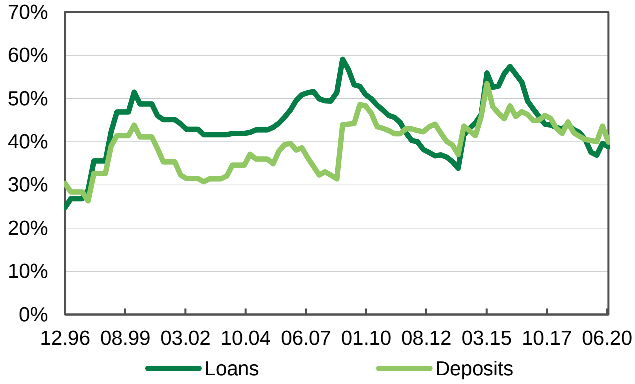
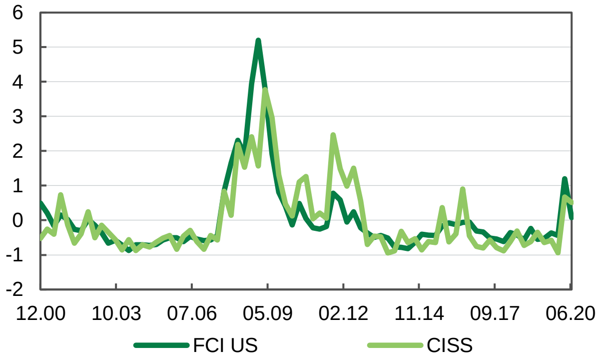


Figure 7 – CISS and FCI for US Indices, %



*Standardized value

Dealing with missing values

After constructing the dataset, we faced two issues related to the missing values of some variables. Firstly, we had variables, which were available for a shorter period. Secondly, we had some indicators, which were available only yearly at the early period of the sample. For the first type of issues, we decided to fill missing values in the following way.

Initially, all indicators were standardized (demeaned and divided by variable`s standard deviation). Then, we took the simple cross-sectional average of indicators for each partition. Consequently, we use the information on the indicators available on the entire sample to proxy for the missing values of each of the indicators that have a shorter history (i.e., becomes available only later in the sample). Specifically, we take the indicators that are continuously available over the sample and construct a common index as the cross-sectional average of the standardized indicators. We then project this common index into each of the indicators with a shorter history to proxy for the missing history of the indicator. This procedure will deliver a good fit of the data so far as the series within each group have a clear common factor structure (hence the simple common index of the available indicator can be considered a good proxy for the missing values of the shorter indicator). Concerning the second type of issues, the indicators, which were yearly at the early period, are assumed to be constant over the year.

Figure 8 – Fitting index for Financial Conditions.

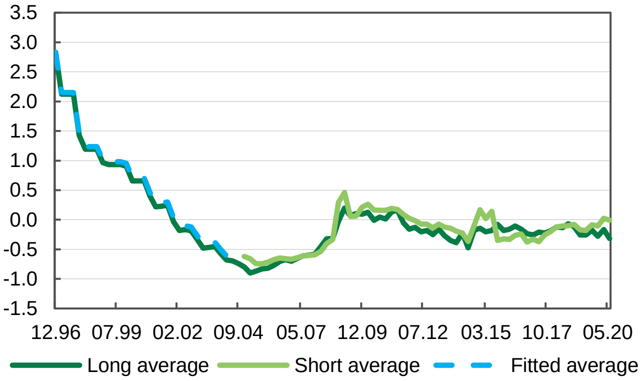


Figure 9 – Fitting index for Credit and Sectors` Activity.

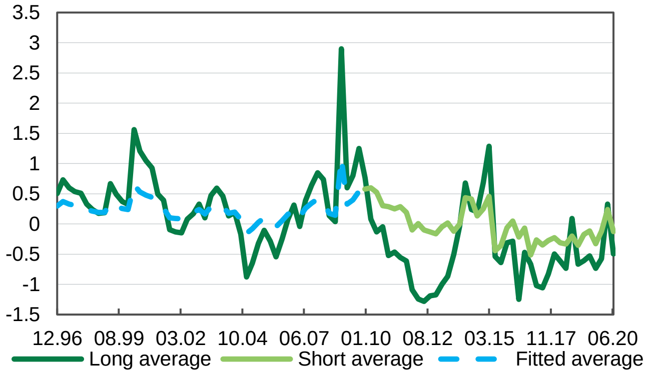
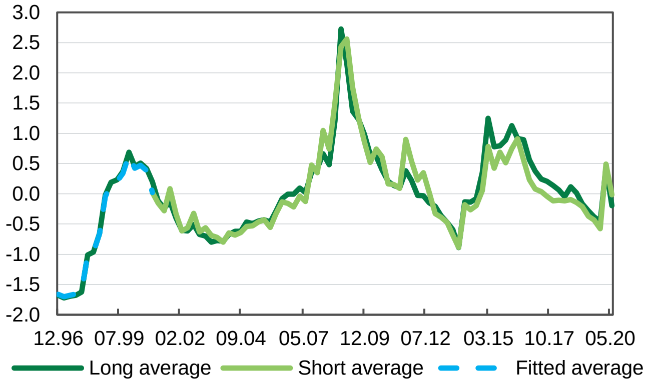


Figure 10 – Fitting index for External conditions.



V. Results

Constructed Indices and the results of PCA

Next, we conduct principal component analysis, and because some variables are available for a shorter period, we use data starting from IV Q 2001. Since we employed two approaches to construct the macrofinancial indices (cross-sectional average and principal component analysis), we scaled indices under PCA by indices under simple aggregation to obtain comparable results. For this purpose, we regressed the index built under cross-sectional average on index under PCA and scaled the latter by the beta coefficient of this regression.

Financial Conditions. The index of financial conditions partition is based on funding and financing costs, bond yields, and capital adequacy ratio. Figure 11 shows that the financial conditions index captures two peaks at the end of 2008 and the end of 2014, which are the crisis periods for Ukraine, suggesting that the increase in the index value indicates the tightening of financial conditions. Figure 11 also illustrates the dynamics of the index based on a simple aggregation of the standardized underlying indicators. These two approaches produce similar results in terms of dynamics. Furthermore, the analysis shows that government and Eurobond yields and inverse capital adequacy ratio have the largest effect on the financial conditions index. In contrast, interest rate indicators have almost no impact on the index.

Figure 11 - Financial conditions index

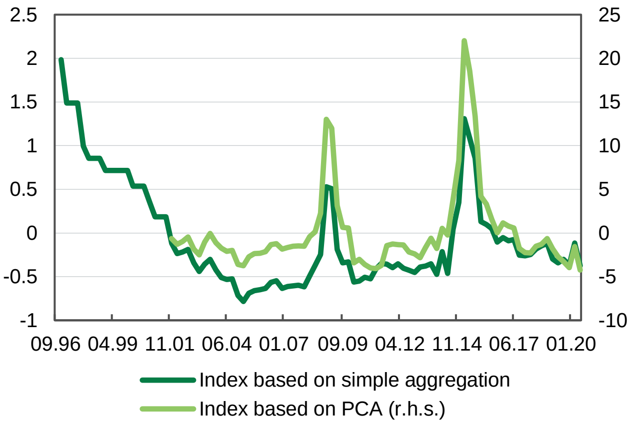
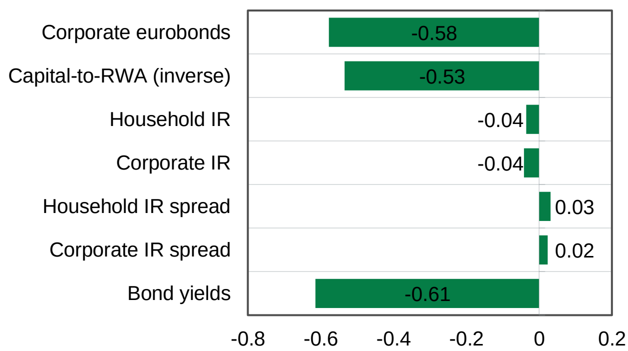


Figure 12 - Relative contribution of the indicators: financial condition index



Credit and Sectors` Activity. The index consists of 4 sub-indices, representing the state of different sectors of the economy (banking, government, household, and corporate) and credit cycle indicator. Although credit and sectors' activity indices computed with two approaches are different in magnitude, they are similar in terms of the dynamics. Figure 13 shows that credit and sectors` activity index based on simple aggregation is slightly more volatile than the indicator based on the PCA. Credit-to-GDP gap and the corporate sectors' activity have the largest effect on this index, while the relative contribution of the other sectors is also significant.

Figure 13 – Credit and Sectors` Activity

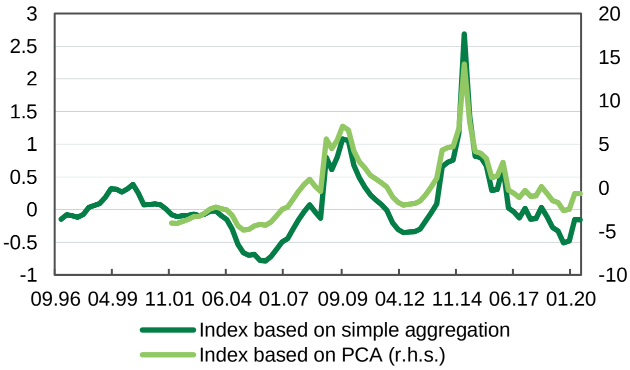
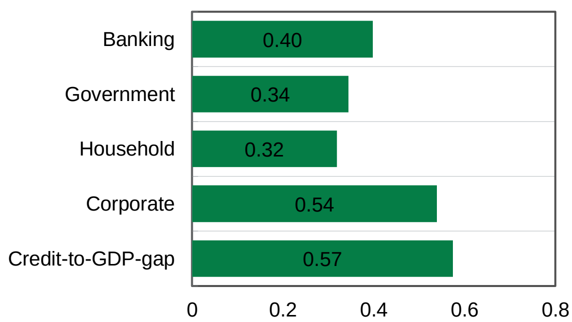


Figure 14 - Relative contribution of the indicators: Credit and Sectors` Activity



External Conditions. This partition represents external conditions, which influence the GDP growth. The index built under the PCA looks almost the same as the index based on the simple aggregation. Figure 16 illustrates the relative importance of the indicators. All three indicators have a relatively significant impact on the index; however, the financial conditions indices for the US and CISS appear to be the main drivers of the external conditions index. In addition, Current Account deficit and commodity price index have a relatively high contribution to the index.

Figure 15 – External conditions index

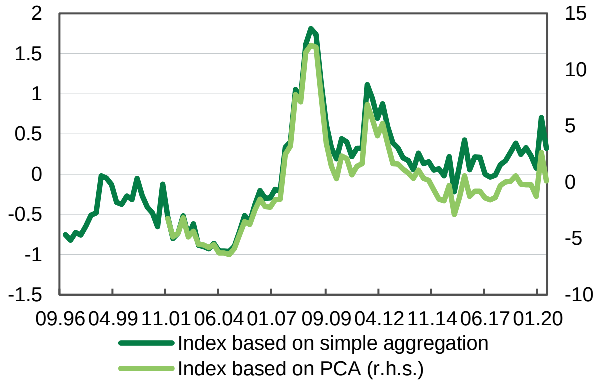


Figure 16 - Relative contribution of the indicators: external conditions index

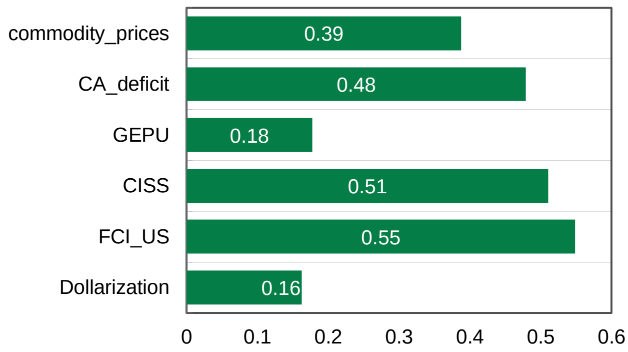


Table X illustrates the regression results below.

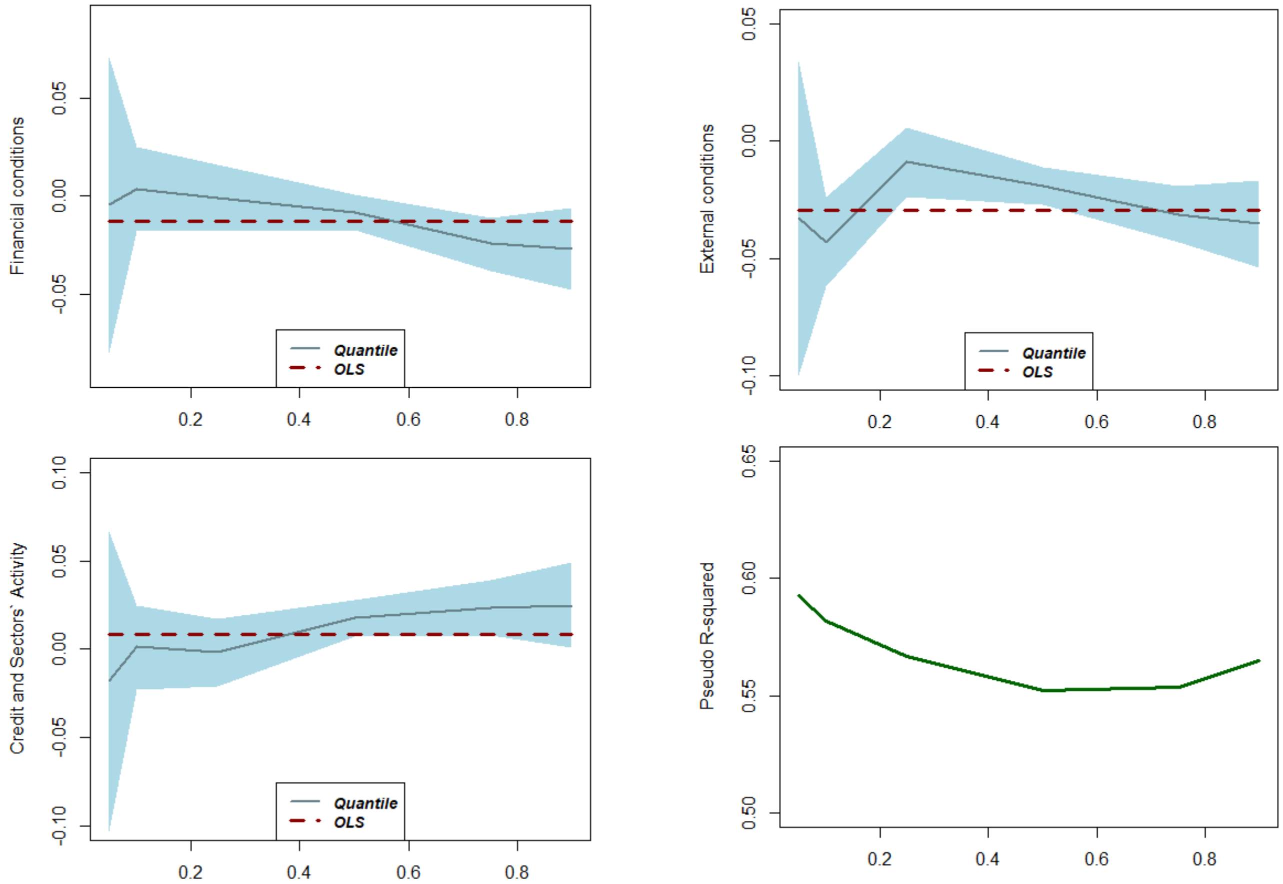
Baseline regression. In estimating baseline regression, we use the approach described by Adrian et al. (2019). In the first estimation, we use financial, credit and sectors' activity, and external conditions indices constructed using simple cross-averaging standardized values of indicators.

Table 2 – Regression results for indices under simple cross-sectional averaging.

	GDP 1q ahead					
Tau	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**
Financial conditions	-0.004	0.004	-0.001	-0.008^{*}	-0.024^{***}	-0.027^{**}
Credit and Sector\`s Activity	-0.018	0.001	-0.002	0.018^{***}	0.024^{***}	0.025^{**}
External Conditions	-0.033	-0.043^{***}	-0.009	-0.019^{***}	-0.031^{***}	-0.035^{***}
GDP t0	0.750^{*}	0.821^{***}	0.816^{***}	0.845^{***}	0.698^{***}	0.677^{***}
Constant	-0.061^{***}	-0.042^{***}	-0.008^{*}	0.006^{**}	0.022^{***}	0.036^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 2 presents the results of quantile regressions to predict future GDP growth one quarter ahead and is estimated at the six quantiles (5%, 10%, 25%, 50%, 75%, and 90%). The relationship between financial conditions and future GDP growth is inverse across almost all quantiles. Moreover, the magnitude of the coefficients suggests that the impact of the financial conditions index is more significant at the 90% percentile than at the 5% one. Considering that this index represents mostly the price of risk included in assets price, our results suggest that tighter financial conditions (e.g., higher the cost of funding and financing) are associated with lower GDP growth.

Figure 17 – Coefficients of the baseline regression and its pseudo R-squared



In the lower quantiles, the negative relationships between credit and sectors' activity imply that a small change of this index would generate significant downside risks to the economic activity. On the upper quantiles, future GDP growth and credit and sectors' activity are positively correlated. This result suggests that when the economy is weak, more credit will aggravate the economic downturn due to debtors` inability to repay their liabilities. In contrast, when the economy is in the upturn, credit growth will boost s the GDP growth.

Regardless of the quantile, there is an inverse relationship between the external conditions index and future GDP growth. Moreover, a comparison of the lowest and the highest quantile shows that the influence of the external conditions is almost the same despite whether the economy is in an upturn or downturn. Since the external conditions index represents the level of global economic stress and the risks of currency depreciation, the increase of this index would drive significant downside risks to the country`s economy.

In addition, the results show that our model better explains future GDP growth on the tails of its distribution. Also, the credit and sectors` activity shifts the GDP distribution to the right, while financial conditions and external conditions indices make the distribution more left-skewed.

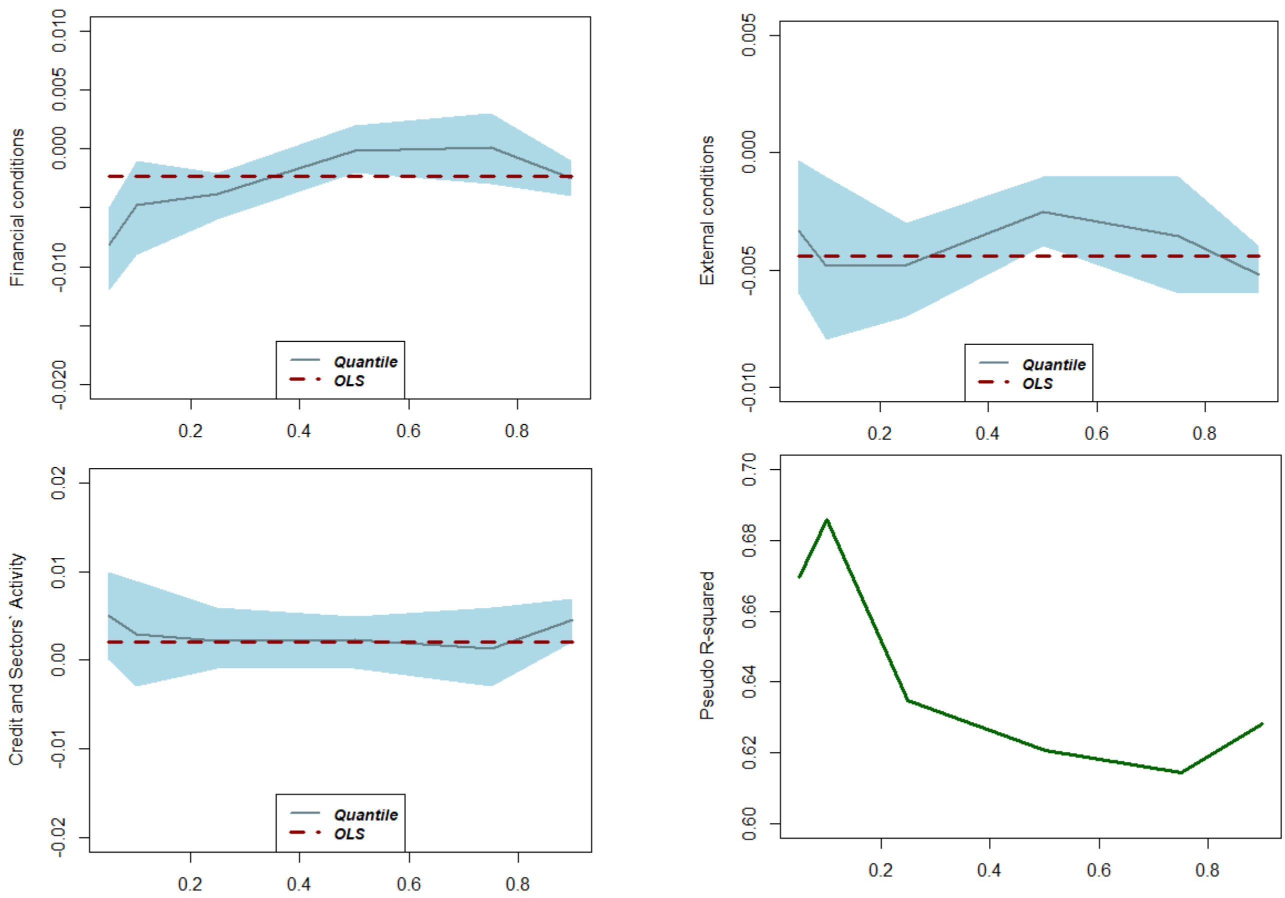
Regression under PCA. Next, we utilize the indices computed by applying principal component analysis. In this case, we have a shorter period (from the IVQ 2001) due to the data availability. Table X displays the results of the estimation.

Table 3 – Regression results for indices under the PCA.

	GDP 1q ahead					
Tau	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**
Financial conditions	-0.008***	-0.005**	-0.004***	-0.0002	0.0001	-0.003***
Credit and Sector`s Activity	0.005*	0.003	0.002	0.002	0.001	0.005***
External Conditions	-0.003**	-0.005***	-0.005***	-0.003***	-0.004***	-0.005***
GDP t0	0.904***	0.711***	0.646***	0.884***	0.782***	0.715***
Constant	-0.058***	-0.041***	-0.009**	0.005	0.022***	0.038***
Observations	74	74	74	74	74	74
Note:	*p<0.1; **p<0.05; ***p<0.01					

Due to the differences in constructing the dependent variables and the differences in the data period, there are some discrepancies in the regression results. Despite the differences in the magnitude of the coefficients, the relationships between financial conditions and future GDP growth are negative across all quantiles. In contrast with CSA regression results, financial conditions have a larger impact on the future economic activity on the lower quantiles than on the upper ones. Thus, when the economy is weak, tightening financial conditions will bring the economy under more stress than when the economy is in an upturn.

Figure 18 – Coefficients of the regression under PCA and its pseudo R-squared



Another difference in the regression results is that there is no change in the coefficient sign of the credit and sectors' activity index when we move from the lower to the upper quantiles. The regression results under show that sectors' activity index is positively correlated with future GDP growth at each quantile, suggesting that, increasing the level of credit and sectors' activity will induce economic growth in any stage of economic development

Results demonstrate a negative relationship between external conditions and GDP growth one quarter ahead. The effect of external conditions increases over quantiles and reaches the highest level when the growth is at a high pace (90% quantile).

Finally, while CSA regression results suggest that the influence of all three explanatory variables is stronger on the upper quantiles, only external factors partition shows a similar tendency in the regression under PCA. Conversely, the coefficients of the regression under the PCA suggest that the impact of financial conditions is much higher when the economy is weak.

In addition, the explanatory power in terms of pseudo R-squared is higher for the regression under the PCA, and it is the highest for the 5th percentile.

Stability of the coefficients. To look at the stability of the coefficients over time, we utilized the same quantile regressions for different periods. We do it by estimating regressions for 1996-2006 and then gradually add one year to our sample and repeat our estimations. The results are represented in the figures below.

For both models, the coefficients become more stable for latter periods when longer data are employed. For the CSA regression, the coefficients of all indices are more volatile than for the PCA regression. Moreover, coefficients become stable after the global financial crisis (2008-9), and there is another slight movement after 2015, which corresponds to another crisis Ukraine experienced. Overall, the volatility of coefficients is much higher on the lower quantiles than on the upper quantiles. External conditions index coefficients are relatively stable for both models. In addition, the confidence intervals for the CSA regression are much wider than for the PCA regression. Thus, we can conclude that the PCA regression produced better results in terms of stability.

Figure 19 - Financial conditions coefficients over time for regression under CSA (right panel) and regression under PCA (left panel), 5th percentile

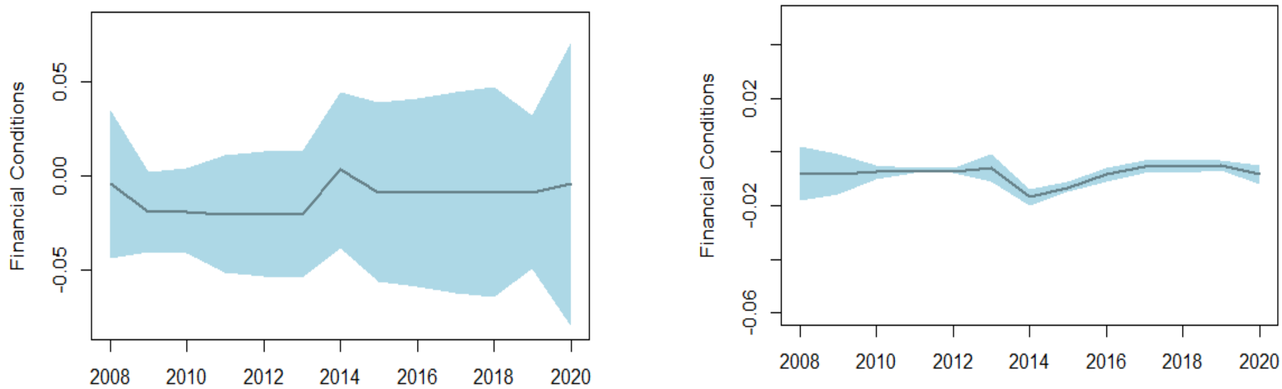
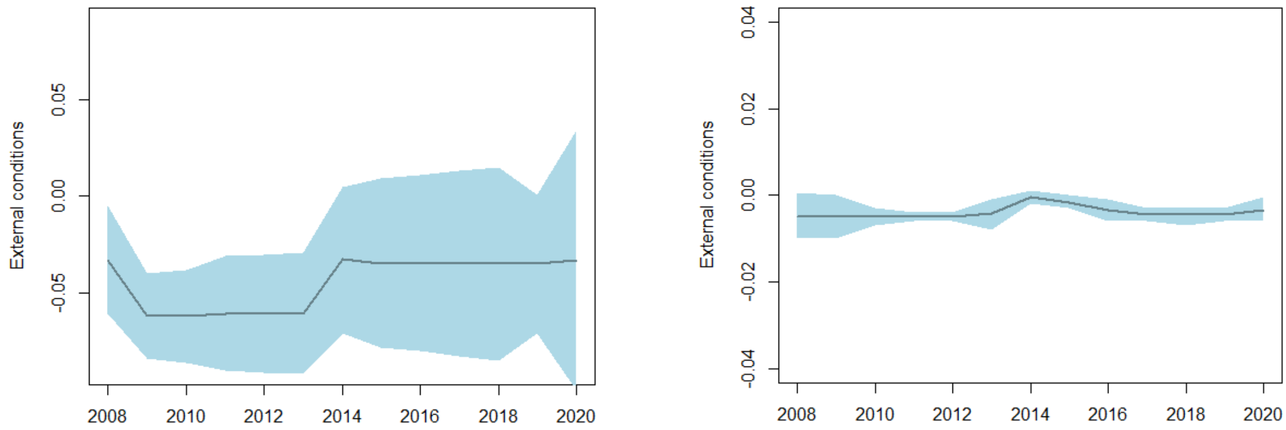


Figure 20 - Credit and Sectors` Activity coefficients over time for regression under CSA (right panel) and regression under PCA (left panel), 5th percentile

Figure 21 - External conditions coefficients over time, regression under CSA (right panel) and regression under PCA (left panel), 5th percentile



To decide between PCA or CSA model, we will use three criteria. The first criterion is pseudo R-squared. According to our results, the model based on PCA produced a higher pseudo R-squared than the one with cross-sectional average indices. The second criterion is the significance and stability of the coefficients. The results of the model with PCA indices displayed the significance of the coefficients. In addition, in terms of the stability of the coefficients, the second model showed better results as well. Finally, the predictions of the model under PCA outperformed projections of the CSA model, which is demonstrated in more detail in the following sections. All the things considered, the model, which used PCA indices as independent variables, is considered as our baseline model and used in further analysis.

Appropriate time horizons. Further, we check what are the time horizons on which our baseline model would return the most meaningful results. We do it by regressing GDP with a lead from 1 to 12 quarters on the set of standardized variables derived under the PCA method and real GDP growth as an autoregressive term at time 0. Based on the statistical significance of the outcomes and common sense needed for the interpretation of results described below, we choose two time horizons: 1-quarter ahead for the short horizon and 4-quarter ahead for the long horizon. Results are depicted in Figure 22.

Figure 22 - Impact of factors on Real GDP Growth 1 to 12 quarters ahead

Note: This Figure show results of quantile coefficients for three standardized variables and Real GDP growth at time 0 as the controlling variable (autoregressive term) in regression with Real GDP growth over different horizons, 1 to 12 quarters ahead, estimated at the 5th percentile. Points marked with triangles represent the statistically significant coefficients at p < 0,01.

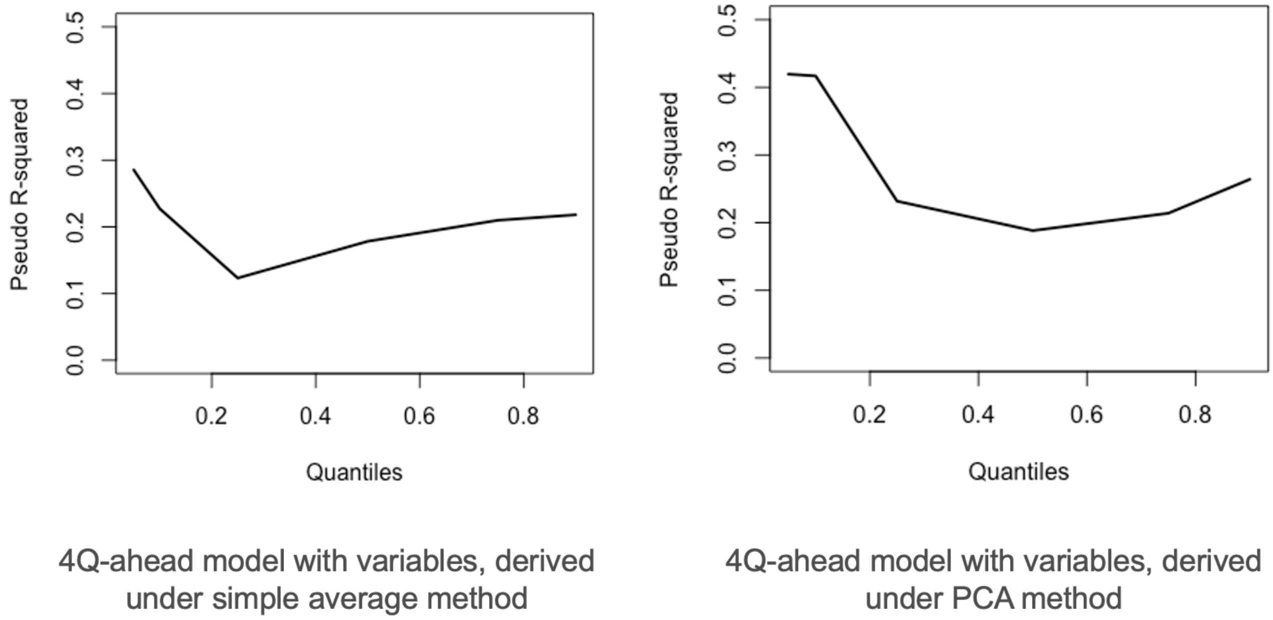
Except for selecting appropriate time horizons, which was the primary goal of this exercise, these results illustrate how economic cycle is affected by financial conditions and macrofinancial variables. Firstly, the negative sign of autoregressive term coefficient in the four quarters ahead model suggests that economic trends tend to revert on average every year. That means the one stage of the economic cycle is usually replaced by the opposite one. Another observation is that tightening of financial conditions on the 5th percentile results in a slowdown in the short term but has a beneficial impact on the growth in the following periods. The opposite situation is with the credit and sectors' activity performance: buoyant credit activity is beneficial mostly on the short-time horizon, followed by a weaker economy in the subsequent periods.

Since our baseline model has two time horizons, it may be useful to introduce the specification for the additional, 4-quarter ahead baseline model of the following form:

$$Q_\tau(Y_{t+4}) = \beta_0(\tau) + \beta_1(\tau)X_{t0} + \beta_2(\tau)X_{t0} + \beta_3(\tau)X_{t0} + \varepsilon(\tau)_{t+4},$$

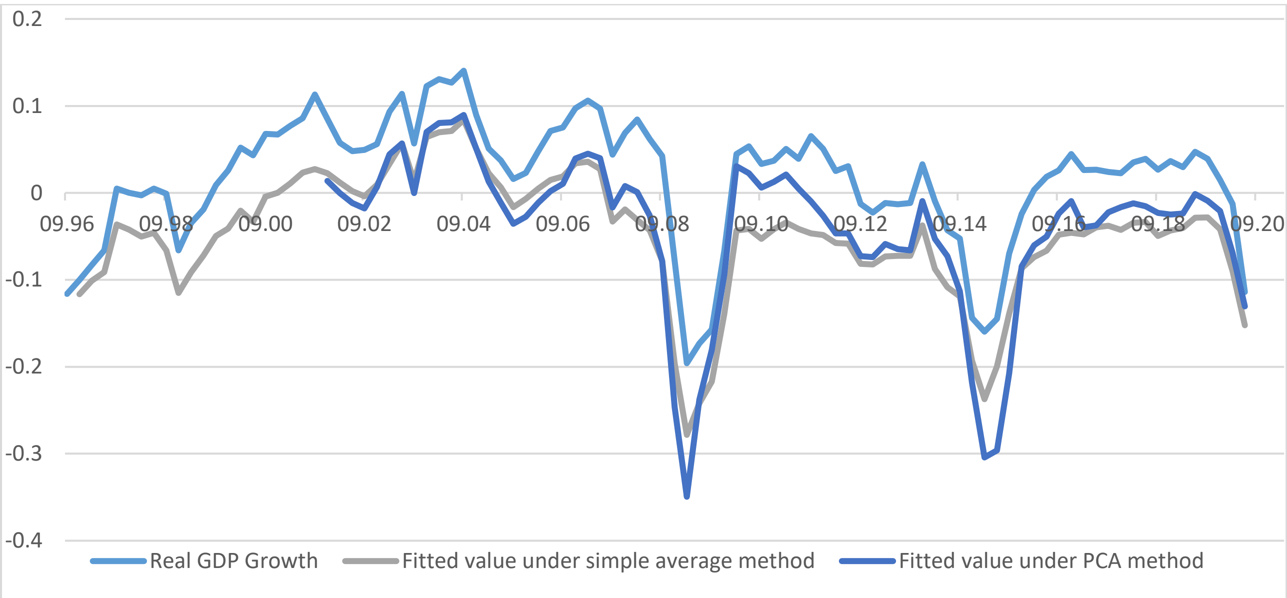
where dependent variable is Real GDP growth with a lead of 4 quarters and all independent variables are measured at time 0.

Figure 23 – Pseudo R-squared for the models with autoregressive term and a lagged dependent variable



Comparison of the values of Pseudo R-squared suggests that PCA is a preferred model. Figure 23 shows that the R-squared is higher on the lower quantiles, which is especially useful, as it closely follows the primary goal of our research – to investigate the downside risks to economic growth.

Figure 24 - Comparison of fitted values of GaR and actual GDP values

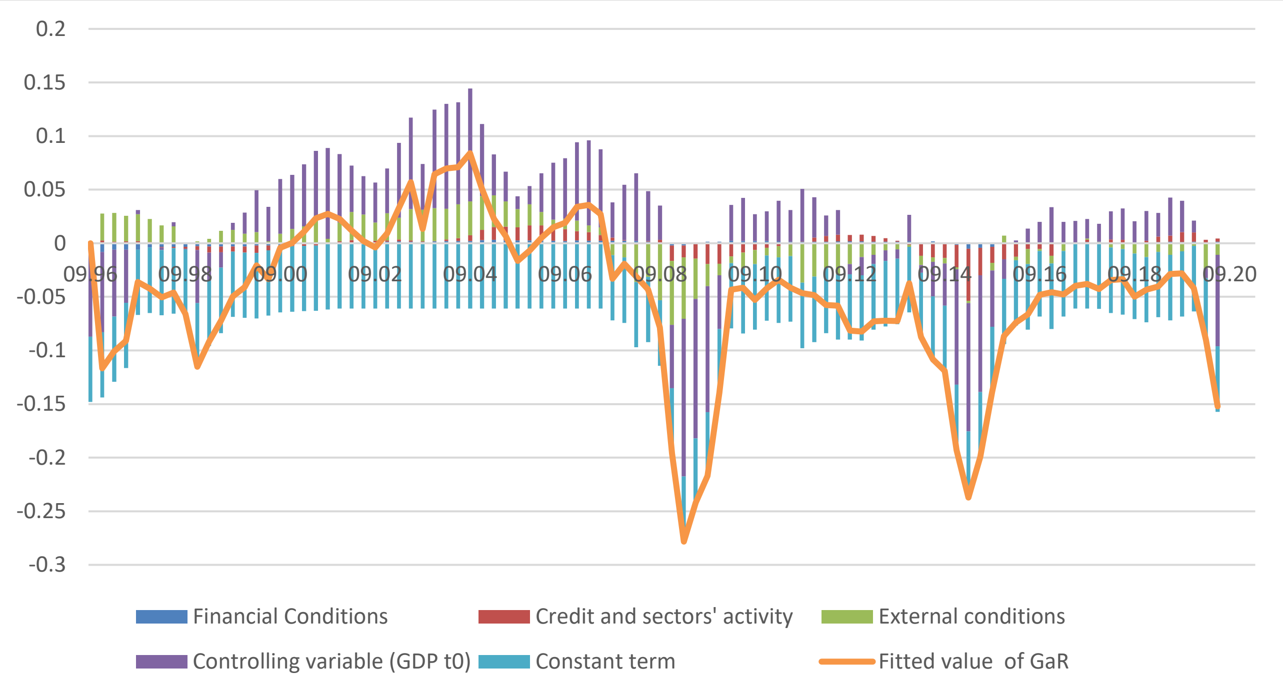


Note: This Figure compares the real GDP growth with fitted values of Growth-at-risk with inputs under different methods, estimated at the 5th percentile.

Comparison of fitted values. According to Figure 24, two models are doing well explaining the crisis of 2008-9 and 2014-15 at the 5^{th} percentile. The fitted values are moving close, but our baseline PCA model follows the movement of GDP growth more closely on the lowest quantiles. Figure 24 shows that the main difference in fitted values is the difference of magnitude of large-scale downside events projected by the two models. The model with variables derived under CSA method returns more modest results in the 5^{th} percentile during the crisis periods when to the PCA-formed model. The latter can be explained by higher statistical significance and larger magnitude of the coefficients on the 5th percentile and by the lower number of observations used in the PCA model.

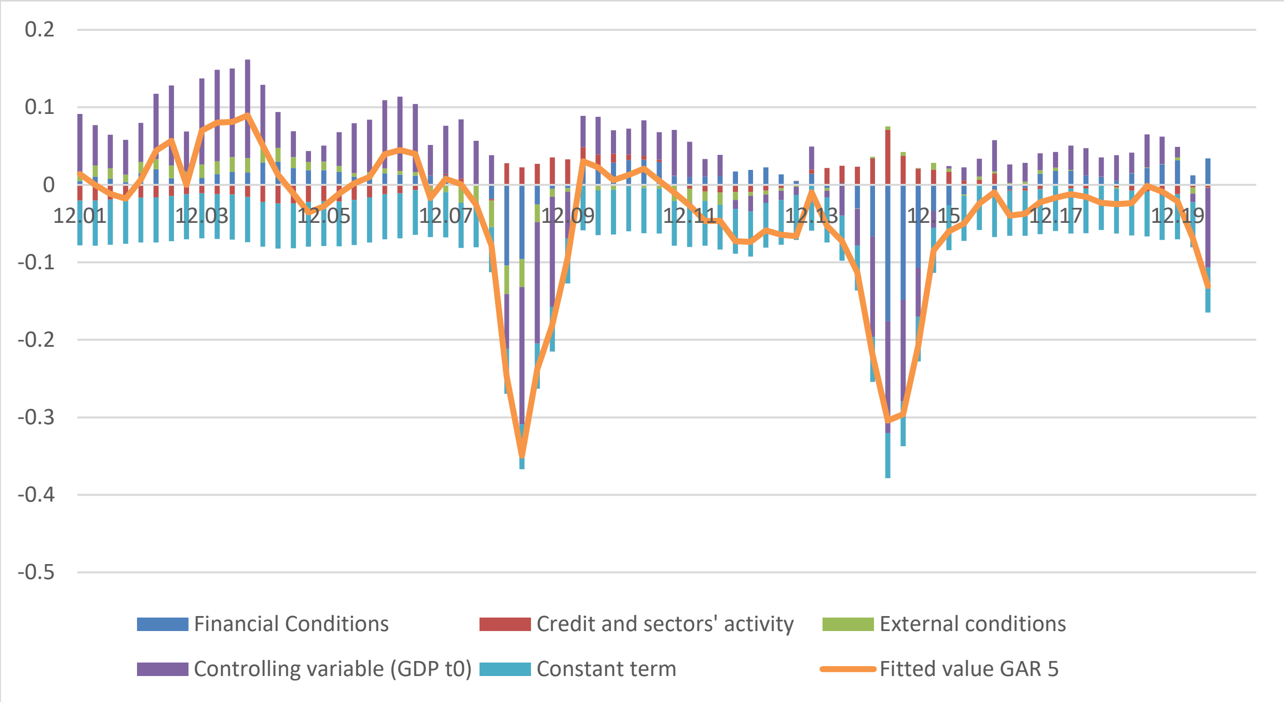
Distribution of factors. Further, we investigate the determinants of the movement of our fitted values of GaR in PCA and CSA models. The distribution of factors in the model under CSA method shows that the external conditions partition explains the biggest portion of downside movement of GDP. It was offsetting the downside pressure from other components during the periods preceding the 2008-9 crisis, as well as explaining the biggest part of the adverse impact during the crisis. It also had a detrimental effect during the recovery period up to the next crisis of 2014-16. During this crisis of mid-2010, credit and sectors' activity partition has the largest negative effect, as this crisis was accompanied by the sharp depreciation of hryvnia and turmoil in the banking sector. During the period up to 2020, the distribution of factors was virtually constant, with no apparent downturns predicted up to the second half of the last year under observation.

Figure 25 - Factors affecting the GDP growth fitted by the 1-quarter ahead model under CSA method at 5th percentile



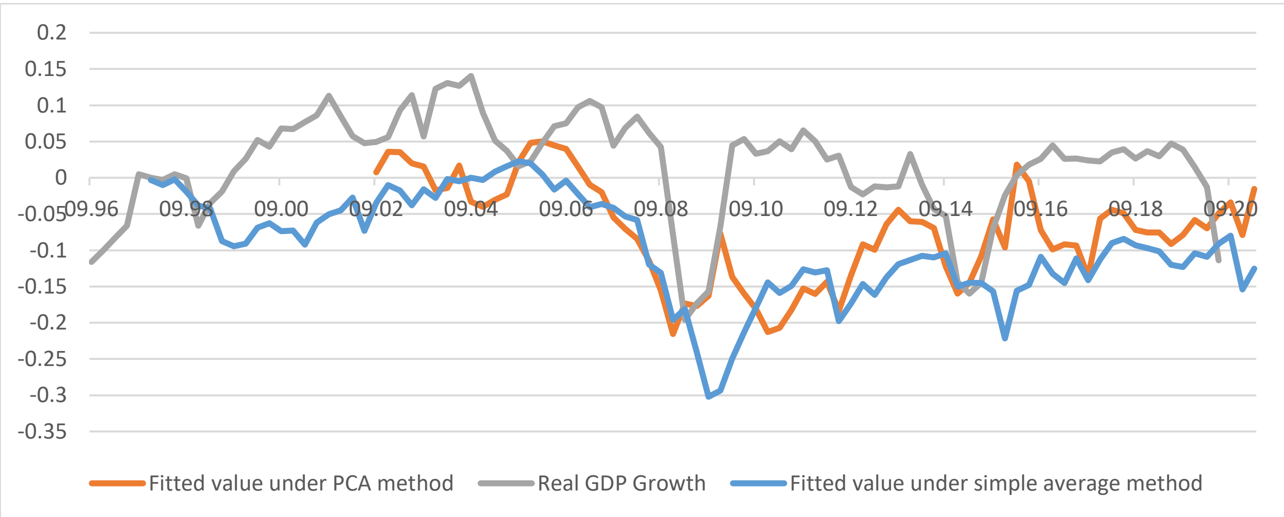
The model under PCA provides a more distinct pattern of fitted values during crisis vs non-crisis periods and more meaningful distribution of factors. Here, all partitions explain the movement of fitted values almost equally. Financial and external conditions offset detrimental effects from other elements of the model from the early 2000s to the onset of the global financial crisis. While these two partitions were the biggest contributors to the economic downturn, their impact was partly offset by the credit and sectors' activity partition. During the early 2010s economic recovery, the effect of partitions was equal; during the crisis of 2014-16, financial conditions partition has the biggest detrimental impact. Up to late 2020, the distribution of factors was almost even, as the fitted line of GaR at 5th percentile did not predict any significant downturn.

Figure 26 - Factors affecting the GDP growth fitted by the 1-quarter ahead model under PCA method at 5th percentile



Fitting values for the regression with 4-quarter ahead horizon. We next compare the fitted values of our models if we make it predict GaR values four quarters ahead. Figure 27 illustrates that both fitted lines contain lots of uncertainty and hardly follow the pattern of the actual GDP trend. However, the fitted trend of GaR with variables under the PCA method did a better job in predicting the major economic downturns during crises. In the case of the global financial crisis of 2008-9, the fitted value reacted in advance, preceding the crisis half a year before its onset. We thus prefer PCA model considering the purpose of our research. In addition, the PCA model succeeded in predicting the crisis of 2014-16 in time. Both models failed to predict the downturn of 2020 one year before, as none of the external, financial, or macrofinancial conditions could forecast the crisis induced by the pandemics.

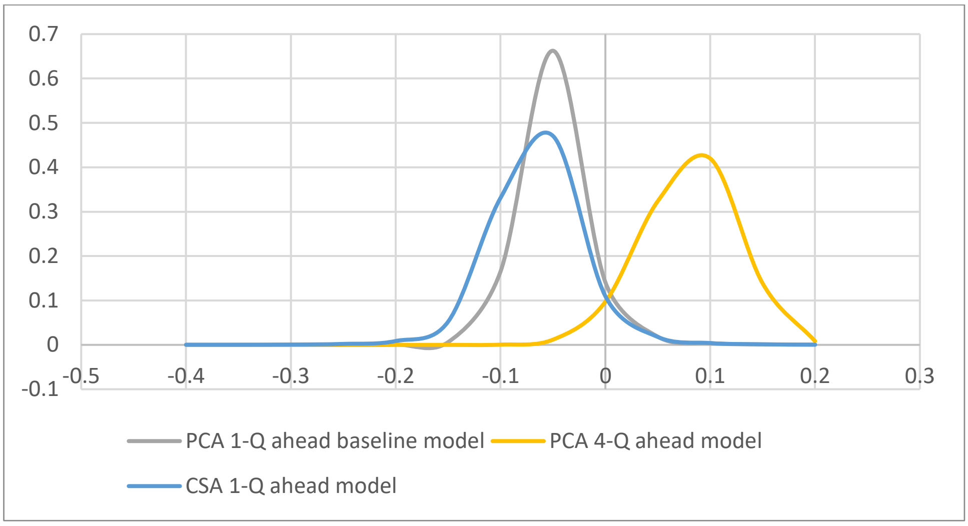
Figure 27 - Comparison of fitted values of GaR 4 quarters ahead and actual GDP values



Deriving distribution

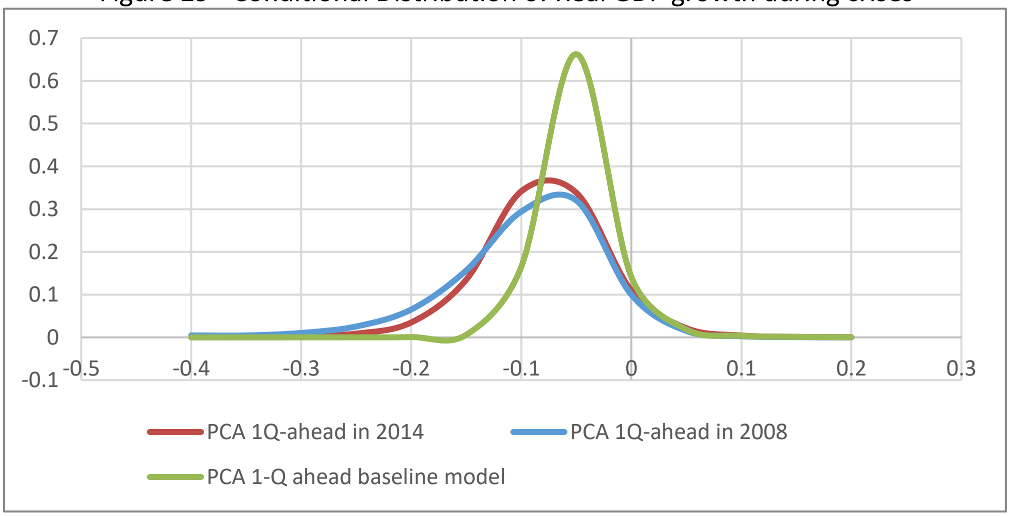
Based on the baseline regression results, we derive future GDP growth distribution one quarter and four quarters ahead. Using the forecasted values of quantile regressions, we fitted skew t-distribution and found its parameters (scale, skewness, location, and degrees of freedom) that minimize the gap between empirical and theoretical quantiles. As a result, we obtained the probability density function of GDP growth. Our conditional GDP growth projections are based on the three indices estimated above.

Figure 28 - Conditional Distribution of Real GDP growth, two models



Under this conditional distribution of future GDP growth, the fitted quantiles for the last available date are imposed. This is our baseline GDP growth distribution. The distribution of outcomes, derived under the PCA model 1 quarter ahead, is leptokurtic and shifted to the left, as the median is about -5%. The value of GaR at 5^{th} percentile is -11.8%, which corresponds to the 5% of probability that GDP will fall by at least 11.8% next quarter. The comparison with CSA model shows that the distribution formed under CSA method is closer to mesokurtic and the median values for both distributions are very close. However, the CSA model is more negatively skewed, which results in a higher value of a 5-percentile GaR of -15.7%. The conditional distribution of GDP growth four quarters ahead, derived from the PCA model, has a modest, 5% probability that GDP will drop by at least 2.1% next year. This corresponds to the economic reality, as the largest economic contraction due to the pandemics was experienced in the 2020, while in 2021 the economy is expected to rebound slowly.

Figure 29 - Conditional Distribution of Real GDP growth during crises



Additionally, we check how the distribution looks during the most severe crises hitting the Ukrainian economy. The distribution of the lowest point of one-quarter ahead projected GDP growth during the 2008-9 crisis indicates the high probability of economic downturn since the distribution is negatively skewed. The distribution for the deepest decline of the 2014-15 recession looks very similar. The mode for both distributions is around -5%, and they are very close in terms of kurtosis since both are platykurtic. The values of GaR at 5th percentile for both distributions indicate the active phase of crises since in 2008 it was -24.4% and in 2014 it was slightly less – -19.9%. The values of low-percentile GaR here look quite reasonable – as the economic downturn during the crisis 2008-9 was deeper compared to the 2014-16 crisis. Comparison with the baseline distribution shows that both distributions indicate more large-scale downside movement of economic activity since they are more negatively skewed.

Scenario analysis.

We further perform scenario testing to test how the distribution behaves under different scenarios of a mix of financial conditions, macrofinancial variables, and external and other conditions development. In the baseline scenario, our inputs are our variables derived under the principal components analysis at the last point of the time series, the first quarter of 2020. Since our model is trained to fit the value one quarter ahead, the projected fitted value of GDP and its distribution were derived for the second quarter of 2020.

Next, we test how our model behaves under adverse and severely adverse scenarios. In the adverse scenario, apply the shock of 1.5 standard deviations to the baseline values of financial conditions, macrofinancial variables, and external conditions. In the severely adverse scenario, we assume a much worse scale of disruption of economic and financial conditions, equivalent to 2 standard deviations from the baseline. We apply the severely adverse scenario given the unpredicted nature of the economic cycle behavior and an absence of a lower limit of downturns under extreme events, such as the spread of Covid-19 disease.

Figure 30 - Distribution of the projected fitted value of GDP for the second quarter of 2020 under different scenarios

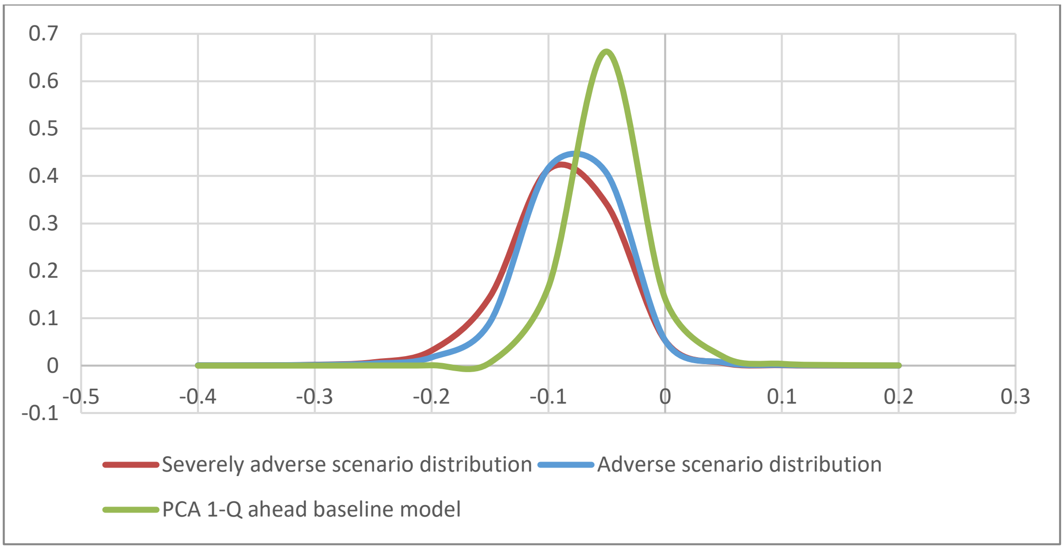


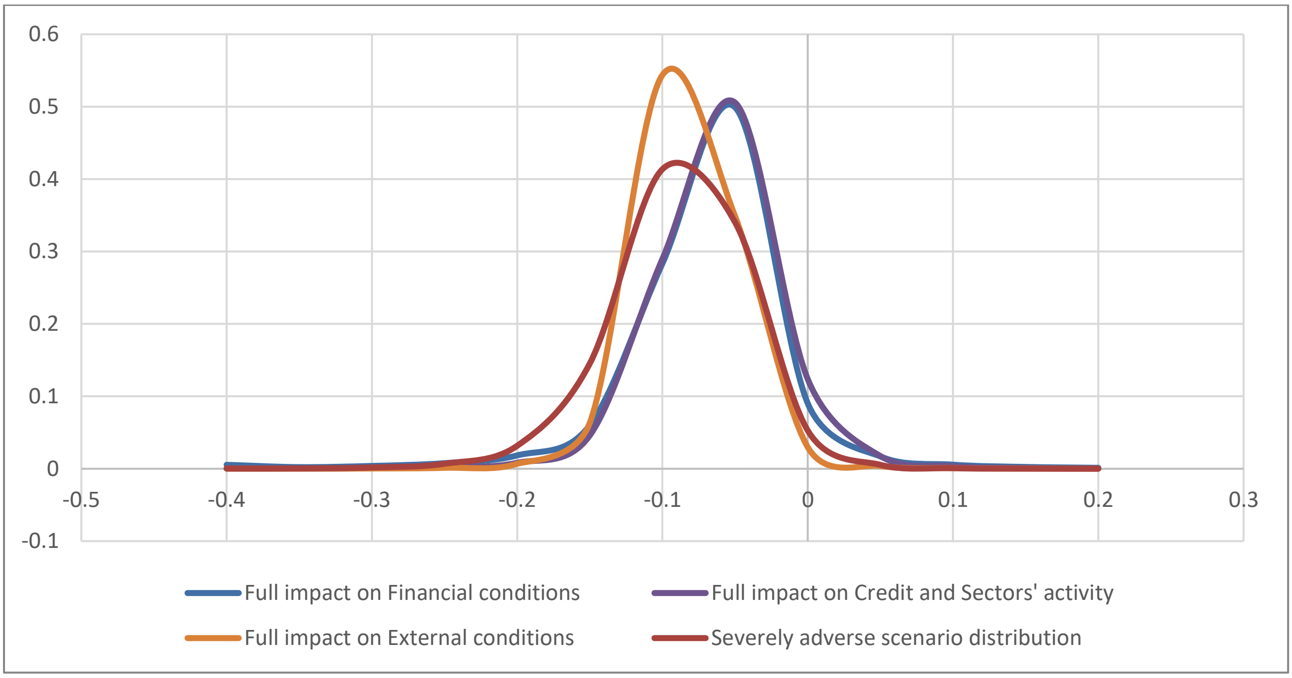
Figure 30 shows that both unfavorable scenarios follow the platykurtic and negatively skewed distribution; however, they differ in terms of median value and tails. Expectedly, the severely adverse scenario is more negatively skewed with a median close to -10%, while the distribution of the adverse scenario has a thinner left tail and a median of about -5%. In the adverse scenario, the value of GaR at 5th percentile of the distribution is 17.6%, while for the severely adverse scenario, it is-19.4%. Both values of GaR for unfavorable scenarios are lower than those observed during the latest crisis periods of 2008-9 and 2014-16.

We further explored the severely adverse scenario and enhanced it with three other sub-scenarios. We simulate an impact of 2 standard deviations shock to each partition separately, then consider the comovement of the other two partitions. We do it by estimating the correlation between the partitions, which are inputs for our baseline model.

Then we simulate the two standard deviations worsening of each partition sequentially, then adding the two standard deviations worsening on the other two conditions, multiplied by the correlation between the respective partition and the one that received the full impact of worsening.

The resulting three sub-scenarios became less adverse compared to simple severely adverse scenario, based on the value of GaR at 5th percentile and skewness, although the median value became even more negative in one sub-scenario. The *sub-scenario with the full impact on the financial conditions partition* looks very close to the one *with a full impact on the credit and sectors' activity*, however, it has a wider left tail which results in a higher value of GaR at 5th percentile – -18.3%, compared to -15.5%. The *sub-scenario with a full impact on the external conditions partition* has a lower median value when compared to the other two sub-scenarios – around -10%. However, this distribution has a thinner left tail and a value of GaR at 5th percentile of -15.8%.

Figure 31 - Distribution of the projected fitted value of GDP for the second quarter of 2020 under different scenarios with impulse responses



Based on the tails of the distribution and value of GaR at 5th percentile, we conclude that the sudden and adverse shock in the financial conditions will lead to the most adverse downside events in the national economy. In contrast, a similar shock in the external conditions will lead to a more moderate decline in the GDP trend, but with a higher probability. The resulting three sub-scenarios became less adverse compared to simple severe adverse scenario, with a much lower probability of downside movement since the correlation between partitions is moderate.

VI. Conclusions

In this paper, we applied and adapted the GaR framework for Ukraine to explore the association between macrofinancial environment and economic activity on different stages of development of the Ukrainian economy. In addition, we examined the behavior of future GDP growth distributions under different future and historical scenarios of economic development.

We first constructed three indices that reflected financial conditions, credit and sector's activity and external conditions. The indices were developed from 23 indicators, which were prior grouped into the three partitions. As a result, we obtained two versions of each index computed applying two approaches: cross-sectional average (CSA) and principal component analysis (PCA). Both versions of indices have similar dynamics; however, quantile regressions, in which these indices were employed as explanatory variables, yielded different results. The model under PCA outperformed the model under CSA in terms of significance and stability of the coefficients and the predicting power. The results of the PCA model imply the negative relationship between financial conditions and future economic growth. Moreover, the impact of financial conditions is more than twice stronger in terms of magnitude on the lower quantiles.

Based on the outcome of factors' distribution, we discovered the strong influence of both financial and external conditions on the downside GDP growth. The analysis of GDP growth distribution and its scenario analysis demonstrated that the highest economic downturn in crisis occurs in case of a full negative impact on the financial conditions partition. So, we managed to prove that the basic concept of the Growth-at-Risk framework holds for Ukraine. The most significant impact on the future downside economic growth is stemming from financial conditions.

Overall, the results of our GaR analysis will enhancethe existing methodology of assessing systemic risks and improve the process of macroprudential policymaking. Moreover, the GaR framework will enable policymakers to assess the probability and magnitude of adverse scenarios for the national economy, thus providing a proactive tool. Finally, the differences in the model results stemming from different model specifications and approaches to constructing indices suggest suggest the need for future research on this topic.

List of Abbreviations

ROA – Return on asserts

ROE – Return on equity

SSSU – State statistical service of Ukraine

IR – interest rate

RWA – risk weighted assets

CA – current account

CSA- cross-sectional average

GEPU – Global Economic Policy Uncertainty Index

PCA – principal component analysis

HH- household

PtR – price-to-rent ratio

PtI – price-to-income ratio

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Appendices

PCA results

Figure 32 – PCA for financial conditions partition

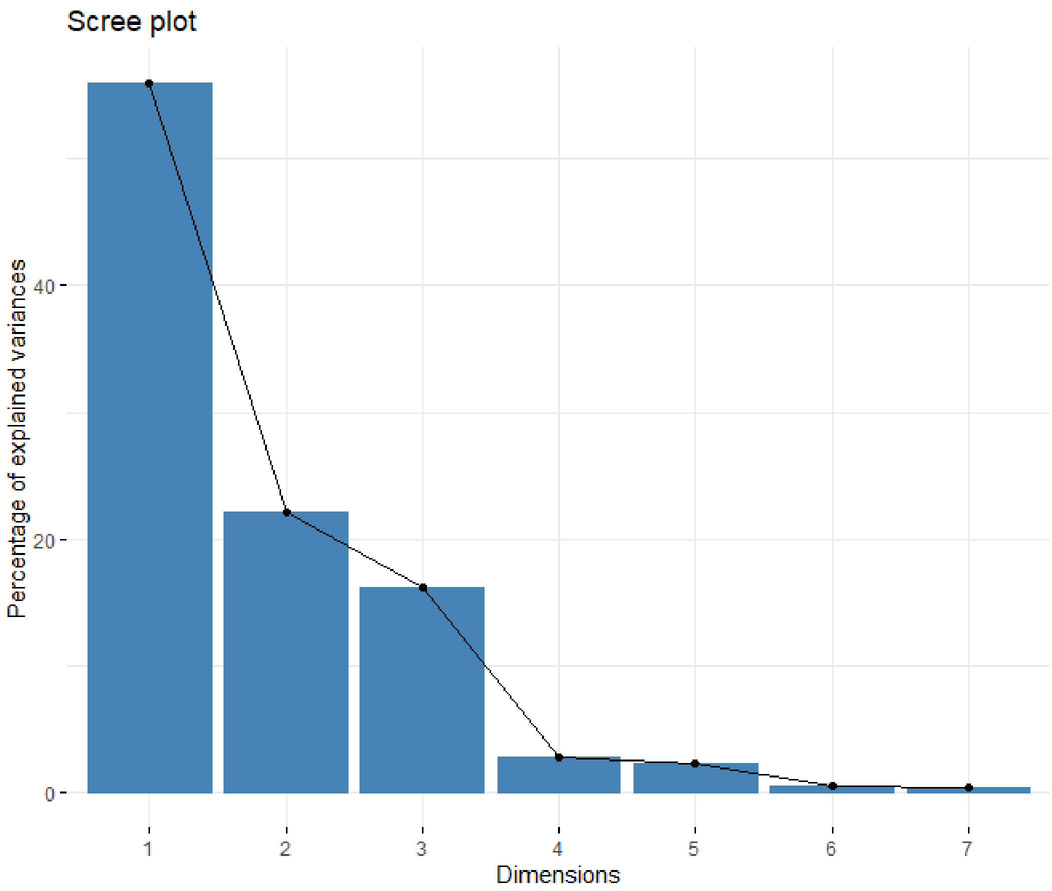

Figure 33 – PCA for credit and sectors` activity partition

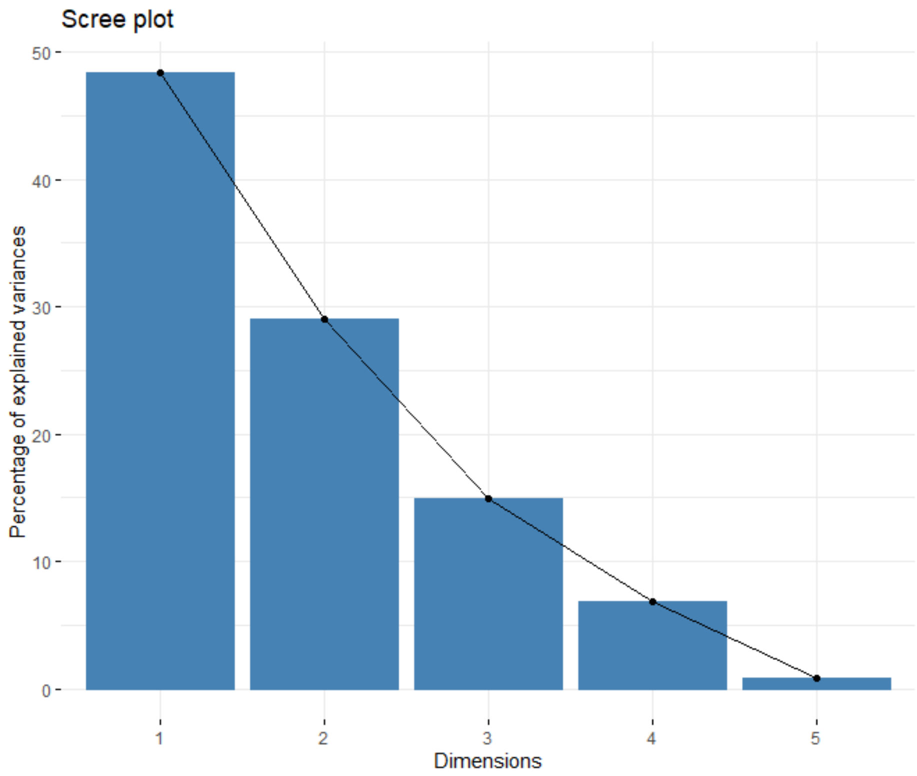

Figure 34 – PCA for external conditions partition

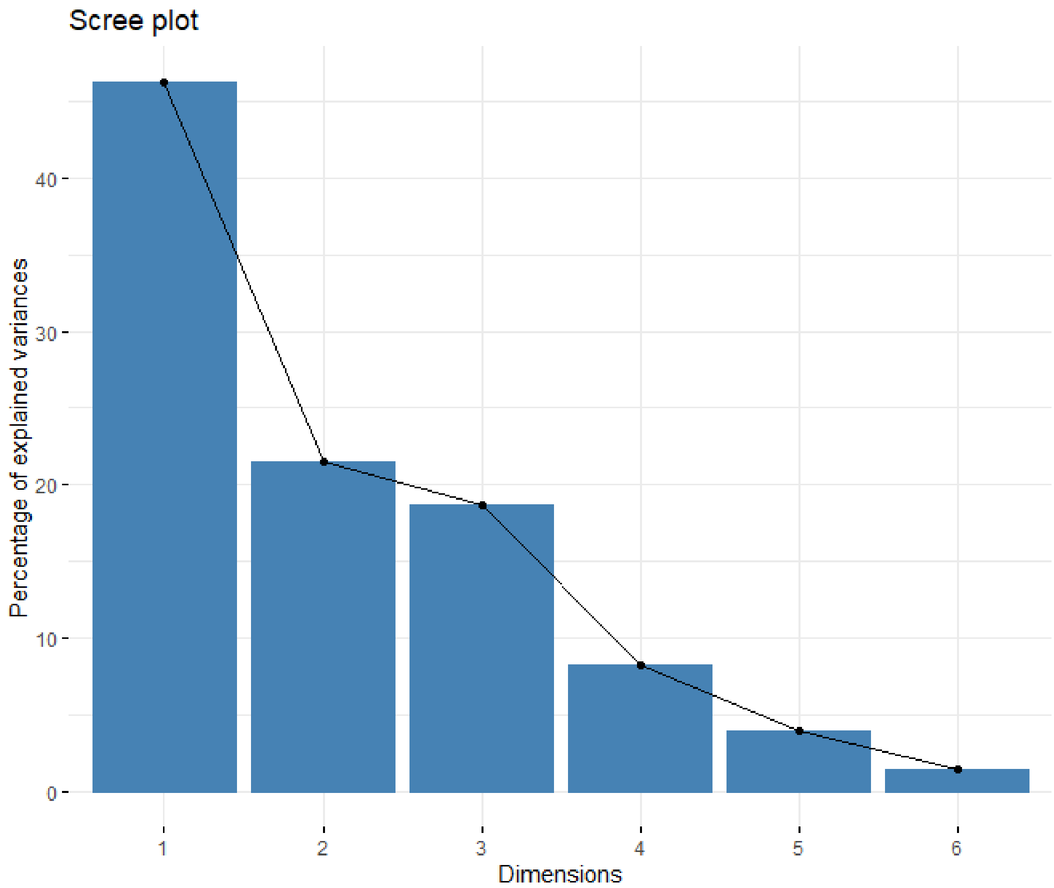

Table 3 - Coefficients of the regression models under PCA, 5th percentile

	Quarters ahead											
	1Q	**2Q**	**3Q**	**4Q**	**5Q**	**6Q**	**7Q**	**8Q**	**9Q**	**10Q**	**11Q**	**12Q**
Financial conditions	-0,008***	0.005	0,011**	0,008***	0,012**	0,011***	0,008**	-0,012***	-0,007***	-0,008***	-0.005	-0.003
Credit and Sectors' Activity	0,005*	-0.007	-0.009	-0,022***	-0,015*	-0,010***	-0.0005	0,028***	0,025***	0,022***	0,017**	0,021***
External conditions	-0,003**	-0.012	-0,015***	-0,010***	-0,018***	-0,020***	-0,020***	-0,005*	0,008***	-0.001	-0.001	-0.003
GDP_t0	0,904***	0.378	0.321	-0,579***	0.047	0.047	0.206	-0.229	0.176	-0.053	-0.01	0.394
Constant	-0,058***	-0,090***	-0,109***	-0,061***	-0,117***	-0,110***	-0,120***	-0,140***	-0,138***	-0,131***	-0,125***	-0,129***
Observations	74	73	72	71	70	69	68	67	66	65	64	63

Note: *p<0,1; **p<0,05; ***p<0,01