BCC 9th Annual Conference

Evaluating Growth-at-Risk as a tool for monitoring macro-financial risks in the Peruvian economy

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September 2021

[1] The views expressed in this article are those of the authors and not necessarily reflect those of the Central Reserve Bank of Peru

Outline

Introduction

- In the wake of the Global Financial Crisis (GFC) there has been an increasing interest in understanding the relation between financial conditions and real activity.
- Growth at Risk (GaR) methodology developed by Adrian et al. (2019) has been of special interest by policymakers since it provides a measure of the relationship among macro-financial variables.
- GaR requires estimating a set of predictive quantile regressions (QR) where future economic activity (GDP growth) is linked to current financial conditions, measured through a set of alternative market or bank related indicators.
- Building on this work, a growing number of countries have implemented this methodology for financial stability purposes. Moreover, Superintendency of Banking and Insurance (2019) and Gondo (2020) have estimated GaR with Peruvian data.

Introduction

- However, as GaR methodology increased in popularity among policymakers, recent literature has stressed the need of model evaluation of GaR results.
- For instance, Reichlin et al. (2020) evaluate the out-of-sample performance of a GaR model and find little evidence of predictability beyond what can be achieved using timely indicators of the real economy.
- Moreover, Brownless and Souza (2020) use a Garch-type model to forecast the distribution of future economic growth, and compare their forecasting power against GaR model, finding that a Garch-type model outperforms a GaR model.

This paper

- Our work implements several model evaluation techniques to increase the accuracy of a Growth at Risk model for the Peruvian Economy.
- Considering a broad sample of parametric and nonparametric distributions to fit the GaR results, we use log scoring, probability integral transform and entropy tests as model evaluation tools to select the best density forecast that fits Peruvian data.
- Once we obtain a more reliable GaR results, we use this model to implement a counterfactual analysis to evaluate the impact of Reactiva Peru, a government program that support the credit to firms during the lockdown due the Covid-19 crisis.
- Our results show that Reactiva Peru had a sizable impact in macroeconomic and financial stability, since it avoided a much deeper decrease in economy activity during the covid-19 crisis.

Growth-at-Risk Model for Peru

The proposed Growth at Risk model for Peru consists of the following steps:

1. Obtain factors summarizing a broad set of macrofinancial variables.

$$\begin{bmatrix} X_{1,t} \\ X_{2,t} \\ X_{3,t} \\ X_{4,t} \\ X_{5,t} \\ Y_t \end{bmatrix} = \begin{bmatrix} \text{Credit market} \\ \text{Financial market} \\ \text{Financial strength} \\ \text{External financial conditions} \\ \text{Macroeconomic conditions} \\ \text{Current GDP growth} \end{bmatrix}$$

2. Use Quantile Regression (QR) estimation to obtain percentiles of future GDP growth:

$$Y^q_{t+h} = \alpha^q + \beta^q_1 X_{1,t} + \beta^q_2 X_{2,t} + \beta^q_3 X_{3,t} + \beta^q_4 X_{4,t} + \beta^q_5 X_{5,t} + \beta^q_6 Y_t$$

3. Use density estimation techniques to obtain a distribution that fits the quantiles estimated in the previous step.
4. Implement different model evaluation criteria for selecting the density that best fit the Peruvian data.

Step 1: Efficient Selection for the factors $(X_{i,t})$

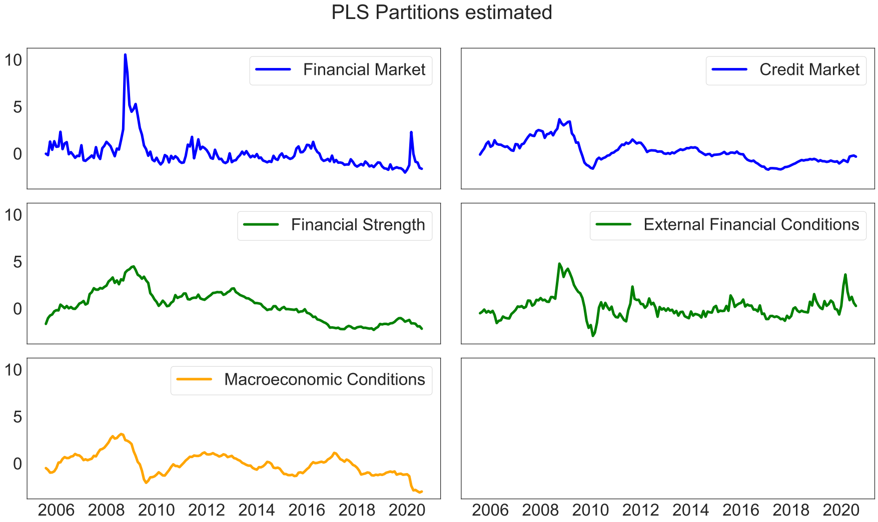
- We use Orthogonal Projection for Latent Structures (O-PLS) to estimate a small set of factors.
- Unlike calculating the factors through standard principal component model (PCA), the O-PLS model allows the correlation between financial variables and a target variable to be used for determining the factors, thus increasing their predictive power.
- Monthly data frequency from 31/08/2005 to 31/08/2020.

Table: Partition groups (factors) and target variables

Factor	**Credit Market**	**Financial Market**		**Financial Strength**		**External Financial Conditions**		**Macroeconomic Conditions**
Target	**Credit to businesses**	**Credit to businesses**		**Credit to businesses**		**Credit to businesses**		**GDP**
Variables	Credit to businesses Household credit	EMBIG Return IGBVL Volatility BVL Liquidity BVL	CDS Pension fund ret Spread node 10 Non-resident holdings	Financial income Opex Net profit Equity capital	Dependence on external funding Liquid assets/ Short-term Liab	Copper S&P500 USA Spread	VIX Global spread Index	Terms of trade Inflation Exchange rate Monetary stimulus

Step 1: Efficient Selection for the factors ($X_{i,t}$)

Figure: Evolution of the O-PLS factors, $X_{i,t}$



Step 2: Quantile Regression (QR) estimation

The Growth at Risk model consists of the following quantile equations:

$$Y^q_{t+h} = \alpha^q + \beta^q_1 X_{1,t} + \beta^q_2 X_{2,t} + \beta^q_3 X_{3,t} + \beta^q_4 X_{4,t} + \beta^q_5 X_{5,t} + \beta^q_6 Y_t$$

where:

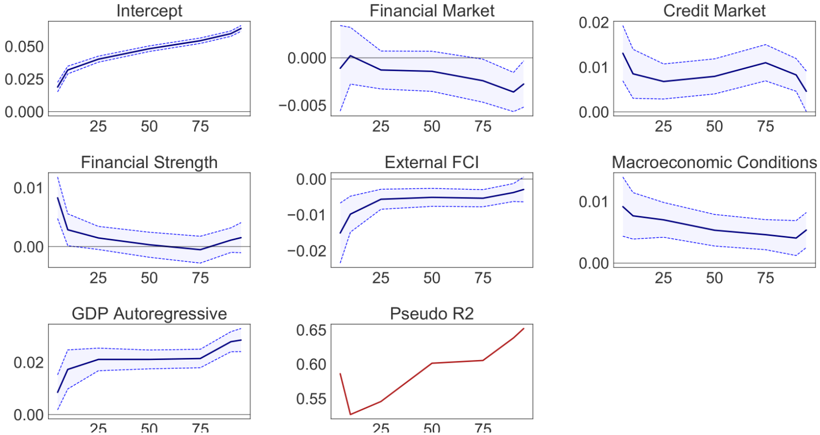
- Y^q_{t+h} corresponds to the p-percentile of the projected cumulative GDP growth in the period $t+h$.
- $X_{i,t}$ corresponds to the factors obtained using O-PLS

$$\begin{bmatrix} X_{1,t} \\ X_{2,t} \\ X_{3,t} \\ X_{4,t} \\ X_{5,t} \end{bmatrix} = \begin{bmatrix} \text{Credit market} \\ \text{Financial market} \\ \text{Financial strength} \\ \text{External financial conditions} \\ \text{Macroeconomic conditions} \end{bmatrix}$$

- Y_t correspond to GDP growth at period t.
- β^q_i represents the contribution of factor i in the q-percentile projection of cumulative GDP growth distribution.

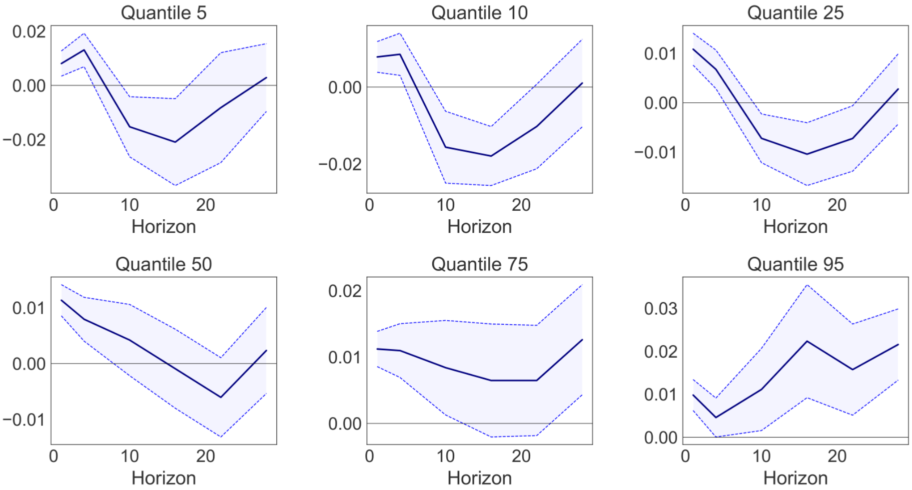
Step 2: Quantile Regression (QR) estimation

Figure: Quantile coefficients of the O-PLS factors 4-month horizon (Confidence interval at 5%)



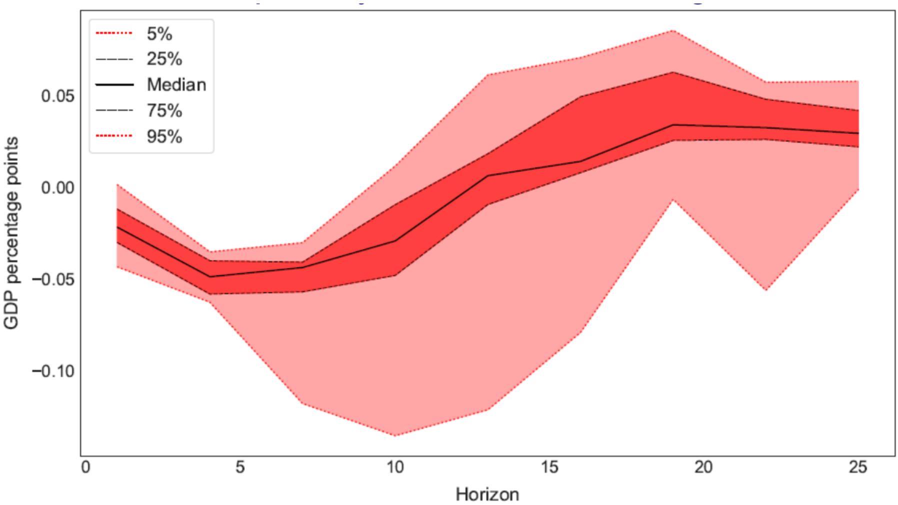
Step 2: Quantile Regression (QR) estimation

Figure: Term structure of Quantile Coefficients for credit market factor (Confidence interval at 5%)



Step 2: Quantile Regression (QR) estimation

Figure: Fan chart of QR results

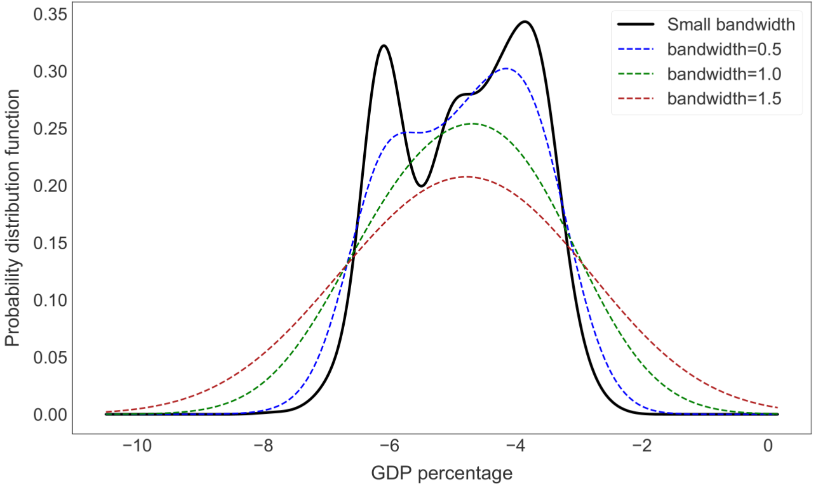


Step 3: Density fitting

- With the conditional quantiles estimated from the QR at each forecasting period, we fit distributions (pdf) as following:
- Different from Adrian et al. (2019), who are fitting conditional quantiles, here we work at the sample level, so we have many more choices of fitting pdfs.
- Obtain a large sample from the interpolation of the estimated quantiles of GDP growth, following Schmidt and Zhu (2016).
- Use a diverse group of PDFs (non parametric, parametric and mixture of normal) to fit the sample of conditional forecast of GDP growth.

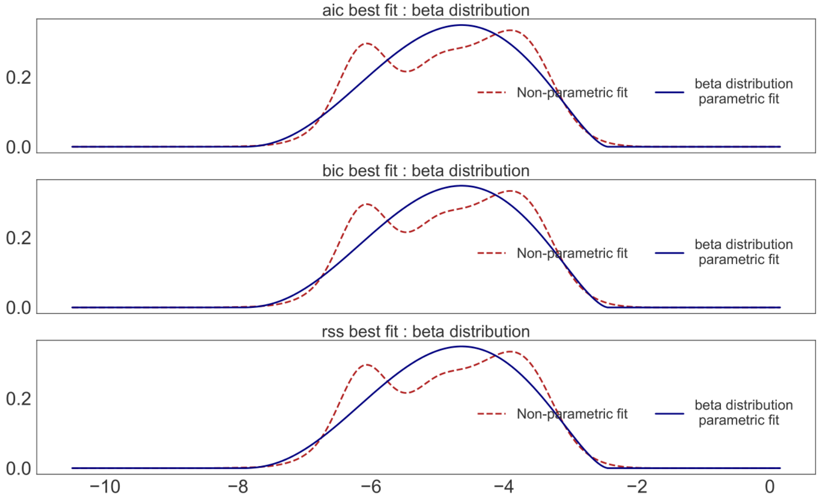
Step 3: Density fitting - Kernel PDFs

Figure: Gaussian Kernel Fit with Different Bandwidths 4 months ahead



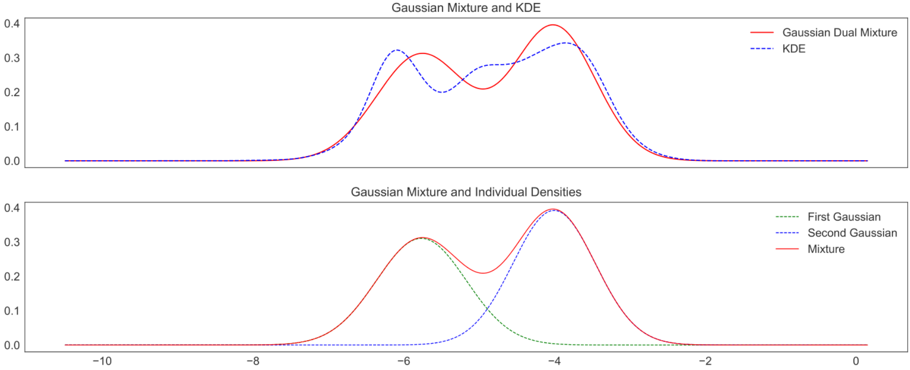
Step 3: Density fitting - Parametric PDFs

Figure: Parametric distribution fitting: selection criteria (4-month ahead)



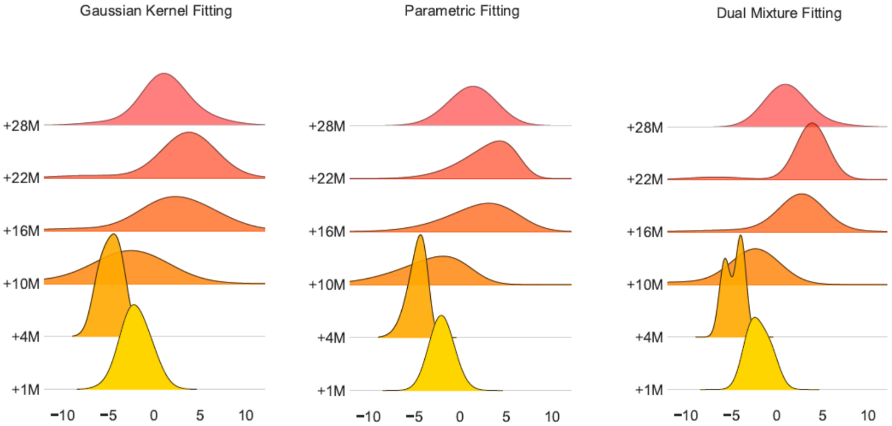
Step 3: Density fitting - Mixture of Gaussian PDFs

Figure: Mixture of Normal density fitting (4-month ahead)



Step 3: Density fitting - Comparison

Figure: Term Structure of Growth-at-Risk



Step 4: Model evaluation tools

Accuracy test: Log score comparisons via Diebold Mariano test statistic

Let $\hat{f}(Y_{t+h})$ and $\hat{g}(Y_{t+h})$ two different density forecasts and define $S(\hat{f}, Y_{t+h})$ as the score rule of the form:

$$S(\hat{f}, Y_{t+h}) = log[\hat{f}(Y_{t+h})]$$

then the log score difference is define as

$$d_{t+h} = S(\hat{f}, Y_{t+h}) - S(\hat{g}, Y_{t+h})$$

with the mean score difference as:

$$d_{m,n} = \frac{1}{n} \sum_{t=m}^{T-h} d_{t+h} \;\; with \;\; n = T - m$$

therefore, it is possible to implement a Diebold-Mariano type of test:

$$t_{m,n} = \frac{d_{m,n}}{\sqrt{\frac{\hat{\sigma}^2_{m,n}}{n}}} \sim \mathcal{N}(0, 1)$$

where the null hypothesis is that both PDFs have the same accuracy.

Step 4: Model evaluation tools

Accuracy test: Log score comparisons via Diebold Mariano test statistic

Table: Log score comparisons (Diebold-Mariano test statistic)

Log Score Diff.	test statistic	p-value
KDE against Unconditional	3.733	0.000
Parametric against Unconditional	3.722	0.000
Dual Mixture against Unconditional	3.73	0.000
KDE against Parametric	2.672	0.004
Dual Mixture against Parametric	2.988	0.001
KDE against Dual Mixture	0.215	0.415

Step 4: Model evaluation tools

Probability Integral Transform test

- Let $f_t(Y_{t+h})$ the forecasted density function of a random variable Y_{t+h} from Growth at Risk model, then the cumulative density function (CDF) can be represented as:

$$F_t(Y_{t+h}) = \int_{-\infty}^{Y_{t+h}} f_t(z)\, dz$$

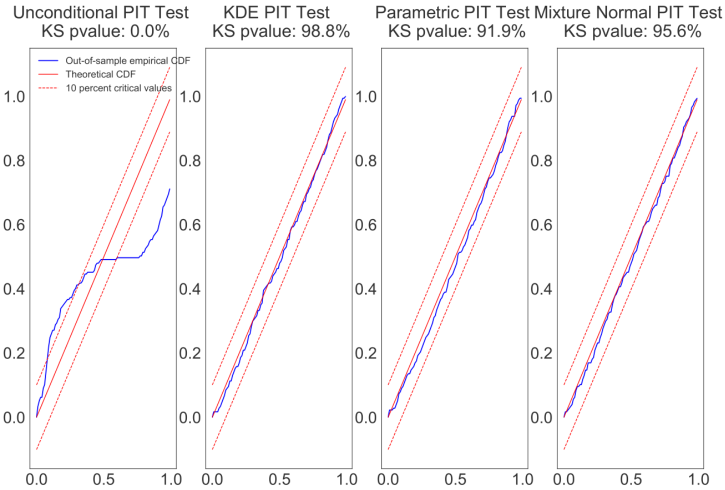
Using this CDF, the Probability Integral Transform (PIT) is defined as the transformation of the random variable Y_{t+h}:

$$U_{t+h} = F_t(Y_{t+h})$$

- Diebold(1998) Demonstrates that the PIT is *iid* if the density forecast is correctly specified. Then, the sequence of all U_{t+h} is *iid* Uniform (0,1) and its cumulative distribution is the 45-degree line.
- Rossi and Shekopysan (2019) considers testing how close is the CDF of the density forecast to an uniform distribution via a Kolmogorov-Smirnov (KS) test.

Step 4: Model evaluation tools

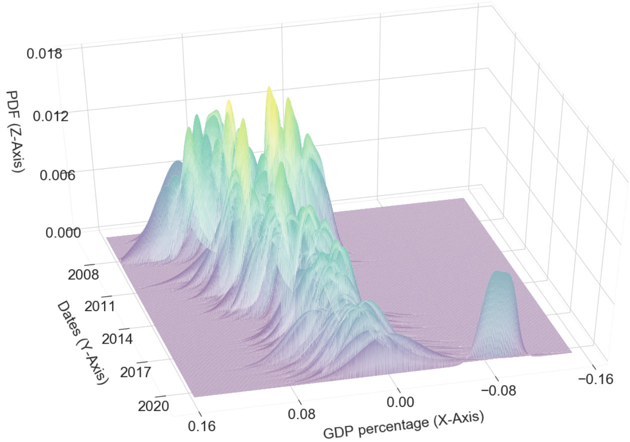
Figure: Probability Integral Transform test



Growth at risk over time

Having a reliable estimation of GaR model allow us to identify the building up of vulnerabilities to economic growth in the Peruvian economy.

Figure: Historical evolution of density forecast of GDP Growth



Counterfactual analysis

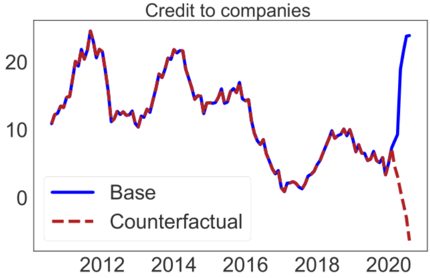
Measuring the impact of program to support credit to business ("Reactiva Perú")

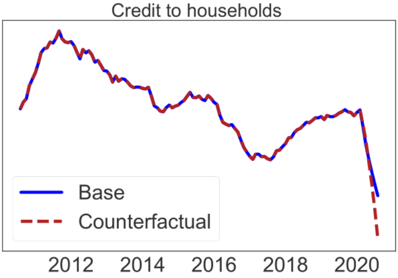
- "Reactiva Perú" is a Guarantee Program designed by the Central Bank and the Ministry of Finance, which allow Central Bank to provide low cost liquidity to banks to supply loans to businesses while those loans are guarantee by the Treasury. By providing a large supply of low cost credit to firms, specially SME, during the lockdown, this program reduced the impact of the Covid-19 shock to the Peruvian economy.
- To test this argument we implement a counterfactual scenario using the GaR Model.

Design of the counterfactual scenario

The counterfactual path of credit to firms is consistent with the evolution of credit growth not related to ”Reactiva Peru”.

Figure: Counterfactual scenario for credit market variables





Design of the counterfactual scenario

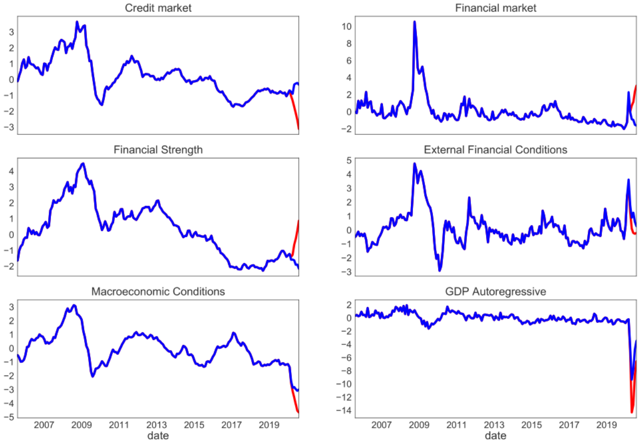
To map this counterfactual scenario to the credit market factor included in the GaR model, we run a OLS regression with the credit market factor against the two credit variables (credit to firms and to households).

Figure: Counterfactual scenario for credit market factor

Design of the counterfactual scenario

In order to transfer the shock of the Credit Market factor to the rest of factors, we followed Kilian (2016) to simulate counterfactual outcomes using a SVAR model.

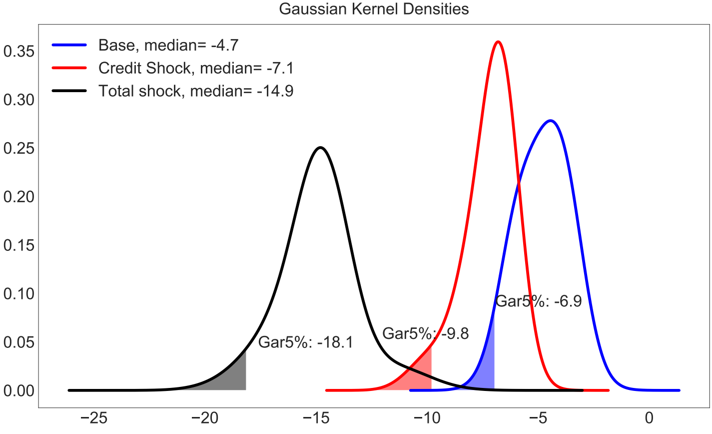
Figure: SVAR: Counterfactual Analysis



Counterfactual Analysis

Results show that without “Reactiva Peru” we could obtain a significant worse impact in economy activity, no only in terms of lower expected growth but also in terms of increased risk.

Figure: Density forcast for GDP growth: Counterfactual Analysis



Concluding remarks

- Growth at risk is a important tool for monitoring macrofinancial risk since it allow to measure the link between macrofinancial conditions and future GDP growth distribution.
- However, for the accuracy of the GaR results it is crucial to implement model evaluation techniques to avoid misleading interpretation.
- Flexibility of the GaR methodology allows to perform counterfactual scenario analysis that can help to identify sources of risks and communicate policy actions.