A high frequency indicator of credit in Peru: A Random Forests and dynamic network connectedness approach

The views expressed in this working paper correspond to those of the authors and do not necessarily reflect the position of the Central Reserve Bank of Peru.

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Motivation

- Traditional monthly reporting of credit data limits the ability of central banks to react quickly to financial instability.
- Need for timely and accurate monitoring of credit growth.
- Develop a daily credit expansion indicator to allow more real-time financial monitoring.
- Rapid credit changes, especially excessive credit growth, can indicate potential financial crises, making early detection crucial for central banks.

Contribution and main ideas

- First Study: Introduces a machine learning-based tool for detecting excessive credit growth in Peru using Random Forests.
- Imputation of Daily Data: Converts monthly credit data into daily observations using a Random Forest model with high-frequency predictors.

Literature

- Recen studies that use machine learning for imputation: Cahan et al.(2023) and Xiong and Pelger(2023).
- mixed frequency analysis using machine learning methods: Giraldo et al. (2024), Chuliá et al.(2023) and Lima et al. (2020).
- Focus on early warning systems and credit growth monitoring:
- Schwaab et al. (2014): Importance of tracking credit markets before financial crises.
- Recent advancements in machine learning like Random Forests show superior prediction accuracy for complex financial data (Breiman 2001, Hastie et al. 2009).
- Studies like Kant et al. (2022) and Bitetto et al. (2023) underline Random Forest's effectiveness in financial predictions, particularly GDP nowcasting and credit risk.

Metodology

- $X = (X_1, X_2, ..., X_p)$ to be a $n \times p$-dimensional data matrix
- For any lower frequency variable X_s,including missing points at entries $i_d^{NA} \epsilon \{1, \ldots, n\}$ the data set can be split into four sets:
- 1)the non-missing values of X_s,which are denoted by y_s^{obs};
- 2) the missing observations, y_s^{NA} ;
- 3) variables different from s , with higher frequencies, with observations $i_s^{obs} = \{1, \ldots, n\} \setminus i_s^{NA}$ denoted as X_s^{obs}
- 4) indicators different than X_s with observations i_s^{NA} ,denoted by x_s^{NA}. Note that x_s^{obs} is typically not completely observed since the index i_s^{obs} corresponds to the observed values of the variable X_s. Likewise, x_s^{NA} is typically not completely missing.

Quantile Regression Forest

Quantile regression forests (Meinshausen,2006) generalizes the standard random forests to provide information for the full conditional distribution of the response variable, not only about the conditional mean.

$$Q_\alpha(Y|X) = inf\{y : F(y|X) \geq \alpha\}$$
$$F(y|X) = Pr(Y \leq y|X) = E(I_{\{Y \leq y\}}|X)$$

$$\hat{F}(y|X) = \sum_{i=1}^{n} w_i(x) I_{\{Y_i \leq y\}}$$

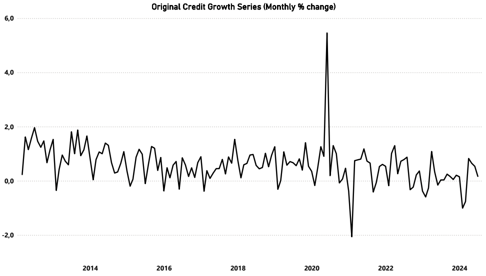
Data

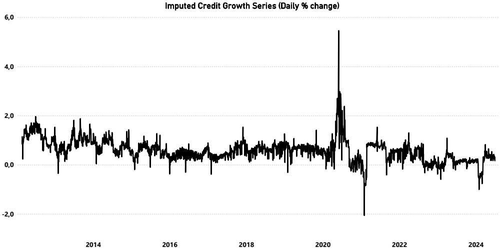
- Covers 2012-2024 with 4508 daily observations.

Table: Descriptive Statistics

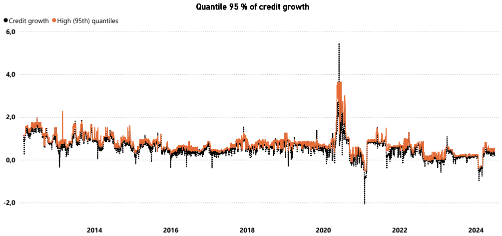
Indicator	**Frequency**	**Abreviation**	**Source**
Spread 10 years- 2 years bond	Daily	10y-2y	Bloomberg
Spread 10 years- 5 years bond	Daily	10y-5y	Bloomberg
Spread LIBOR USD 3 months - 2 years bond	Daily	LIBOR-2y	Bloomberg
Spread LIBOR USD 3 months - 5 years bond	Daily	LIBOR-5y	Bloomberg
Interbank Interest Rate	Daily	Interbank	Central Bank of Peru
MSCI Peru	Daily	MSCI	Bloomberg
Variation of Total Loans	Monthly	Credit	Central Bank of Peru

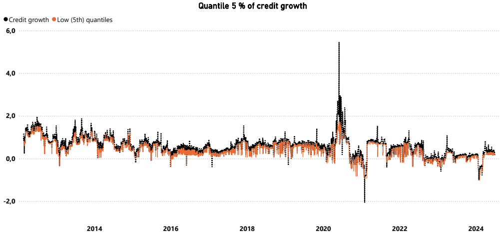
Results - Imputed Credit Growth Series





Quantiles of credit growth





Regular versus stress periods.

	Regular	Stress
Credit	0.584	1.358
10y-2y	1.536	2.160
10y-5y	1.568	1.783
LIBOR-2y	-2.703	-2.613
LIBOR-5y	-2.671	-2.989
Interbank	0.000	0.000
MSCI	0.013	0.599

Table: This table displays the average values of the variables under two different states: when credit growth is below its 95th percentile (considered regular- left column) and when it exceeds this threshold (considered stressed- right column).

Implications and Conclusions

- The estimated credit quantiles display clustering patterns that underscore the role of financial and macroeconomic cycles in pinpointing periods of notably high or low credit growth
- Additionally, our approach supports the use of various percentage cutoffs, providing greater flexibility for policymakers
- Instances where credit growth exceeds or falls below a certain threshold indicate unusually high or low daily credit growth values. Importantly, these periods are not randomly spread over time but instead form discernible clusters
- The daily credit indicator allows central banks to detect unusually high or low credit growth in real time, aiding in quicker and more informed policy interventions.

Future Research Agenda

- Future work could expand the model to incorporate more financial variables, including external shocks like commodity prices and foreign capital flows.
- Apply this machine learning approach to other emerging economies to assess the generalizability of results.
- Explore how early warning systems based on daily credit indicators can enhance the effectiveness of macroprudential tools like countercyclical capital buffers