High Frequency Monitoring of Credit Creation: A New Tool for Central Banks in Emerging Market Economies

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Abstract

This study utilizes weekly datasets on loan growth in Colombia to develop a daily indicator of credit expansion using a two-step machine learning approach. Initially, employing Random Forests (RF), missing data in the raw credit indicator is filled using high frequency indicators like spreads, interest rates, and stock market returns. Subsequently, Quantile Random Forest identifies periods of excessive credit creation, particularly focusing on growth quantiles above 95%, indicative of potential financial instability. Unlike previous studies, this research combines machine learning with mixed frequency analysis to create a versatile early warning instrument for identifying instances of excessive credit growth in emerging market economies. This methodology, with its ability to handle nonlinear relationships and accommodate diverse scenarios, offers significant value to central bankers and macroprudential authorities in safeguarding financial stability.

Keywords: Credit growth; Machine learning methodology; Excessive credit creation; Financial stability.
JEL Codes: C45; G21; E44.

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Content

1. Introduction

A fundamental tenet of contemporary economic theory, as explained by Cecchetti and Kharroubi (2012), highlights the beneficial role of finance in fostering economic growth. Despite the well-established advantages associated with the development of credit markets and their positive impact on long-term economic prosperity, it is crucial to recognize that an unrestrained surge in loan activity may yield adverse consequences for both the financial system and the broader economy (Schularick and Taylor, 2012; Caballero, 2016).

The annals of financial history, notably exemplified by the Global Financial Crisis (GFC), offer a poignant illustration of the perils associated with excessive credit expansion. Numerous instances of financial crises have been foreshadowed by periods characterized by abnormal credit growth, giving rise to the formation of asset price bubbles. This deleterious scenario is likely to materialize when, during periods of economic expansion, entities such as banks, firms, and households systematically underestimate risk. In consequence, their actions may augment the likelihood of encountering financial distress in the future, as expounded in studies by Altunbas et al. (2010, 2012).

This phenomenon is often attributed to myopic behavior exhibited by private agents, as discussed by García-Suaza et al. (2012) and Borio et al. (2001). Alternatively, other scholars emphasize the fundamental role played by asymmetric information and financial frictions in credit markets, as emphasized by Holmstrom and Tirole (1997) and Mendoza and Bianchi (2010). Recognizing and addressing these nuanced dynamics is imperative when navigating the realms of financial growth, risk perception, and the stability of the economic system.

Numerous nations, particularly, emerging market economies, have implemented a repertoire of measures aimed at curbing unwarranted credit expansion, thereby safeguarding future financial stability (see, for example, Giraldo et al., 2023). An essential query, however, pertains to the strategic considerations surrounding the intervention to restrain excessive credit growth. Crucially, determining the threshold that characterizes excessive credit growth and, devising timely mechanisms for its identification, constitutes a formidable challenge.

Notably, the immediacy with which credit growth unfolds eludes swift observation by policymakers. Even individual commercial banks, engrossed in extending loans to households and businesses, lack real-time visibility into aggregate credit growth. Consequently, the development of early warning indicators assumes utmost significance to proactively identify and address burgeoning instances of excessive credit expansion.

Early warning systems represent a crucial asset for regulatory bodies and financial system overseers. While on-site monitoring stands out as a premier means through which authorities can glean both quantitative and qualitative insights into the fiscal well-being of the entities under scrutiny, the execution of such monitoring at a high frequency can incur substantial costs. Moreover, an additional concern arises in the form of potential perceptual biases on the part of those conducting the monitoring, as underscored by Audit and Alam (2022). Given these challenges associated with on-site monitoring, statistical models for early warning assume a notable role, serving as a valuable adjunct for supervisors and regulators in their endeavor to discern and address vulnerabilities within the financial system.

Here, we leverage weekly datasets pertaining to loan growth in the Colombian context. Employing a two-step machine-learning methodology, we systematically craft a daily indicator encapsulating the dynamics of credit growth. This approach not only allows for a granular assessment of credit expansion daily but also facilitates the identification of periods characterized by excessive credit growth.

Concretely, in the first step we use Random Forests (RF) for constructing a daily indicator of credit growth, which is originally sampled on a weekly basis. Specifically, we identify the missing dates in the raw credit indicator and employ RF to fill these gaps, harnessing the information contained in our high frequency indicators which include various spreads (e.g. TED, TERM spreads), overnight interbank interest rates, and stock market returns. Subsequently, we use Quantile Random Forest, a fusion of quantile regression and RF, to identify periods of excessive credit creation, which are of concern for regulators. We specifically focus on the credit growth quantiles above 95%, which correspond with scenarios of rapid credit growth and likely predict future scenarios of financial and macroeconomic stability.

Our work aligns with recent studies that leverage machine learning for imputation, such as Cahan et al. (2023) and Xiong and Pelger (2023). Notably, these studies predominantly focus on linear factor models and do not explore mixed frequency scenarios. Our research also intersects with the literature on mixed frequency analysis using machine learning methods, as evidenced by works like Chuliá et al. (2023) and Lima et al. (2020). Interestingly, these later studies have neither utilized random forest for imputation nor for estimating the tails of the distributions as we do. The strength of the RF lies in its ability to effectively handle complex and nonlinear relationships within the data. Its ensemble nature not only mitigates overfitting but also makes it versatile and less susceptible to noise.

To the best of our knowledge, this study stands as the inaugural endeavor to devise a pragmatic early warning instrument tailored for identifying instances of excessive credit growth within an emerging market economy.

The subsequent sections of this paper are structured as follows. Section 2 delineates the methodology employed in this study, elucidating the intricacies of our analytical approach. Following this, Section 3 provides a comprehensive overview of the data utilized in our investigation. The ensuing Section 4 unveils the primary findings derived from our analysis. Finally, the last section encapsulates our conclusions, summarizing the key insights garnered from this study.

2. Methodology

Our methodology consists of two parts. In the first part, we describe how to use RF for mixed frequency data analysis. In the second part, we introduce Quantile Random Forest.

2.1. Random Forest for Mixed Frequency Data

We address the challenge posed by the mixed frequency in our dataset by framing it as a task of predicting missing values. In doing so, we draw inspiration from the methodology outlined by Stekhoven and Bühlmann (2012), who employed a RF approach to impute missing data. However, unlike their standard frequency setup, our dataset encompasses daily and weekly frequencies.

Following Stekhoven and Bühlmann (2012), suppose $x = (x_1, x_2, \dots, x_p)$ is a $n \times p$ dimensional matrix that contains our data, irrespective of the frequency of the variables. In this way, by construction, the lower frequency variable is going to contain missing values. We directly predict such missing values using RF, which is estimated on the observed higher frequency variables in our dataset. For any lower frequency variable x_s, including missing points at entries $i_s^{NA} \in \{1, \dots, n\}$ the dataset can be split into four sets: 1) the non-missing values of x_s, which are demoted by y_s^{obs}; 2) the missing observations, y_s^{NA}; 3) variables different from s, with higher frequencies, with observations $i_s^{obs} = \{1, \dots, n\} \backslash i_s^{NA}$ denoted as x_s^{obs}, and 4) indicators different than x_s with observations i_s^{NA}, denoted by x_s^{NA}.

The random forest algorithm makes an initial conjecture for the missing values in x, based on the observed frequency (e.g. the mode value). Subsequently, it sorts the variables x_s, $s = 1, \dots, p$ according to the number of missing observations. For each variable x_s the missing values are filled in by estimating a RF model with response variable y_s^{obs} and predictors the rest of the variables in a given day, x_s^{obs}, which in our case correspond to the higher frequency variables.

The model proceeds by predicting the missing values y_s^{NA} by applying the estimated RF to the x_s^{NA}. This procedure is repeated until a stopping criterion is met.

In principle, nothing prevents that there are other missing points in the dataset, which are totally unrelated to the frequency of the variables. The algorithm operates similarly to the previously described method to address these missing values. It uses the available variables at specific dates to make predictions for those NA records.

2.2. Quantile Random Forest

Random Forest (Breiman, 2001) employed in a traditional contexts, unlike the previous one of missing data, consists of a collection of trees assembled by utilizing n distinct observations (Y_i, X_i) for $i = 1, \ldots, n$, which are used to make predictions of a dependent variable Y, using covariates contained in X.

The general algorithm proceeds as follows. A multitude of trees are growth. Within each tree and node, RF introduce variability by randomly choosing a variable for branching. Only a randomized subset of predictors is examined when determining split points at each node. This subset's size, stands as the primary parameter to adjust in the algorithm, although its performance is known to remain robust across a broad range of values.

RF predict a new data point $X = x$ by averaging the responses from all trees, according to equation 1:

$$\hat{\mu}(x) = \sum_{i=1}^{n} w_i(x) Y_i. \tag{1}$$

Where, w_i is the weight assigned to the original observation i, which in turn, corresponds to the average weight that each three in the forest assigns to the original values in the dataset. The weights vary with the co-variate $X = x$ and tend to be large for those $i \in \{1, \ldots, n\}$ where the conditional distribution of Y, given $X = X_i$, is the conditional distribution of Y given $X = x$.

The prediction within a single tree is given by:

$$\hat{\mu}(x) = \sum_{i=1}^{n} w_i(x, \theta) Y_i. \tag{2}$$

Where θ is a random parameter that determines how a tree is grown, by specifying which variables are considered for split-points at each node. Every leaf of a tree, R_l, for $l = 1, \ldots, L$ corresponds to a rectangular subspace of the space of X, denoted by B. For every $x \in B$, there is one and only one leaf l such that $x \in R_l$ (matching the leaf acquired upon dropping x down the tree). The prediction of a single tree for a new data point $X = x$ is obtained by averaging over the observed values in leaf $l(x, \theta)$.

Quantile Regression Rorest (Meinshausen, 2006) extends RF into a flexible method for estimating any quantile of the dependent variable, as opposed to estimating the mean value. To compute the estimate $\widehat{Q}_{\alpha}(x)$, which in our case correspond to an estimate of a high quantile (i.e., 0.95) of credit growth, we need to grow k trees, similar to the RF approach. However, for each leaf in every tree, you need to record all observations within that leaf, rather than just their average values.

In continuation, given $X = x$, we drop x down through all trees. Then, we determine the weight $w_i(x, \theta)$ for observation i as described before in equation 2 and, calculate the overall weight for each observation as presented in equation 1.

Lastly, using the weights from the previous step, we derive the estimate of the distribution function for all $y \in \mathbb{R}$, given by:

$$\hat{F}(y|X = x) = \sum_{i=1}^{n} w_i(x) 1_{\{Y_i \leq y\}}. \quad (3)$$

The estimates $\widehat{Q}_{\alpha}(x)$, for the conditional quantiles $Q_{\alpha}(x)$, are determined by substituting $\hat{F}(y|X = x)$ for $F(y|X = x)$ into the following equation that defines a quantile α:

$$Q_{\alpha}(x) = inf\{y: F(y|X = x) \geq \alpha\}. \quad (4)$$

In summary, the fundamental distinction between Quantile Regression Forests and Random Forests lies in their treatment of node data. While RF only retains the mean of observations within a node and disregards other details, QRF retain the individual values of all observations in that node. In our empirical section we use $\alpha = 0.95$ to approximate a scenario of rapid credit growth, which could be associated with episodes of financial instability or bubble formation in housing and financial markets, and contrast the results with the case in which $\alpha = 0.05$.

3. Data

Table 1. Summary Statistics of the Sampled Variables

Indicator	Frequency	Abreviation	Source	Mean	Median	Std.Dev	Max.	Min.
Spread 10 years-2 years bond	Daily	MinorTERM	Investing	1.85	1.75	2.33	5.8	-100.27
Spread 10 years-5 years bond	Daily	X5TERM	Investing	0.68	0.63	1.89	92.63	-24.13
Spread LIBOR USD 3 months- 2 years bond	Daily	MinorTED	Capital IQ-Investing	-4.29	-4.34	3.32	-1.69	-106.68
Spread LIBOR USD 3 months- 5 years bond	Daily	X5TED	Capital IQ-Investing	-5.47	-5.45	2.65	-2.7	-113.46
Interbank Interest Rate	Daily	INTERBANK	Central Bank of Colombia	4.78	4.26	2.25	12.95	1.65
MSCI Colombia	Daily	VAR_R_STOCKS	Investing	-0.03	-0.02	1.77	17.28	-19.67
Variation of Total Loans	Weekly	VAR_CREDIT	Central Bank of Colombia	0.18	0.19	0.29	1.28	-0.82

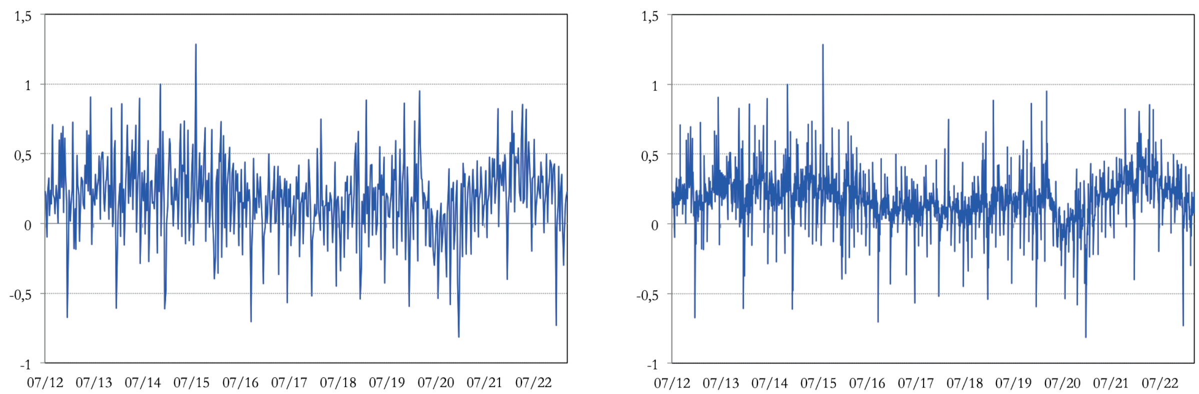
Note: This table shows the description, frequency, codes, sources and summary statistics of the variables used. The last variable is weekly, while all other variables are daily. The stocks and credit variables are used in percentage variation.

4. Results

Figure 1 juxtaposes the original (left panel) and imputed (right panel) credit series, employing a MIDAS approach. Notably, the imputed credit series impeccably mirrors the original series, aligning with anticipated outcomes. A noteworthy distinction lies in the temporal granularity of the data; whereas the original series is based on weekly intervals, the imputed credit series offers a daily perspective. This temporal refinement enables policymakers to expediently discern instances of abnormal credit growth. It is pertinent to observe that both credit series manifest substantial variation and evince short-term inertia. This implies that credit growth undergoes noteworthy fluctuations over time, and in the immediate context, heightened credit growth today (within the current week) is more probable if it exhibited a similar trend in the recent days (or weeks).

Figure 1. Analysis of missing values across the whole dataset

Panel A. Original Credit Growth Series (weekly) | Panel B. Imputed Credit Growth Series (daily)



Note: The figure presents the original series of weekly credit growth in Colombia on the left, while it shows the constructed series of weekly credit growth with a daily frequency using a Mixed Data Sampling approach with Random Forest.

Figure 2 unveils the principal findings of this study, illustrating the series encompassing the high (95th) and low (5th) quantiles of daily credit growth juxtaposed against the overall daily credit growth trajectory. The blue curve in the graph depicts the daily credit growth series, while the green curve represents the high quantiles (left panel) and low quantiles (right panel) of daily credit growth. Several noteworthy outcomes merit attention. Firstly, both high and low quantiles of credit growth exhibit temporal variability, highlighting the influence of macroeconomic and financial cycles in discerning instances of exceptionally high or low credit growth. Consequently, the practice of establishing ad hoc definitions for high or low credit growth, as commonly undertaken by central bankers, is deemed less advisable. In this context, our model furnishes an endogenous and more precise means of identifying the significance of high and low credit growth for any given day. This intrinsic quality facilitates the efforts of central bankers aiming to implement macro-prudential policies for curbing abnormal credit growth.

It is imperative to emphasize that our methodology allows for the definition of different percentage cutoffs to identify episodes of abnormally high and low periods of credit growth. While in this paper we employ the 95% and 5% cutoffs, the flexibility of our approach permits the utilization of any other quantiles deemed appropriate by policymakers.

Secondly, it is noteworthy that instances of credit growth surpassing (falling below) the green line signify abnormally high (low) values of daily credit growth. Intriguingly, these periods do not appear to be randomly distributed across time; instead, discernible clusters merit attention. Notably, a substantial number of days characterized by high credit growth are concentrated between 2012 and early 2015, a timeframe marked by elevated international oil prices and significant capital inflows to Colombia—a notable oil-producing nation. Another noteworthy period of abnormally high credit growth occurred during the Covid-19 pandemic, characterized by a substantial reduction in the policy interest rate by the central bank of Colombia and various government measures aimed at enhancing credit availability in the Colombian economy. This observation suggests that in Colombia, and likely in many other commodity-dependent emerging market economies, there is a positive correlation between periods of abnormally high credit growth and periods when commodity prices in international financial markets are also unusually elevated. This underscores the importance for policymakers to exercise vigilant monitoring of credit growth during phases characterized by surges in commodity prices.

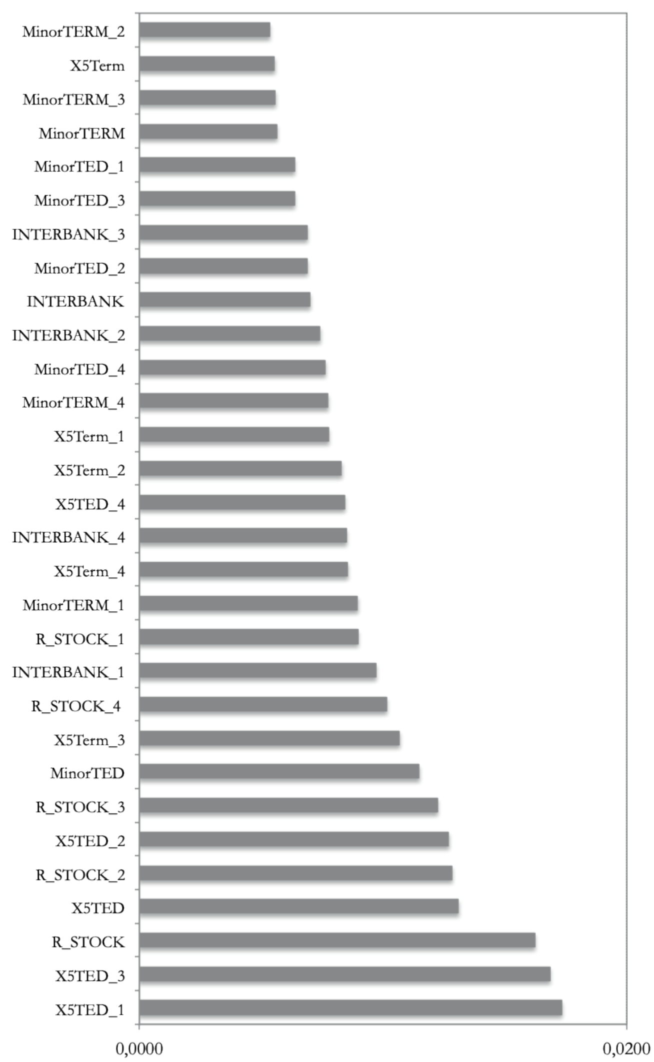
Thirdly, it is crucial to observe that periods of abnormally low credit growth are more prone to occur after phases characterized by high credit growth, as evident during the 2015-2020 period and the aftermath of the Covid-19 pandemic. This pattern aligns with predictions from various studies on financial cycles, suggesting that prolonged periods of abnormally high credit growth have an adverse impact on the overall health of banks and other financial institutions. Such scenarios tend to erode confidence and impede the capacity to extend credit in the immediate aftermath.

Figure 2. High (95th) and low (5th) quantiles of credit growth versus credit growth

Note: The figure presents the 95th and 5th quantile of credit growth estimated using quantile random forest against the series of credit growth (with a daily frequency).

A pivotal consideration pertains to the selection of high-frequency (daily) variables for imputing the daily credit growth series. Figure 3 provides insight into the Variable Importance, as gauged by node purity, of the credit growth at risk indicator across the full conditional distribution of credit growth, including high credit growth and abnormally low credit growth. In this context, two variables emerge as paramount when accounting for both their current and lagged values—namely, the spread between the LIBOR USD 3 months and the 5-year bond yields, and the MSCI of Colombia.

Figure 3. Variable Importance (node purity) of the credit growth at risk indicator



Note: The figure shows the variable importance from most important at the bottom to least important at the top. In the left panel the variable correspond to the 95th quantile, while in the right panel correspond to the 5th quantile. The number in front of the variables correspond to the lag of the variable.

In Table 2, we further explore these relationships and present the values of the predictive variables during normal periods (when the credit risk indicator is below its 95th percentile) and during stressed periods characterized by abnormally high credit growth, recorded above the 95th percentile. From this analysis, we observe that Term spread variables tend to be higher during periods of elevated credit creation, whereas Ted spreads tend to be lower, even turning negative when credit growth rates are exceptionally high. The interbank interest rate shows a significant increase during periods of excessive credit creation, reflecting the central banks' efforts to curtail credit expansion. Furthermore, for the sample periods considered, days marked by excessive credit creation coincide with higher market returns compared to regular periods. Similar patterns are detected in Figure A1 of the Appendix.

Table 2. Average Value of the Indicator in Regular Versus Stress Periods

	Mean	
	Regular	Stress
Credit	0.182	0.570
Minor Term	0.410	1.943
5 Term	0.045	0.640
Minor Ted	1.855	-4.55
5 Ted	0.658	-5.941
Interban	-4.288	4.458
Stock Returns	-5.469	0.049

Note: 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).

5. Conclusions

This study pioneers the construction of a high-frequency early warning indicator for abnormally high and low credit growth, utilizing weekly data from a commodity-dependent emerging market economy. Through a meticulous two-step machine-learning methodology, we systematically generate a daily indicator capturing the nuances of credit growth dynamics. This approach not only facilitates a detailed daily assessment of credit expansion but also enables the identification of periods characterized by excessive credit growth.

In the initial step, we employ Random Forests to construct a daily credit growth indicator from the original weekly sampling. Specifically, we identify missing dates in the raw credit indicator and leverage RF to fill these gaps, drawing on information embedded in our high-frequency indicators, which encompass diverse spreads (e.g., TED, TERM spreads), overnight interbank interest rates, and stock market returns. Subsequently, we employ quantile random forest—a hybrid of quantile regression and RF—to pinpoint periods marked by excessive credit creation, a matter of regulatory concern. Our focus centers on credit growth quantiles above 95%, indicative of instances characterized by rapid credit expansion and likely predictors of future scenarios affecting financial and macroeconomic stability.

This study yields three key findings. Firstly, both high and low credit growth quantiles exhibit temporal variability, highlighting the influence of macroeconomic and financial cycles in identifying instances of exceptionally high or low credit growth. Consequently, the practice of establishing ad hoc definitions for such extremes, as commonly done by central bankers, is less advisable. Our model provides an endogenous and precise means of identifying the significance of high and low credit growth for any given day, facilitating the implementation of macro-prudential policies by central bankers. Our methodology allows for the definition of different percentage cutoffs, offering flexibility for policymakers beyond the 95% and 5% cutoffs employed in this paper.

Secondly, instances of credit growth surpassing or falling below a certain threshold signify abnormally high or low values of daily credit growth. Notably, these periods are not randomly distributed over time; clusters are discernible. Specifically, elevated credit growth days were concentrated between 2012 and early 2015, marked by high international oil prices and significant capital inflows to Colombia, a major oil-producing nation. Another period of abnormally high credit growth occurred during the Covid-19 pandemic, correlating with a substantial reduction in Colombia's policy interest rate and government measures to enhance credit availability. This observation implies a positive correlation in Colombia, and likely in other commodity-dependent emerging markets, between abnormally high credit growth and periods of elevated commodity prices. Policymakers are thus urged to exercise vigilant credit growth monitoring during commodity price surges.

Thirdly, periods of abnormally low credit growth are more likely to follow phases of high credit growth, evident during the 2015-2020 period and post-Covid-19. This pattern aligns with predictions from financial cycle studies, indicating that prolonged periods of abnormally high credit growth adversely impact the overall health of banks and financial institutions. These scenarios erode confidence and hinder credit extension immediately thereafter.

A critical consideration revolves around selecting high-frequency (daily) variables to impute the daily credit growth series. Our results indicate that in instances of abnormally high credit growth, two variables stand out as paramount, considering both their current and lagged values—specifically, the spread between LIBOR USD 3 months and 5-year bond yields, and the MSCI of Colombia.

References

Altunbas, Y., Gambacorta, L., & Marques-Ibanez, D. (2010). Bank risk and monetary policy. Journal of Financial Stability, 6, 121-129.

Altunbas, Y., Gambacorta, L., & Marques-Ibanez, D. (2012). Do bank characteristics influence the effect of monetary policy on bank risk? Economics Letters, 117, 220-222.

Audit, D., & Alam, N. (2022). Why have credit variables taken centre stage in predicting systemic banking crises? Latin American Journal of Central Banking, 3(1), 100047.

Breiman, L. (2001). Random forests. Machine learning, 45, 5-32.

Borio, C., Furfine, C., & Lowe, P. (2001). Procyclicality of the financial system and financial stability: issues and policy options, Bank for International Settlements Working Paper 1.

Caballero, J.A. (2016). Do surges in international capital inflows influence the likelihood of banking crises? Economic Journal, 126, 281-316.

Cahan, E., Bai, J., & Ng, S. (2023). Factor-based imputation of missing values and covariances in panel data of large dimensions. Journal of Econometrics, 233(1), 113-131.

Cecchetti, S.G., & Kharroubi, E. (2012). Reassessing the impact of finance on growth. Bank for International Settlements Working Paper 381.

Chuliá, H., Garrón, I., & Uribe, J. M. (2023). Daily Growth at Risk: financial or real drivers? The answer is not always the same. International Journal of Forecasting.

García-Suaza, A., Gomez-Gonzalez, J.E., Murcia Pabón, A., & Tenjo-Galarza, F. (2012). The cyclical behavior of bank capital buffers in an emerging economy: size does matter. Economic Modelling, 29, 1612-1618.

Giraldo, C., Giraldo, I., Gomez-Gonzalez, J. E., & Uribe, J. M. (2023). Banks' leverage in foreign exchange derivatives in times of crisis: A tale of two countries. Emerging Markets Review, 55, 101028.

Holmstrom, B., & Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. Quarterly Journal of Economics, 112, 663-692.

Lima, L. R., Meng, F., & Godeiro, L. (2020). Quantile forecasting with mixed-frequency data. International Journal of Forecasting, 36(3), 1149-1162.

Meinshausen, N (2006). Quantile regression forests. Journal of machine learning research, 7(6).

Mendoza, E., & Bianchi, J. (2010). Overborrowing, financial crises and 'macro-prudential' taxes. In: Proceedings, Federal Reserve Bank of San Francisco.

Schularick, M., & Taylor, A.M. (2012). Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870-2008. American Economic Review, 102, 1029-1061.

Stekhoven, D. J., & Bühlmann, P. (2012). MissForest—non-parametric missing value imputation for mixed-type data. Bioinformatics, 28(1), 112-118.

Xiong, R., & Pelger, M. (2023). Large dimensional latent factor modeling with missing observations and applications to causal inference. Journal of Econometrics, 233(1), 271-301.

Appendix

Figure A1. Indicators versus daily credit in times of distress

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