Volume LIX No. 2
ISSN 1655-1516
December 2022

The Philippine Review of Economics

SPECIAL ISSUE ON MONETARY POLICY AND CENTRAL BANKING

Issue Editor **Faith Christian Q. Cacnio**

ARTICLES IN THIS ISSUE

A joint publication of the
University of the Philippines School of Economics
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PRE

The Philippine Review of Economics

A joint publication of the UP School of Economics (UPSE)
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Acknowledgements: The PRE gratefully acknowledges the financial support towards its publication provided by the Philippine Center for Economic Development (PCED). The Review nonetheless follows an independent editorial policy. The articles published reflect solely the editorial judgement of the editors and the views of their respective authors.

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The Philippine Review of Economics

Vol. LIX No. 2
December 2022
ISSN 1655-1516
DOI: 10.37907/ERP2202D

PRE The Philippine Review of Economics
59(2):1-40. DOI:10.37907/1ERP2202D

Nowcasting domestic liquidity in the Philippines using machine learning algorithms

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This study utilizes a number of algorithms used in machine learning to nowcast domestic liquidity growth in the Philippines. It employs regularization (i.e., Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO), Elastic Net (ENET)) and tree-based (i.e., Random Forest, Gradient Boosted Trees) methods in order to support the BSP's current suite of macroeconomic models used to forecast and analyze liquidity. Hence, this study evaluates the accuracy of time series models (e.g., Autoregressive, Dynamic Factor), regularization, and tree-based methods through an expanding window. The results indicate that Ridge Regression, LASSO, ENET, Random Forest, and Gradient Boosted Trees provide better estimates than the traditional time series models, with month-ahead nowcasts yielding lower Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Furthermore, regularization and tree-based methods facilitate the identification of macroeconomic indicators that are significant to specify parsimonious nowcasting models.

JEL classification: E40, E47, E50
Keywords: nowcasting, domestic liquidity, machine learning, ridge regression, LASSO, elastic net, random forest, gradient boosted trees

1. Introduction

1.1. Background of the study

Timely estimates or forecasts of different macro and socioeconomic indicators are needed to monitor developments in numerous sectors of the economy (e.g., households, depository corporations) and formulate appropriate policy (e.g., fiscal, monetary) responses. A reliable dataset allows assessment of an economy's overall condition and monitoring of situations that suggest imbalances or potential vulnerabilities. Some recent developments can allow policymakers to improve their ability to implement these forecasts and assessments.

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** The views, errors, and omissions are the sole responsibility of the author and not those of the institution represented.

One is the increased access to larger and more granular datasets that can potentially offer new insights (e.g., transactions level data in finance), and two is the use of modern data analysis techniques, including machine learning techniques, that are particularly suited for analyzing large and complex datasets [e.g., Carriere-Swallow and Haksar 2019].

However, management and analysis of economic data pose challenges. For example, certain types of official statistics, such as the Gross Domestic Product (GDP), may be hard to produce promptly and accurately (Dafnai and Sidi [2010]; Bragoli and Modugno [2016]; Chikamatsu et al. [2018]; Richardson et al. [2018]). The reasons may include the complex process of adequately classifying accounts, changes in the overall compilation framework, and inevitable delays in receiving source documents (Dafnai and Sidi [2010]; Chikamatsu et al. [2018]). As a result, policymakers from some countries are forced to formulate policies and address economic phenomena (e.g., inflation, business cycle) using outdated or lagged datasets [Richardson et al. 2018].

Nowcasting has been proposed as a tool to address some of these data challenges by International Financial Institutions (IFIs) (e.g., International Monetary Fund, World Bank), National Government Agencies (NGAs), and central banks from various countries. The objective of nowcasting is to provide estimates that could serve as early warning signals (EWS) to monitor the growth or development of certain indicators. Nowcasting, however, mainly aims to predict specific information or scenarios in the short run or in real-time (Bańbura et al. [2013]; Tiffin [2016]).

The International Monetary Fund (IMF), World Bank (WB), and Asian Development Bank (ADB) are among the IFIs that conduct comprehensive studies regarding the use of nowcasting in different fields of study (e.g., economics, finance). Meanwhile, the central banks of Indonesia, Japan, and New Zealand have implemented research that attempted to use nowcasting to estimate their respective GDP growth in the short run.[1]

1.2. Economic nowcasting, big data, and machine learning

Forecasts of the overall growth of an economy, quantitative analyses of the progress of a particular economic sector, or the transmission mechanism of policies have been commonly performed by using time series analysis, particularly univariate (e.g., Autoregressive Integrated Moving Average or ARIMA) and multivariate (e.g., Vector Autoregression (VAR), Dynamic Factor) models. These traditional methods are widely used due to their straightforward approach and ability to decompose the factors that mainly contribute to the movement of a particular target variable of interest.[2]

[1] See Dafnai and Sidi [2010], Chikamatsu et al. [2018], Richardson et al. [2018], and Tamara et al. [2020].

[2] Impulse Response Functions (IRFs) and Variance Decomposition are among the main characteristics of VAR.

However, in most cases, time series models depend on the timeliness of data or information. The publication delay of variables included in a particular model could hamper the attempt to estimate the future condition of the target output. For instance, to estimate the GDP for Q2:2020 using a simple AR(1) model, GDP as of end-Q1:2020 is needed.[3] In a typical situation, the publication of GDP for Q1:2020 is not released exactly at the end of said period. The latest figure is usually posted within one or three months after the reference date (e.g., GDP for Q2:2020 is published in August 2020, rather than end-June 2020).[4] Therefore, an individual or institution that aims to forecast the economic growth for Q2:2020 using an AR(1) model should wait until the data for GDP at the end-Q1:2020 is published.

The presence of lags in data availability is one of the main reasons for the adoption of nowcasting in economics. The advantage of nowcasting models (e.g., Mixed Data Sampling, Ridge Regression) is that they can use real-time information or higher-frequency data (e.g., daily financial data, survey results) in order to estimate a particular macro or socioeconomic variable (Bańbura et al. [2013]; Chikamatsu et al. [2018]; Richardson et al. [2018]). Hence, in contrast to a typical time series model used in economic forecasting, nowcasting models can also estimate the current state of a target variable of interest using data or information with different granularity levels [Tiffin 2016]. Moreover, since most conventional macroeconomic indicators are published with lags and frequent revisions, nowcasting has become an essential tool for policymakers to minimize the usual approach of attempting to estimate an economic variable using outdated or lagged data [Richardson et al. 2018].

Lastly, the emergence of nowcasting has been supported by recent trends favoring the use of big data and machine learning. This is mainly due to the potential of big data to provide supplementary information regarding current macro and socioeconomic data that may not be available yet. At the same time, machine learning can process the immense and sometimes difficult to manage information provided by big data (Hassani and Silva [2015]; Baldacci et al. [2016]; Richardson et al. [2018]).

1.3. The Philippines and domestic liquidity

Domestic liquidity (M3) is the total amount of broad money available in an economy, usually determined by a central bank and banking system. In the IMF's Monetary and Financial Statistics Manual (MSFM), this monetary indicator is similarly defined as the sum of all liquid financial instruments held by money-holding sectors, such as Other Depository Corporations (ODCs).

[3] Autoregressive Model of Order 1 or AR(1) model is defined as $y_t = \alpha_0 + \alpha_1 y_{t-1} + \epsilon_t$.
[4] Depending on the statistical calendar (or advance release calendar) of a specific country.

It can be categorized as an instrument widely accepted as (1) a medium of exchange or (2) a close substitute for the medium of exchange with a reliable store value [IMF 2016: 180].[5,6]

The change in its overall growth is considered an essential dynamic that most central banks closely monitor mainly because it is an essential element to the transmission mechanism of monetary policy, particularly its influence on aggregate demand, interest rates, inflation, and overall economic growth. For this reason, policymakers from different central banks diligently observe its expansion or contraction to formulate an effective and timely monetary policy response, especially when there are predicaments that require them to adjust policy rates to impede the negative implication of increasing inflation rates.

In the Philippines, domestic liquidity likewise plays an important role in an economy with a fractional-reserve banking system (e.g., US, Japan).[7] The Bangko Sentral ng Pilipinas (BSP) monitors its level and growth because the main components of this monetary aggregate are primarily used to measure liquidity in the country, input for early warning systems (EWS) models on the macroeconomy, and indicators to formulate and implement timely monetary policy, among others.[8,9]

The BSP announces domestic liquidity statistics in the Philippines on a monthly basis. Its Department of Economic Statistics (DES) consolidates the balance sheet of the BSP and ODCs to calculate this monetary indicator in a given period. However, for the domestic liquidity to be released promptly, the DES and Department of Supervisory Analytics (DSA) of the BSP need to ensure that punctual submission of bank reports (e.g., Financial Reporting Package for Banks) is observed.

1.4. Statement of the problem

Delay in data publication is one of the most common difficulties government institutions encounter. This scenario, unfortunately, is also observed in producing domestic liquidity statistics in the Philippines. Even though the BSP may meet the deadline to announce its latest available figure based on their advance release calendar (ARC), the publicly shared data on domestic liquidity are not based on real-time position. As seen in Table 1, data from the Depository Corporations Survey (DCS) dated November 15, 2021 actually refers to domestic liquidity statistics at end-September 2021 (e.g., the current release has lags of four to six weeks).

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[5] The MFSM is the official guideline of IMF member countries in the compilation of monetary statistics.

[6] ODCs refer to financial corporations (other than the central bank) that incur liabilities included in domestic liquidity [IMF 2016: 405].

[7] Fractional-reserve banking system refers to a system in which banks retain a portion of their overall deposits on reserves [Mankiw 2016: 620].

[8] Based on the DCS conducted by the BSP, domestic liquidity in the Philippines is mainly composed of currency in circulation and transferable deposits (M1), other deposits such as savings and time deposits (M2), and deposit substitutes such as debt instruments. The DCS is a consolidated report based on the balance sheets of BSP and ODCs, such as universal and commercial banks, thrift banks, rural banks, non-stock savings and loan associations, non-banks with quasi-banking functions [BSP, 2018].

[9] See BSP [2018].

Aside from this concern, the official data on domestic liquidity is also subject to revisions. Based on the publication policy of the BSP, the latest statistical reports (which include the DCS) are treated as preliminary information (Table 1).

The initial publication is revised within two months to reflect any changes in the reports submitted by the banks under its jurisdiction.[10] This procedure also applies to the other key statistical indicators produced by the said institution, such as the balance of payments (BOP) and flow of funds (FOF), to name a few. However, the preliminary and revised data have significant numerical discrepancies in some cases.

This study aims to mitigate these issues and concerns by investigating the use of different machine learning algorithms to estimate domestic liquidity growth in the Philippines. This research primarily intends to formulate a quantitative model that could support the BSP's suite of macroeconomic models used in forecasting (e.g., GDP, inflation, domestic liquidity) and policy analysis.

1.5. Significance of the study

For the past years, an increasing number of studies have focused on utilizing time series models and machine learning techniques to estimate different macro and socioeconomic indicators. The studies of Rufino [2017], Mapa [2018], and Mariano and Ozmucur [2015; 2020] are among the recent ones that have established the use of these methods to nowcast GDP and inflation in the Philippines. However, none of these published studies has explored the usefulness of nowcasting in monetary policy, particularly in using machine learning algorithms to estimate domestic liquidity growth in the country. This study contributes to the growing body of literature regarding the application of time series and machine learning models in economic forecasting or nowcasting.

In addition, although the BSP shifted to inflation targeting, domestic liquidity remains a critical indicator in monetary policy formulation. Liquidity forecasting is currently part of the institution's Multi-Equation Model (MEM) [Abenoja et al. 2022].[11] Therefore, the output of this study could serve as a supplementary tool to estimate domestic liquidity growth and input for MEM. The BSP is conducting MEM as part of its scenario-building and policy simulations.

Further, during a period of unstable inflation and significant change in the monetary policy transmission mechanism, a better understanding of how certain monetary variables, such as the behavior of domestic liquidity, could help formulate timely monetary policy.

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[10] See https://www.bsp.gov.ph/SitePages/Statistics/Financial%20System%20Accounts.aspx?TabId=2.

[11] Multi-equation Model (MEM) is part of the suite models of the BSP to capture the impact of main monetary policy transmission channels on inflation.

TABLE 1. Depository corporations survey SRF-based* (in million pesos)

	Levels (as of end period)				Changes in levels			Percent change		
					m-o-m	y-o-y		m-o-m	y-o-y	
	Aug-20	Sep-20	Aug-21[r,p]	Sep-21[p]	Sep 21-Aug21	Aug 21-Aug 20	Sep 21-Sep20	Sep 21[p]	Aug 21[r,p]	Sep 21[p]
1. Net foreign assets	**5,824,130**	**5,820,825**	**6,389,895**	**6,478,202**	**88,306**	**565,765**	**657,377**	**1.4**	**9.7**	**11.3**
A. Central bank	4,810,018	4,876,070	5,403,016	5,449,416 **a**	46,400	592,998	573,346	0.9	12.3	11.8
Claims on non-residents	4,886,081	4,952,171	5,620,943	5,670,102	49,159	734,862	717,931	0.9	15.0	14.5
Less: Liabilities to non-residents	76,063	76,101	217,927	220,686	2,759	141,864	144,585	1.3	186.5	190.0
B. Other depository corporation	1,014,112	944,755	986,880	1,028,786	41,906	-27,233	84,031	4.2	-2.7	8.9
Claims on non-residents	1,824,329	1,780,523	1,832,284	1,869,384	37,099	7,955	88,860	2.0	0.4	5.0
Less: Liabilities to non-residents	810,217	835,769	845,404	840,598	-4,806	35,187	4,829	-0.6	4.3	0.6
2. Domestic claims	**13,395,104**	**13,419,434**	**14,298,755**	**14,453,939**	**144,777**	**903,652**	**1,024,098**	**1.0**	**6.7**	**7.6**
A. Net claims on central government	2,734,907	2,795,251	3,374,427	3,475,636	101,209	639,520	680,385	3.0	23.4	24.3
Claims on central government	4,492,141	4,212,202	5,545,403	5,704,164	158,761	1,053,262	1,491,962	2.9	23.4	35.4
less: Labilities to central government	1,757,234	1,416,951	2,170,977	2,228,528	57,552	413,743	811,577	2.7	23.5	57.3
B. Claims on other sectors	10,660,197	10,624,183	10,924,329	10,967,896	43,567	264,132	343,713	0.4	2.5	3.2
Claims on other fnancial corporations	1,170,415	1,177,373	1,163,359	1,184,593	21,234	-7,056	7,220	1.8	-0.6	0.6
Claims on state andlocal government	98,124	98,663	114,742	116,642	1,901	16,618	17,979	1.7	16.9	18.2
Claims on public nonfinancial corporations	231,711	231,854	265,915	268,356	2,441	34,205	36,502	0.9	14.8	15.7
Claims on private sector	9,159,948	9,116,293	9,380,313	9,398,304	17,992	220,365	282,011	0.2	2.4	3.1

TABLE 1. Depository corporations survey SRF-based* (in million pesos) (continued)

	Levels (as of end period)				Changes in levels			Percent change		
					m-o-m	y-o-y		m-o-m	y-o-y	
	Aug-20	Sep-20	Aug-21^{r,p}	Sep-21^{p}	Sep 21-Aug21	Aug 21-Aug 20	Sep 21-Sep20	Sep 21^{p}	Aug 21^{r,p}	Sep 21^{p}
3. Liquidity aggregates										
M4 (M3 + 3.e)	15,603,502	15,583,711	16,591,084	16,785,106	194,022	987,382	1,201,395	1.2	6.3	7.7
M3 (M2 + 3.d)3	13,510,788	13,498,470	14,446,660	14,610,565	163,905	935,871	1,112,094	1.1	6.9	8.2
M2 (M1 + 3.c)	12,773,018	12,832,393	13,802,137	14,003,725	201,587	1,029,120	1,171,332	1.5	8.1	9.1
M1 (3.a + 3.b)	5,004,217	5,028,958	5,682,135	5,758,369	76,233	677,918	729,411	1.3	13.5	14.5
3.a Currency outside depository corporations	1,540,227	1,533,370	1,657,808	1,680,864	23,056	117,581	147,494	1.4	7.6	9.6
3.b Transferable deposits included in broad money	3,463,991	3,495,587	4,024,327	4,077,504	53,177	560,337	581,917	1.3	16.2	16.6
3.c Other deposits included in broad money	7,768,800	7,803,435	8,120,002	8,245,356	125,354	351,202	441,921	1.5	4.5	5.7
Savings deposits	5,340,769	5,396,116	5,983,301	6,075,436	92,135	642,532	679,320	1.5	12.0	12.6
Time deposits	2,428,032	2,407,319	2,136,701	2,169,921	33,219	-291,330	-237,398	1.6	-12.0	-9.9
3.d Securities other than shares included in broad money	737,771	666,078	644,522	606,840	-37,682	-93,249	-59,238	-5.8	-12.6	-8.9
3.e Transferable and other deposits in foreign currency (FCDs-residents)	2,092,714	2,085,240	2,144,425	2,174,541	30,116	51,711	89,301	1.4	2.5	4.3
4. Liabilities excluded from broad money	**3,615,732**	**3,656,548**	**4,097,567**	**4,136,628**	**39,061**	**481,834**	**480,080**	**1.0**	**13.3**	**13.1**

Source: BSP (accessed on November 15, 2021)

2. Review of related literature

2.1. Regularization methods[12,13]

Tiffin [2016] and Dafnai and Sidi [2010] used regularization methods to formulate nowcasting models that could accurately estimate GDP growth in Lebanon and Israel, respectively. To address data publication lags, the studies by these authors show how current economic growth can be estimated, despite data lags, to improve policy decisions. Their attempt to formulate nowcasting models also aimed to address the difficulty of their stakeholders from the domestic (e.g., NGAs, central banks) and international (e.g., IFIs, bilateral partners) landscape in assessing the overall economic health of their respective countries (Tiffin [2016]; Dafnai and Sidi [2010]).

The authors used higher-frequency data as explanatory variables to their corresponding GDP nowcasting models. Tiffin [2016] used 19 monthly macroeconomic variables (e.g., customs revenue, tourist arrivals) to observe economic growth in Lebanon.[14] Through regularization methods, the author found that the Elastic Net (ENET) is the most suitable machine learning algorithm to estimate the short-run economic development of Lebanon. Mainly because the result (i.e., in-sample, out-of-sample) systematically traces the cyclical movement of Lebanon's GDP with a small Root Mean Square Error (RMSE).

Dafnai and Sidi [2010], on the other hand, used 140 domestic indicators and 15 global indicators as input variables to nowcast the GDP in Israel.[15] The authors found that ENET is the most comprehensive method to forecast the country's economic growth. Furthermore, compared to other regularization models used in their study, Dafnai and Sidi [2010] argued that ENET is the only model that successfully captured the timing and magnitude of Israel's economic cycle while generating a low Mean Absolute Forecast Error (MAFE).

Hussain et al. [2018] used similar machine learning algorithms to nowcast the short-run growth of Large-Scale Manufacturing (LSM) in Pakistan to compensate for lags in the publication of official GDP data. The authors also used high-frequency data or information as explanatory variables to nowcast LSM, including monthly data regarding financial markets, confidence surveys,

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[12] Regularization methods constrain coefficient estimates to reduce their variance with the intention to improve the overall model fit. Moreover, these approaches incorporate penalties to their regression coefficient(s) to address the issue of bias-variance tradeoff [James et al. 2013].

[13] Among the regularization methods used in this study are (1) Ridge Regression, (2) LASSO, and (3) ENET. Ridge Regression imposes a penalty to their regression coefficient(s) which shrink all of them towards zero. This is also the case for LASSO. However, it forces some of its coefficient estimates to be exactly equal to zero when parameter is large. ENET contains both properties of Ridge Regression and LASSO [James et al. 2013]. Equations of these methods are presented in Section 4 of this paper.

[14] See page 10 of Tiffin [2016].

[15] See Annex of Dafnai and Sidi [2010].

interest rate spreads, credit, and the external sector in Pakistan.[16] Hussain et al. [2018] concluded that regularization methods such as Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO), and ENET are useful quantitative tools for estimating the overall growth of LSM. These models are able to observe trends and cyclical movement of LSM with minor forecast errors. However, LASSO had the lowest RMSE [Hussain et al. 2018].

Regularization methods were likewise used by Cepni et al. [2018] as well as Ferrara and Simoni [2019]. These authors utilized the said concepts to formulate models that could accurately nowcast the GDP of emerging economies (i.e., Brazil, Indonesia, Mexico, South Africa, Turkey) and the US, respectively. Again, similar to the previous studies discussed, numerous high-frequency data or information were used as explanatory variables to estimate the economic growth of said countries.

Cepni et al. [2018], in particular, utilized country-specific macroeconomic indicators such as industrial production, demand, and consumption indices and survey data from Market Purchasing Managers' Index (PMI).[17] On the other hand, Ferrara and Simoni [2019] used a large set of data from Google (e.g., Google Trends) to nowcast GDP in the US.[18] The former authors notably used LASSO to augment the nowcasting activity through DFM. Meanwhile, the latter authors utilized Ridge Regression and compared it with their bridge equation benchmark model since numerous variables were included in their model.

Both studies have concluded that these machine learning models give an empirically accurate estimate of the short-run growth of GDP. This is because Ridge Regression and LASSO provide a parsimonious set of nowcasting models with accurate results (Cepni et al. [2018]; Ferrara and Simoni [2019]).

2.2. Tree-based methods[19]

Biau and D'Elia [2010] used the Random Forest (RF) algorithm to forecast short-term GDP growth in Europe. The authors used numerous datasets—under the European Union Business and Consumer Survey—to improve prediction accuracy.[20] Based on this approach, the authors concluded that the particular tree-based machine learning algorithm estimates the short-term growth of GDP in Europe more accurately than the univariate autoregressive (AR) model and is somehow tantamount to the quarterly projections of the *eurozone economic outlook*.[21] This is mainly due to the RF's low forecast error,

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[16] See page 13 of Hussain et al. [2018].
[17] See page 2 of Cepni et al. [2018].
[18] See page 7 of Ferrera and Simoni [2019].
[19] Tree-based methods are non-parametric techniques that do not require underlying relationship between dependent and independent variables. It involves stratifying or segmenting the predictor space into a number of simple regions. Hence, the mean or mode of the (training) dataset is used in the region to which it belongs to estimate a given observation [James et al. 2013: 303].
[20] See page 6 of Biau and D'Elia [2010].
[21] Official economic expectation/forecast of Eurosystem.

which only generated an MSE of 0.43. Meanwhile, the univariate and official economic outlook produced 0.64 and 0.15 MSE, respectively. Supplemental to this result, the machine learning-based GDP forecast for Europe specified a parsimonious model by identifying which predictive variables included in their model are useful [Biau and D'Elia, 2010].

Drawing on the methodology of Biau and D'Elia [2010], Adriansson and Mattsson [2015] also used RF to estimate Sweden's quarterly economic growth. The authors support this objective by using the data from the Economic Tendency Survey—conducted by the National Institute of Economic Research (NIER)—as inputs for their tree-based nowcasting. Based on this research framework, Adriansson and Mattsson [2015] found that RF provides a better prediction performance (RMSE 0.75) against the ad hoc linear model and ARIMA (RMSE 0.79 and 0.95, respectively) in forecasting the GDP growth of Sweden [Adriansson and Mattsson 2015].

Aside from RF, Adaptive Trees (AT)—based on Gradient Boosted Trees (GBT)—was also used as a primary machine learning technique in forecasting. This is because of its ability to deal with nonlinearities and structural changes, among others (James et al. [2013]; Woloszko [2020]). The paper of Woloszko [2020] was one of the recent studies that specifically used AT to provide a 3- to 12-months ahead GDP growth forecast for the Group of Seven (G7) countries.[22] In this study, the author employed country-specific information (e.g., expectation surveys, consumer confidence) and macroeconomic data (e.g., housing prices, employment rate) as explanatory variables to the tree-based forecasting model.[23]

Based on the forecast simulations, Woloszko [2020] concluded that the RF algorithm is a valuable tool in economic forecasting, yielding more accurate prediction results than the traditional time series models. In contrast to univariate models, the 3- and 6-months ahead GDP growth forecast for the US, UK, France, and Japan using AT displayed lower RMSEs. However, the forecasting performance of AT worsened for the 1-year-ahead forecast. Woloszko [2020] therefore argued that despite having the advantage of handling a large number of variables in economic forecasting, AT might not be a suitable model to predict long-run effects.

Other empirical studies utilized both RF and GBT as models to forecast economic growth. Among these were the papers of Boluis and Rayner [2020] as well as Soybilgen and Yazgan [2021]. In particular, these authors used the said methods to forecast the GDP growth in Turkey and the US, respectively.

Similar to the previous studies discussed in this section, these authors aimed to determine the best-performing tree-based method to estimate economic growth using higher-frequency data or information, similar to the previous studies discussed in this section. In particular, the study of Boluis and Rayner [2020] used 234 country-specific and global indicators from Haver Analytics. This includes

[22] Canada, however, was not included in the analysis of Woloszko [2020].
[23] See page 11 of Woloszko [2020].

macroeconomic indicators regarding the financial, labor, and external sectors.[24] Meanwhile, Soybilgen and Yazgan [2021] utilized more than 100 financial and macroeconomic variables, including the labor market, money and credit, and stock market data.[25]

Using these input variables, Boluis and Rayner [2020] as well as Soybilgen and Yazgan [2021] concluded that the tree-based methods provide superior forecasts than the benchmark models. This is due mainly to low forecast errors of tree-based methods against DFM. Specifically, Boluis and Rayner [2020] mentioned that RF and GBT respectively registered RMSE of 1.26 and 1.29 compared to the benchmark models, which displayed an RMSE of 1.66.[26] Aside from their outstanding individual accuracy, these authors also cited that the tree-based methods can estimate economic volatility and determine which variables included in the forecasting model are better predictors.

2.3. The utilization of two approaches

Several studies also utilize the strengths of both regularization and tree-based methods to perform forecasting or nowcasting. Authors of these studies have considered this approach in order to distinguish the accuracy of each machine learning algorithm in estimating the growth of a particular macroeconomic indicator or phenomenon and assess the overall fit (e.g., linear, nonlinear) of the variables in a particular model (Richardson et al. [2018]; Aguilar et al. [2019]; Tamara et al. [2020]).

Richardson et al. [2018] used regularization and tree-based methods to formulate a model that could accurately predict the movement of GDP growth in New Zealand. The goal was to reduce the reliance on non-related, outdated, or lagged data in policymaking. To attain this objective, the authors used several higher frequency macroeconomic and financial market statistics as explanatory variables to their simulated nowcasting models. These include data from business surveys, consumer and producer prices, and general domestic activity production, among others.[27]

By using these as regressors for the different models, Richardson et al. [2018] concluded that regularization and tree-based methods could both be used as the primary methods to nowcast the economic growth in New Zealand because of lower forecast errors than traditional time series models. In particular, the authors found that LASSO, GBT, and Ridge Regression had RMSE of 0.45, 0.47, and 0.57, respectively, lower than time series models, such as ARIMA, DFM, and Bayesian VAR.

Tamara et al. [2020] also used regularization and tree-based methods to forecast Indonesia's GDP growth. The authors correspondingly used 18 predictor variables, including quarterly macroeconomic (e.g., consumption expenditure,

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[24] See Tables A5.1 and A5.2, pages 24-25 of Boluis and Rayner [2020].
[25] See Appendix 1, page 23 of Soybilgen and Yazgan [2021].
[26] See Table 1 and 2, page 13 of Soybilgen and Yazgan [2021].
[27] See page 8 of Richardson et al. [2018].

current account) and financial market statistics (e.g., change in stock price) data.[28] Using these indicators as explanatory variables, the authors concluded that regularization and tree-based methods provide better results in estimating the short-run GDP growth of Indonesia, as shown by low RMSE and Mean Average Deviation (MAD). The authors also found that regularization and tree-based methods reduced the average forecast errors from 38 to 63 percent relative to ARIMA. Furthermore, Tamara et al. [2020] find that RF and ENET have the lowest average forecast errors, at 1.27 and 1.31, respectively.

3. Data

3.1. Target variable

The target variable in this study is the monthly data on domestic liquidity growth in the Philippines. This monetary indicator represents the total amount of money available in the economy. The numerical figures (i.e., level, growth rate) of domestic liquidity are acquired from the monthly DCS that the BSP published on its website from January 2008 to December 2020.[29]

3.2. Input variables

Like previous nowcasting studies that use machine learning algorithms, higher-frequency data are used as explanatory variables in this research. These comprise daily or weekly (1) monetary, (2) financial, and (3) external sector indicators.[30] In addition, to capture other determinants that could also influence domestic liquidity growth (i.e., heterogeneity), lagged value of the domestic liquidity is considered an input variable in this study. Data for input variables also cover January 2008 to December 2020 (Table 2).

3.3. Averaging and interpolation[31]

Averaging and interpolating are conducted to correctly align the frequency of all the data used in this study. The former was performed on variables with a daily and weekly frequency. In particular, these data were aggregated and

[28] See Appendix of Tamara et al. [2020].
[29] To ensure that the data on domestic liquidity are not subject to any revisions, the last figure used in this study was as of end-December 2020.
[30] Monetary indicators are composed of available reserves, reserve money, central bank claims on national government, and central bank claims on other sectors of the economy. Financial indicators comprise Weighted Money Operations Rate (WMOR), BSP discount rate, CBOE volatility index, CDS spread, LIBOR, SIBOR, PHIREF, Government Bond Rate, Interbank Call Loan Rate, bank prime rate, treasury bill rate, promissory note rate. External indicators are consisted of foreign portfolio investment and foreign exchange rate.
[31] Averaging and interpolation were conducted to maximize each input variable with a higher frequency (i.e., daily data) to solve the problem caused by the "curse of dimensionality" or fat regression (i.e., various input variables with limited observations).

averaged into two numerical values in a month. The first value is the average from the first until the 15th day of the month, while the other half is the mean from the 16th until the last day of the month (e.g., available reserves data from January 1 to 15 and January 16 to 31 are averaged, respectively). On the other hand, explanatory variables with weekly frequency are averaged. Meanwhile, the latter was implemented on the variables with low frequency (i.e., monthly), such as domestic liquidity, BSP liabilities on NG, and BSP claims on other sectors. The data points between each period of averaged input variable data (e.g., mid-month data) are considered missing values and interpolated using a spline interpolation method commonly used for nonlinear data estimation.

TABLE 2. List of data

No.	Variable	Type	Frequency	Publication delay (days after ref. date)
1	Domestic Liquidity (M3) Growth	Target Variable	Monthly	30
2	M3 Growth (T-1)	Input Variable	Monthly	-
3	BSP Liabilities on National Government	Input Variable	Monthly	15
4	BSP Claims on Other Sectors	Input Variable	Monthly	15
5	Foreign Portfolio Investment (In)	Input Variable	Weekly	30
6	Foreign Portfolio Investment (Out)	Input Variable	Weekly	30
7	Available Reserves	Input Variable	Daily	1
8	Reserve Money	Input Variable	Daily	1
9	CBOE Volatility Index	Input Variable	Daily	1
10	Credit Default Swap	Input Variable	Daily	1
11	London Interbank Reference Rate	Input Variable	Daily	1
12	Singapore Interbank Reference Rate	Input Variable	Daily	1
13	Philippine Interbank Reference Rate	Input Variable	Daily	1
14	Philippine Government Bond Rate	Input Variable	Daily	1
15	BSP Discount Rate	Input Variable	Daily	1
16	Bank Savings Rate	Input Variable	Daily	1
17	Bank Prime Rate	Input Variable	Daily	1
18	Money Market Rate (Promissory Note)	Input Variable	Daily	1
19	Treasury Bill Rate	Input Variable	Daily	1
20	Interbank Call Rate	Input Variable	Daily	1
21	Philippine Peso per US Dollar (FOREX)	Input Variable	Daily	1
22	Weighted Monetary Operations Rate	Input Variable	Daily	1

4. Research methodology

4.1. Models

Two types of models are used in this study. First, as a benchmark, univariate (i.e., ARIMA, Seasonal ARIMA, Random Walk) and multivariate (i.e., DFM) time series models are estimated. Second, machine learning algorithms, namely regularization (i.e., Ridge Regression, LASSO, ENET) and tree-based (i.e., RF, GBT) models, are estimated as alternatives. The objectives are: (1) to establish which quantitative models could accurately estimate the monthly growth of the monetary indicator; and (2) to determine how well recent regularization methods applied to machine learning nowcast vis-à-vis traditional time series models.

4.1.1. Autoregressive Integrated Moving Average (ARIMA)

The forecasting equation using ARIMA is structured as follows:

$$\hat{y}_t = \mu + \phi_0 + \phi_1\, y_{t-1} + \ldots + \phi_2\, y_{t-p}\, \ldots + \theta_1\, e_{t-1} - \ldots - \theta_q\, e_{t-q} \tag{1}$$

In Equation 1, p represents the order of the autoregression, which includes the overall effect(s) of past values under consideration. The notation q, on the other hand, denotes the order of the moving average, constructing the error of ARIMA as a linear combination of the error values observed at the previous time points in the past (Meyler et al. [1998]; Fan [2019: 10-11]).

4.1.2. Random Walk

The general equation of Random Walk is:

$$\hat{y}_t = \epsilon_t + y_{t-1} \tag{2}$$

In Equation 2, the y_t and y_{t-1} represent the observations of the time series and ϵ_t is the white noise with zero mean and constant variance [Fan 2019: 12].

4.1.3. Dynamic Factor Model

The Dynamic Factor Model (DFM) is expressed as:

$$X_t = \lambda(L) f_t + \epsilon_t \tag{3}$$

In Equation 3, notation X_t represents the vector of observed time series variables depending on a reduced number of latent factors f_t and an idiosyncratic component ϵ_t. The $\lambda(L)$ denotes the lag polynomial matrix, which represents the vector of dynamic factor loading (Stock and Watson [2016]; Fan [2019]).

4.1.4. Ridge Regression

Equation 4 depicts the residual sum of squares and the penalty term (λ) in a Ridge Regression:

$$\sum_{t=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \quad (4)$$

The notation n represents the total number of observations included in the model, while p is the number of candidate predictors. The essential factor in this equation is the tuning parameter λ, which controls the relative impact of the regression coefficient estimates [James et al. 2013: 215]. When $\lambda = 0$, the penalty has no effect, and Ridge Regression produces estimates similar to OLS estimates. However, as $\lambda = \infty$, the impact of the shrinkage penalty increases, and the coefficient estimates approach zero [Tiffin 2016].

4.1.5. Least Absolute Shrinkage and Selection Operator (LASSO)

Similar to Ridge Regression, LASSO also includes a penalty term for its RSS (Equation 5).

$$\sum_{t=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} |\beta_j| \quad (5)$$

In contrast with the Ridge Regression, which only shrinks all of its coefficients towards zero, LASSO forces its coefficients to be precisely equal to zero when the tuning parameter λ is adequately large [James et al. 2013]. Therefore, due to its substantial penalty, the main difference between LASSO and Ridge Regression is their ability to select variables and produce a parsimonious model with fewer predictors.

4.1.6. Elastic Net (ENET)

ENET is a regularization method that contains both properties of Ridge Regression and LASSO (See Equation 6).

$$\sum_{t=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} [(1 - \alpha)(\beta_j^2) + \alpha|\beta_j| \quad (6)$$

In particular, it utilizes the shrinkage properties of Ridge Regression and LASSO by selecting the best predictors to provide parsimonious models while still identifying groups of correlated predictors. The respective weights of the two penalties are determined through the additional tuning parameter α [Richardson et al. 2018].

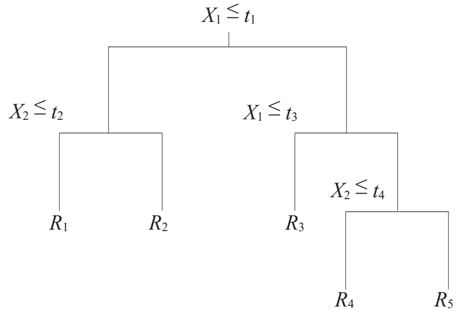
4.1.7. Random Forest (RF)

RF is a tree-based machine learning algorithm that uses combinations of multiple decision trees to formulate a comprehensive forecast.[32] It modifies the decision tree approach to minimize the overfitting problem and maximize the data's information content by using subsamples of observations and predictions (Tiffin [2016]; Bolhuis and Rayner [2020]). In particular, RF uses bootstrap aggregation (also known as bagging) in each decision tree using a random sample of observations in the training dataset. This procedure is repeated k number of times, and the results are averaged to reduce the overall variance without increasing the bias of the dataset. It also uses random sampling in each split to ensure that the multiple trees that go into the final collection are relatively diverse (Tiffin [2016]; Bolhuis and Rayner [2020]).

4.1.8. Gradient Boosted Trees (GBT)

GBT is a machine learning algorithm that formulates sequential decision trees rather than combinations to construct an aggregate forecast (Figure 1). This tree-based model does not involve the bootstrap sampling that RF conducts. Instead, GBT trains an initial decision tree based on the time-series data. It then uses the prediction errors from said decision tree to train a second decision tree. Next, the errors from the second decision tree are used to train the tree, and so on. After the final iteration, the algorithm uses the summation of these predictions to provide a final forecast (James et al. [2013]; Bolhuis and Rayner [2020]).

FIGURE 1. Decision tree growing process
Recursive binary splitting of two-dimensional feature space



Source: James et al. [2013]

[32] Decision Tree is the fundamental structure of any tree-based machine learning method used for classification and regression problems (James et al. [2013]; Fan [2019]). This approach divides categorical (e.g., name, address) or continuous (e.g., level, growth rate) data into two classes in a systematic manner to reduce the prediction error of the target variable of interest. This procedure is repeated until the number of training samples at the branch exceeds the minimum node size. The algorithm, afterward, performs the estimation by using the mean or mode of training observation in that particular region [James et al. 2013].

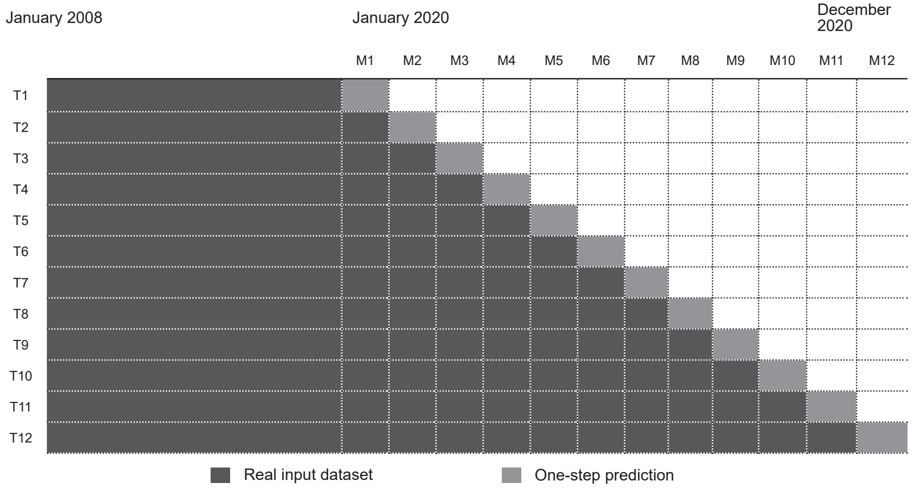
4.2. Nowcast evaluation methodology

In order to estimate domestic liquidity growth in the short run, this study evaluates the performance of time series models and machine learning algorithms based on their one-step-ahead (out-of-sample) nowcast. This approach is preferred over multi-step-ahead (out-of-sample) estimates because it fulfills the objective of providing an estimate for currently unavailable data that can be utilized for more timely prediction and policy analysis.

In addition, it is crucial to determine the consistency of simulated models. Therefore, the benchmark and machine learning models are trained over an expanding window to provide a series of one-step-ahead nowcasts.[33] The dataset covering 13 years from 2008 to 2020 is divided into training and test datasets to perform the said approach. The first training dataset covers the numerical figures of the target and input variables from January 2008 to December 2019. Meanwhile, its corresponding test dataset comprises the numerical statistics of target and input variables as of January 2020. This process is accomplished until the test dataset covers the numerical figures of the target and input variables as of December 2020 (Figure 2).

Under this approach, the accuracy of each time series and machine learning model is measured through their respective forecast errors, such as RMSE and MAE. The forecast errors of regularization and tree-based methods are then individually and collectively evaluated against benchmark (i.e., univariate, multivariate) models in order to determine whether the nowcast results obtained from the former are significantly superior to the latter methods or vice versa.

FIGURE 2. Expanding window process



[33] For conducting an expanding window (or recursive scheme) evaluation in this study, the dataset used for the first nowcast (i.e. January 2020) was based on January 2008 to December 2019. Likewise, the dataset used for the second nowcast (i.e., February 2020) is based on January 2008 to January 2020. This process is done until the last out-of-sample period (December 2020).

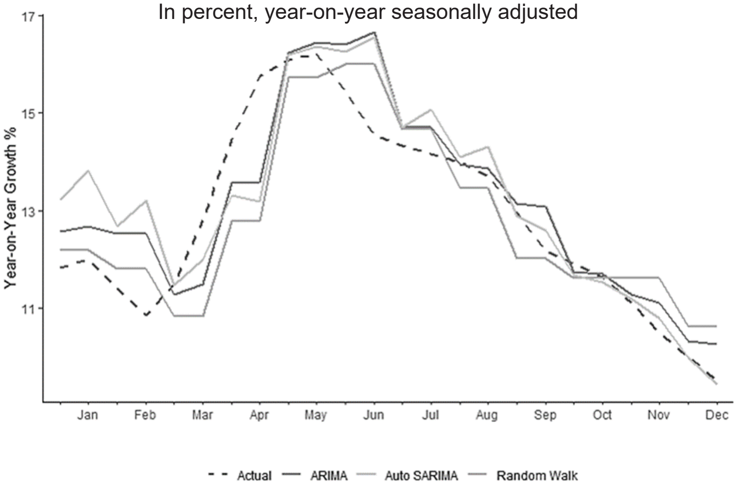
5. Results and analysis[34]

5.1. Univariate models

The results of ARIMA, Random Walk, and Seasonal ARIMA (SARIMA) indicate that their respective one-step-ahead (out-of-sample) nowcasts from January to December 2020 depict the overall trend of domestic liquidity growth in the Philippines (Figure 3).[35] Furthermore, the said univariate models provided reasonable estimates in the months wherein the growth of domestic liquidity (i.e., April, May) suddenly expanded due to the decrease of national government deposits to the central bank (e.g., central bank liabilities to central government).

FIGURE 3. Autoregressive model nowcasts vs. Actual M3 growth (January to December 2020)

In percent, year-on-year seasonally adjusted



However, by comparing their respective monthly forecast errors, it can be observed that SARIMA has provided the highest number of months with low RMSE and MAE (i.e., March, May, September, November, December) (Tables 3 and 4). This was followed by the results from Random Walk (i.e., January, February, June, July) and ARIMA (i.e., April, August, October), respectively.

The overall forecast errors of the three univariate models, on the other hand, gave different results. Based on their overall forecast errors, ARIMA provides relatively reasonable estimates with an RMSE of 0.917 and an MAE of 0.688.

[34] All of the models used in this study are calibrated. Optimal lags for univariate models were based on the result of Partial Autocorrelation Function (PACF) and Akaike Information Criterion (AIC). DFM followed the calibration made by Mariano and Ozmucur [2020], which was centered through the optimal eigenvalues through factor analysis. Lastly, machine learning techniques were calibrated using cross-validation method (i.e., tenfold cross-validation, leave-one-out cross validation).

[35] The decision to consider three univariate models, such as ARIMA, Random Walk, and SARIMA are based on the conducted stationarity (i.e., Augmented Dickey-Fuller, Philips-Perron) tests and the result of lag selection based on their respective AIC and Bayesian Information Criterion (BIC). ARIMA has (4,1,1) parameters, Random Walk has (0,1,0) parameters, and SARIMA has (5,1,1)(1,0,1) parameters.

These are lower than the overall forecast errors of Random Walk (1.016 and 0.766) and SARIMA (1.066 and 0.739), respectively (Tables 3 and 4).

TABLE 3. RMSE of autoregressive models[36]

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
ARIMA	0.716	1.422	0.936	1.663	0.196	1.636	0.474	0.102	0.649	0.117	0.452	0.577	0.917
RWalk	0.288	0.722	1.470	2.415	0.434	1.095	0.425	0.403	0.669	0.199	0.880	0.895	1.016
SARIMA	1.622	1.879	0.556	1.986	0.134	1.535	0.702	0.428	0.299	0.174	0.222	0.057	1.066

TABLE 4. MAE of autoregressive models

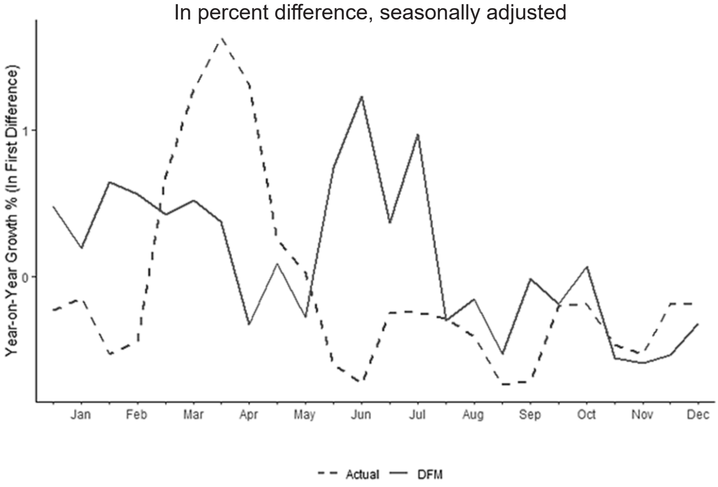
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
ARIMA	0.715	1.395	0.762	1.537	0.194	1.527	0.467	0.088	0.544	0.106	0.389	0.537	0.688
RWalk	0.273	0.669	1.319	2.327	0.428	0.996	0.416	0.380	0.543	0.149	0.825	0.862	0.766
SARIMA	1.609	1.801	0.405	1.854	0.134	1.411	0.650	0.355	0.244	0.162	0.194	0.050	0.739

5.2. Dynamic Factor Model[37,38]

In contrast to the three univariate models, DFM provides inconsistent estimates of the overall movement of domestic liquidity in the first semester of 2020. Notably, the monthly one-step-ahead (out-of-sample) nowcasts of DFM did not capture the sudden expansion of this monetary indicator (Figure 4).

FIGURE 4. DFM nowcasts vs. actual M3 growth (January to December 2020)

In percent difference, seasonally adjusted



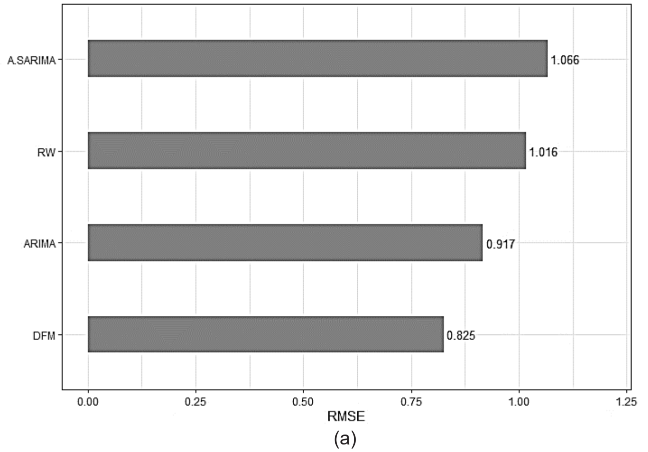
[36] M1 to M12 refers to the months included in the expanding window validation (e.g., January, February 2020).

[37] DFM was utilized as multivariate model because it reduces the dimension of the wide range of high-frequency monetary, financial, and external sector indicators as input variables used in this study.

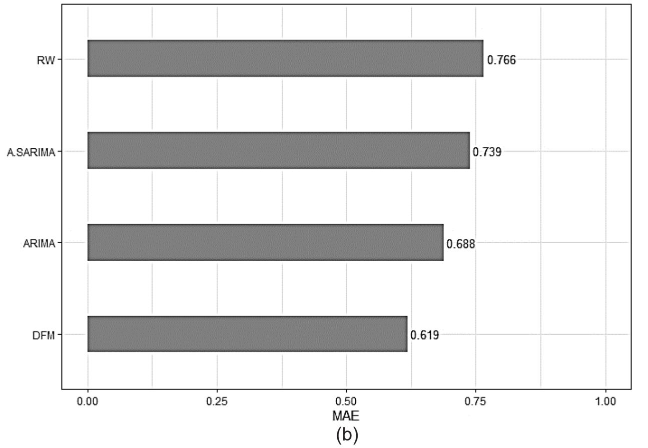
[38] Three factors were extracted from the initial 20 input variables using the method of maximum likelihood by performing factor analysis.

However, DFM provides more accurate results in the latter half of the year. It can be observed that the monthly forecast errors of the said model are relatively lower than those under ARIMA, Random Walk, and SARIMA, particularly from August to December 2020 (Tables 5 and 6). In addition, this particular outcome can similarly be observed in the overall forecast errors of DFM. The multivariate model only conveyed an overall RMSE and MAE of 0.825 and 0.619, respectively. These forecast errors are relatively lower than the ones displayed by the univariate models (Figure 5).

FIGURE 5. Overall (a) RMSE and (b) MAE of autoregressive models and DFM



(a)



(b)

TABLE 5. RMSE of DFM

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
DFM	0.557	1.093	0.565	1.458	0.247	1.678	0.965	0.184	0.513	0.182	0.078	0.267	0.825

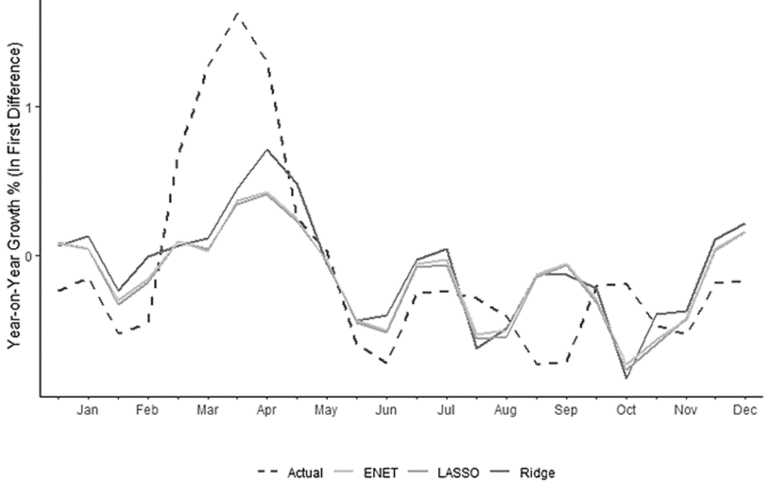
TABLE 6. MAE of DFM

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
DFM	0.526	1.091	0.509	1.446	0.237	1.649	0.918	0.138	0.452	0.136	0.077	0.246	0.619

5.3. Regularization methods[39]

The result showed that Ridge Regression, LASSO, and ENET could provide estimates with relatively higher precision than the benchmark models. In particular, the monthly nowcasts of these models have lower forecast errors than the individual estimates stipulated by ARIMA, Random Walk, SARIMA, and DFM (Tables 7 and 8), except for September and October 2020 (Figure 6). In addition, the regularization methods estimate domestic liquidity with low forecast errors in the months when it unexpectedly expands due to the increase in borrowings and deposits of the national government to the central bank from March to May 2020 (Tables 7 and 8).

FIGURE 6. Regularization method nowcasts vs. actual M3 growth (January to December 2020)
In percent difference, seasonally adjusted



A similar result was observed from the overall forecast errors when using the three regularization methods. In particular, the Ridge Regression, LASSO, and ENET showed lower overall RMSE and MAE than ARIMA (0.917 and 0.688), Random Walk (1.016 and 0.766), SARIMA (1.066 and 0.739), and DFM (0.825 and 0.619) (Figure 7).

[39] All regularization methods used in this study are tuned/calibrated using tenfold cross-validation method.

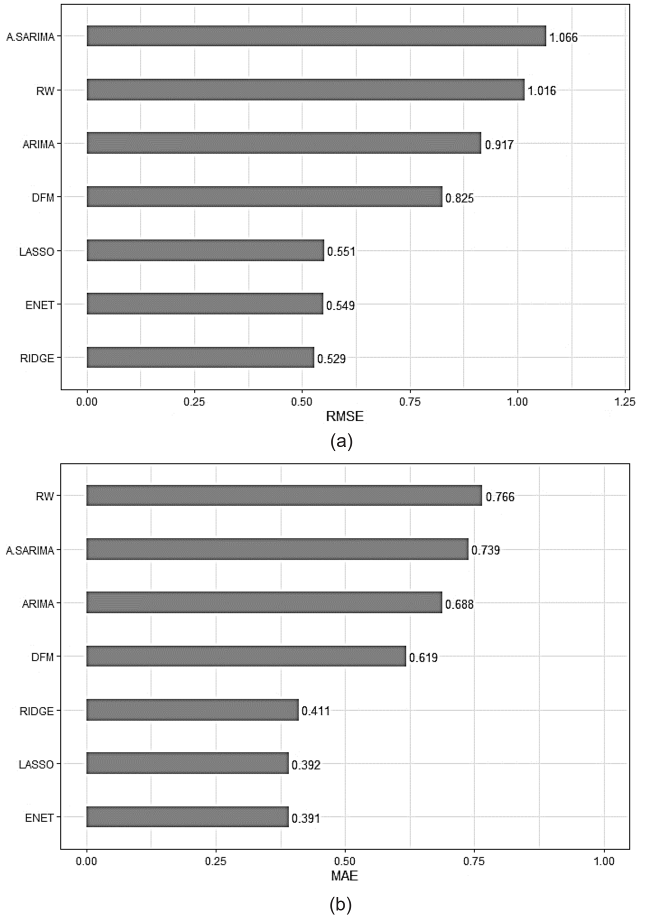
TABLE 7. RMSE of ridge regression, LASSO, and ENET

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
Ridge	0.292	0.372	0.928	1.163	0.173	0.258	0.261	0.248	0.596	0.449	0.123	0.349	0.529
LASSO	0.264	0.237	0.964	1.348	0.046	0.185	0.179	0.215	0.621	0.416	0.115	0.286	0.551
ENET	0.262	0.259	0.973	1.328	0.048	0.199	0.206	0.187	0.631	0.390	0.099	0.291	0.549

TABLE 8. MAE of ridge regression, LASSO, and ENET

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
Ridge	0.292	0.364	0.887	1.136	0.156	0.245	0.259	0.209	0.596	0.325	0.116	0.345	0.411
LASSO	0.257	0.234	0.909	1.340	0.040	0.182	0.179	0.202	0.620	0.345	0.114	0.281	0.392
ENET	0.255	0.257	0.916	1.321	0.036	0.196	0.206	0.171	0.631	0.318	0.099	0.286	0.391

FIGURE 7. Overall (a) RMSE and (b) MAE of benchmark models and regularization methods

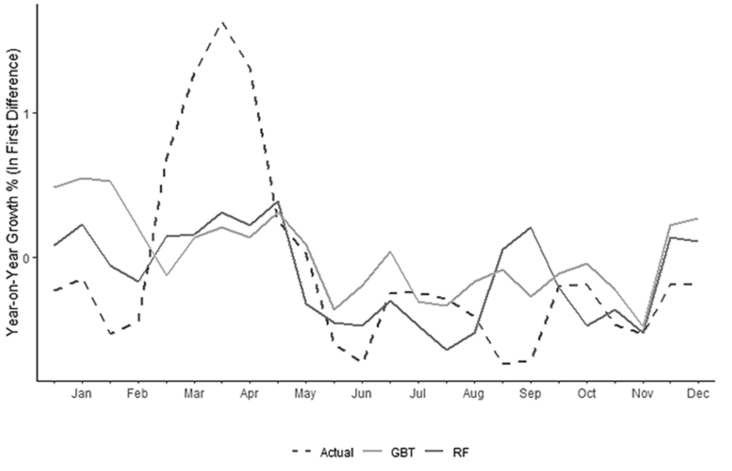


By comparing the three models under the regularization method, it can be observed that LASSO provided the highest number of months (i.e., five months) with relatively low forecast errors from January to December 2020 (Tables 7 and 8). On the other hand, in terms of their overall forecast errors, Ridge Regression and ENET registered low overall RMSE and MAE compared to LASSO, with 0.529 and 0.391, respectively (Figure 7).

5.4. Tree-based methods[40]

Similar to the results under regularization methods, utilizing RF and GBT as nowcasting models provide more consistent estimates with relatively higher precision than the benchmark models used in this study. The monthly forecast errors of the two machine learning models are significantly lower than those under ARIMA, RW, SARIMA, and DFM, except for the nowcast result under RF in September 2020 (Figure 8). Likewise, the results indicate that RF and GBT estimate domestic liquidity growth with low forecast error in the months wherein the growth of this monetary indicator suddenly expanded due to the increased borrowings and deposits of the national government (Tables 9 and 10).

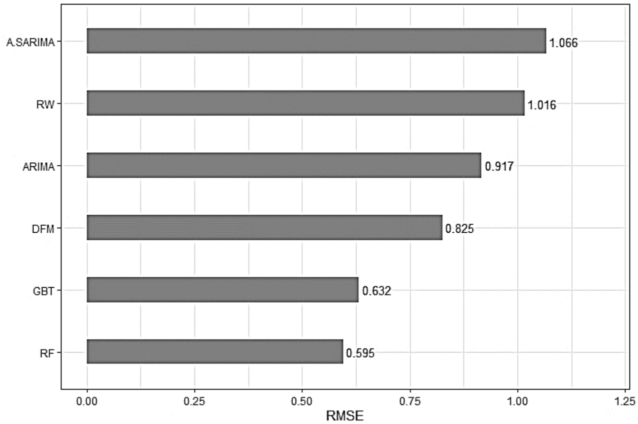
FIGURE 8. Tree-based method nowcasts vs. actual M3 growth (January to December 2020)
In percent difference, seasonally adjusted



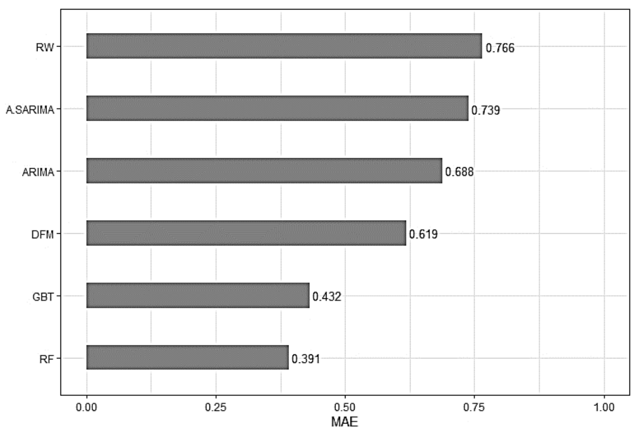
Aside from their robust monthly estimates, the overall nowcasts of RF and GBT also registered lower forecast errors. The result reveals that RF only displayed an RMSE of 0.595 and MAE of 0.432, while GBT provided an RMSE of 0.632 and MAE of 0.469. These figures are significantly lower than the overall forecast errors registered by the univariate and multivariate models performed in this study (Figure 9).

[40] Nowcasts under RF are tuned/calibrated using out-of-bag (OOB) scores, while nowcast under GBT are tuned/calibrated using tenfold cross-validation.

FIGURE 9. Overall (a) RMSE and (b) MAE of benchmark models and tree-based methods



(a)



(b)

In addition, among the tree-based methods used in this study, it can also be established that RF provided the lowest forecast errors. Despite having an inaccurate estimate in September 2020, this model provided the highest number of months (i.e., eight months) with higher precision from January to December 2020. This includes nowcasts for January, February, March, April, June, July, November, and December 2020 (Tables 9 and 10).

TABLE 9. RMSE of RF and GBT

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
RF	0.346	0.389	0.879	1.455	0.265	0.208	0.167	0.265	0.855	0.203	0.077	0.307	0.595
GBT	0.180	0.686	0.986	1.536	0.060	0.495	0.305	0.241	0.636	0.248	0.201	0.216	0.632

TABLE 10. MAE of RF and GBT

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
RF	0.346	0.389	0.879	1.455	0.265	0.208	0.167	0.265	0.855	0.203	0.077	0.307	0.595
GBT	0.180	0.686	0.986	1.536	0.060	0.495	0.305	0.241	0.636	0.248	0.201	0.216	0.632

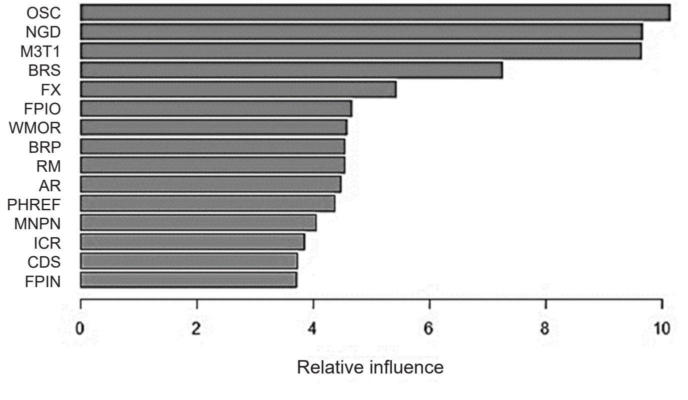
5.5. Variable importance

One of the main advantages of using machine learning algorithms in economic nowcasting is their capacity to identify a subset among selected input variables that better predicts the movement or growth of a particular macroeconomic indicator. In addition, numerous studies have established that these machine learning models can formulate quantitative models with accurate estimates despite using a limited number of indicators.[41] The machine learning algorithms that specifically have this ability are regularization and tree-based methods, such as LASSO, ENET, RF, and GBT.

5.5.1. Regularization methods

The nowcasts conducted by LASSO and ENET from January and December 2020 indicate that (1) foreign exchange rate (FOREX), (2) inflow of foreign portfolio investment (FPI), (3) London Interbank Offered Rates (LIBOR), (4) bank savings rate, (5) national government deposits to the central bank, and (6) liabilities of other sectors to the central bank are among the critical indicators that should be considered in estimating domestic liquidity growth in the Philippines. Mainly because among the 21 indicators used as input variables, these are the consistent determinants under LASSO and ENET that do not stipulate zero coefficients from January to December 2020 (Table 11).[42]

FIGURE 10. Variable importance plot via gradient boosted trees



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[41] See the studies of Cepni et al. [2018], Richardson et al. [2018], Ferrara and Simoni [2019], and Tamara et al. [2020].

[42] BSP Discount Rate, Bank Savings Rate, and WMOR as important indicators were also identified (Annex F and G).

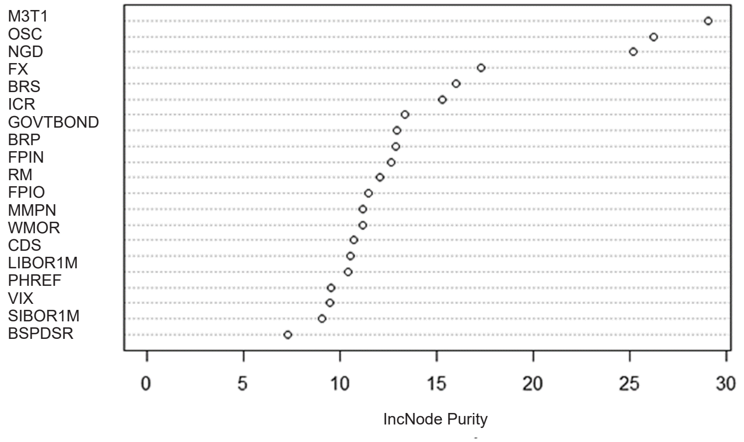
TABLE 11. Variable coefficients via LASSO and ENET (January to February 2020)

No.	Variable	LASSO (Jan. 2020)	LASSO (Feb. 2020)	ENET (Jan. 2020)	ENET (Feb. 2020)
-	Intercept	0.016	0.015	0.016	0.015
1	M3 Growth (T-1)	-	-	-	-
2	BSP Liabilities on National Government	-0.015	-0.015	-0.014	-0.014
3	BSP Claims on Other Sectors	0.235	0.235	0.216	0.216
4	Foreign Portfolio Investment (In)	-0.003	-0.004	-0.010	-0.010
5	Foreign Portfolio Investment (Out)	-	-	-	-
6	Available Reserves	-	-	-	-
7	Reserve Money	-	-	-	-
8	CBOE Volatility Index	-	-	-	-
9	Credit Default Swap	-	-	-	-
10	London Interbank Reference Rate	0.111	0.114	0.097	0.100
11	Singapore Interbank Reference Rate	-	-	-	-
12	Philippine Interbank Reference Rate	-	-	-	-
13	Philippine Government Bond Rate	-	-	-	-
14	BSP Discount Rate	-	-	-	-
15	Bank Savings Rate	-0.103	-0.110	-0.080	-0.087
16	Bank Prime Rate	-	-	-	-
17	Money Market Rate (Promissory Note)	-	-	-	-
18	Treasury Bill Rate	-	-	-	-
19	Interbank Call Rate	-	-	-	-
20	Philippine Peso per US Dollar (FOREX)	0.124	0.124	0.111	0.119
21	Weighted Monetary Operations Rate	-	-	-	-

5.5.2. Tree-based methods

The critical indicators identified under RF and GBT are similar to the input variables that LASSO and ENET provided. However, the main difference is that both of the tree-based methods used in this study have identified that lagged value (t–1) of the target variable, as an input variable, is also critical in estimating domestic liquidity growth in the Philippines. In particular, Figures 10 and 11 indicate that (1) domestic liquidity (t–1), (2) liabilities of other sectors to the central bank (OSC), and (3) national government deposits to the central bank (NGD) are by far the three most significant variables that should be considered in estimating the growth of domestic liquidity.

FIGURE 11. Node impurity via random forest



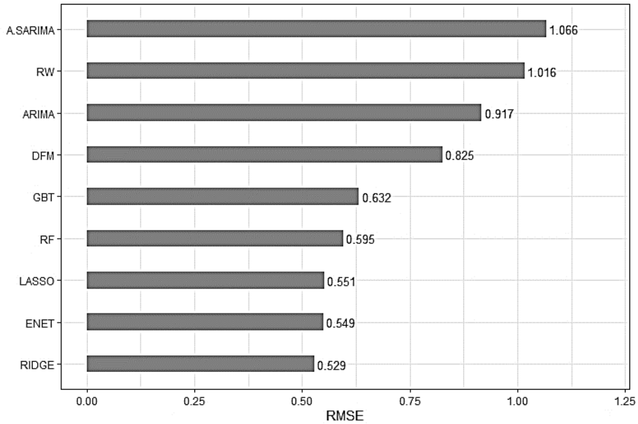
6. Conclusion

This study utilized different methods now popularly used in machine learning to support the BSP's current suite of macroeconomic models used to forecast and analyze domestic liquidity growth in the Philippines. In particular, regularization (i.e., Ridge Regression, LASSO, ENET) and tree-based (i.e., RF, GBT) methods are employed to estimate the year-on-year (Y-O-Y) growth of the said monetary indicator from January to December 2020. The following algorithms are then compared against traditional univariate (i.e., ARIMA, Random Walk, SARIMA) and multivariate (i.e., DFM) time series models. Hence, their respective one-step-ahead (out-of-sample) nowcasts under an expanding window process are evaluated based on monthly and overall RMSE and MAE.

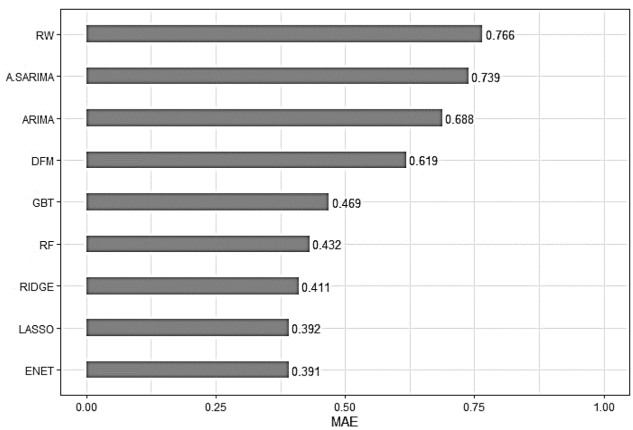
The results indicate that machine learning algorithms provide relatively higher precision estimates than the traditional time series models due to their consistent monthly nowcasts with low forecast errors, especially in the months wherein domestic liquidity suddenly expanded (i.e., increased national government borrowings and deposits). In addition, based on their overall RMSE and MAE, it can be concluded that the two machine learning techniques could be considered as alternative models to estimate the domestic liquidity growth (Figure 12).

However, among these algorithms, LASSO and RF provided the highest number of months with low forecast errors from January to December 2020 (Figure 12). The Ridge Regression and ENET, on the other hand, registered the lowest overall RMSE and MAE with 0.529 and 0.391, respectively (Tables 12 and 13). These results suggest that nowcasting through regularization methods is the most suitable approach to nowcast domestic liquidity growth among the machine learning algorithms used in this study.

FIGURE 12. Overall forecast errors of benchmark and machine learning models



(a)



(b)

TABLE 12. RMSE of benchmark and machine learning models (summary)

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
ARIMA	0.716	1.422	0.936	1.663	0.196	1.636	0.474	0.102	0.649	0.117	0.452	0.577	0.917
RWalk	0.288	0.722	1.470	2.451	0.434	1.095	0.425	0.403	0.669	0.199	0.880	0.895	1.016
SARIMA	1.622	1.879	0.556	1.986	0.134	1.535	0.702	0.428	0.299	0.174	0.222	0.057	1.066
DFM	0.557	1.093	0.565	1.458	0.247	1.678	0.965	0.184	0.513	0.182	0.078	0.267	0.825
Ridge	0.292	0.372	0.928	1.163	0.173	0.258	0.261	0.248	0.596	0.449	0.123	0.349	0.529
LASSO	0.264	0.237	0.964	1.348	0.046	0.185	0.179	0.215	0.621	0.416	0.115	0.286	0.551
ENET	0.262	0.259	0.973	1.328	0.048	0.199	0.206	0.187	0.631	0.390	0.099	0.291	0.549
RF	0.346	0.389	0.879	1.455	0.265	0.208	0.167	0.265	0.855	0.203	0.077	0.307	0.595
GBT	0.180	0.686	0.986	1.536	0.060	0.495	0.305	0.241	0.636	0.248	0.201	0.216	0.632

TABLE 13. MAE **of benchmark and machine learning models (summary)**

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
ARIMA	0.715	1.395	0.762	1.537	0.194	1.527	0.467	0.088	0.544	0.106	0.389	0.537	0.688
RWalk	0.273	0.669	1.319	2.327	0.428	0.996	0.416	0.380	0.543	0.149	0.825	0.862	0.766
SARIMA	1.609	1.801	0.405	1.854	0.134	1.411	0.650	0.355	0.244	0.162	0.194	0.050	0.739
DFM	0.526	1.091	0.509	1.446	0.237	1.649	0.918	0.138	0.452	0.136	0.077	0.246	0.619
Ridge	0.292	0.364	0.887	1.136	0.156	0.245	0.259	0.209	0.596	0.325	0.116	0.345	0.411
LASSO	0.257	0.234	0.909	1.340	0.040	0.182	0.179	0.202	0.620	0.345	0.114	0.281	0.392
ENET	0.255	0.257	0.916	1.321	0.036	0.196	0.206	0.171	0.631	0.318	0.099	0.286	0.391
RF	0.345	0.377	0.830	1.454	0.242	0.201	0.140	0.235	0.852	0.147	0.058	0.307	0.432
GBT	0.179	0.684	0.972	1.530	0.060	0.490	0.243	0.201	0.636	0.218	0.200	0.215	0.469

Aside from their robust one-step-ahead (out-of-sample) estimates, machine learning algorithms also provide substantial advantages against traditional time series models. These models can identify indicators that could stipulate parsimonious nowcasting models with more accurate results. Hence, nowcasts based on LASSO, ENET, RF, and GBT indicate that (1) national government deposits, (2) BSP claims on other sectors, (3) FOREX, and (4) lagged values of domestic liquidity are among the indicators that could be useful in nowcasting the growth of domestic liquidity in the Philippines.

Acknowledgements: The author would like to express his deepest gratitude to Professor Konstantin Kucheryavyy, Ph.D. of the University of Tokyo (UTokyo), Graduate School of Public Policy (GraSPP) for imparting his knowledge on data science and providing technical assistance for this research. The author is also thankful to Dr. Laura Fermo (Senior Researcher, BSP Research Academy), Dr. Ma. Cyd Tuaño-Amador (Former Deputy Governor, BSP Corporate Services Sector), and Dr. Roberto Mariano (BSP Research Expert Panel) for their helpful comments in the BSP Research Community-in-Action (CIA) held last November 24, 2021.

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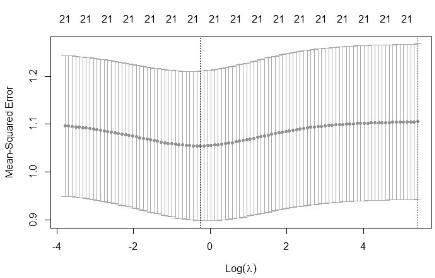
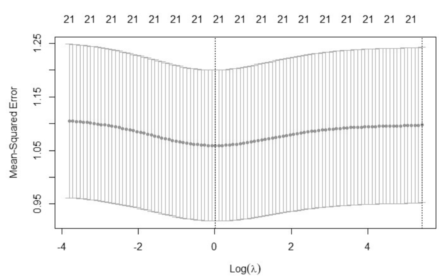
Annex

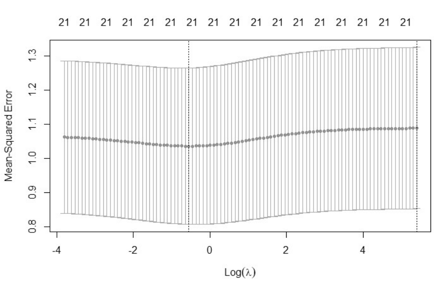
ANNEX A. Optimal shrinkage penalty via ridge regression



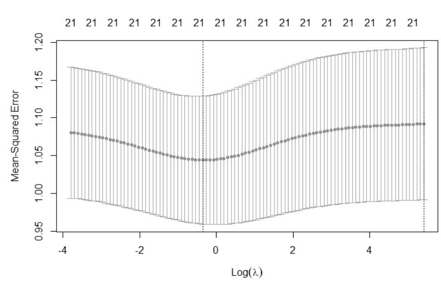
January 2020 – 0.772



February 2020 – 1.012

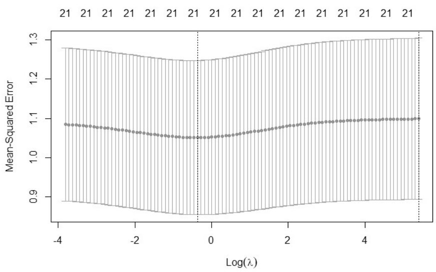


March 2020 – 0.577

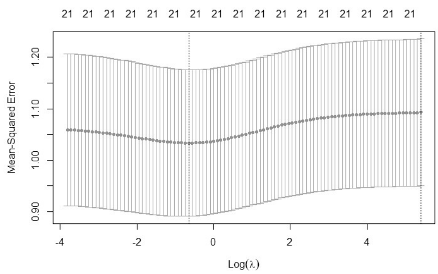


April 2020 – 0.700

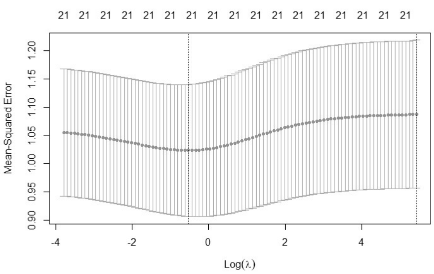
ANNEX A. Optimal shrinkage penalty via ridge regression (continued)



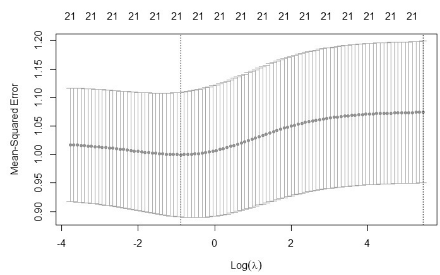
May 2020 – 0.691



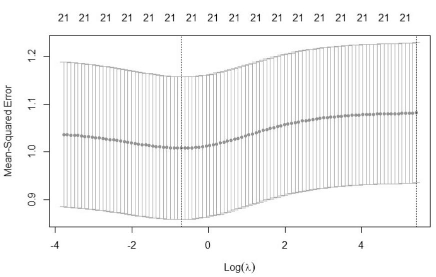
June 2020 – 0.523



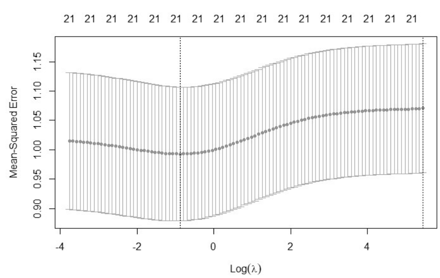
July 2020 – 0.589



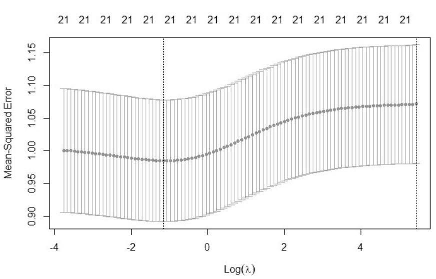
August 2020 – 0.491



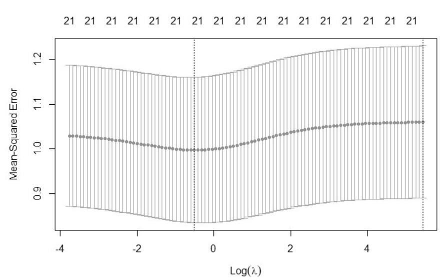
September 2020 – 0.411



October 2020 – 0.415

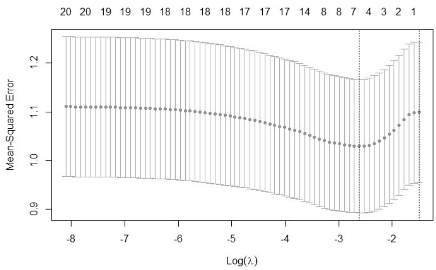


November 2020 – 0.313

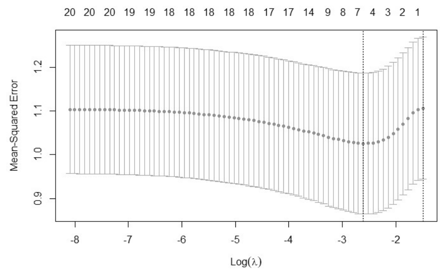


December 2020 – 0.600

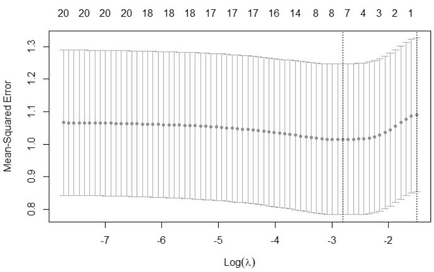
ANNEX B. Optimal shrinkage penalty via LASSO



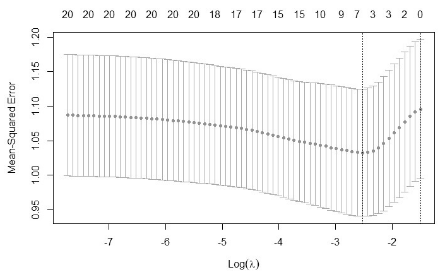
January 2020 – 0.737



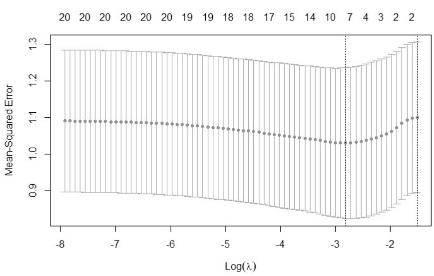
February 2020 – 0.073



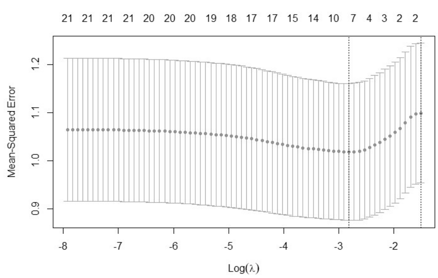
March 2020 – 0.060



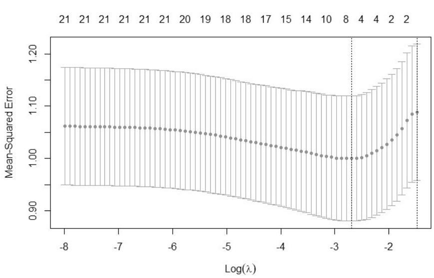
April 2020 – 0.080



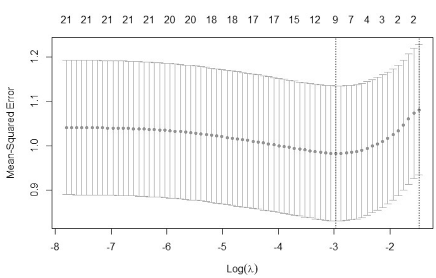
May 2020 – 0.060



June 2020 – 0.060

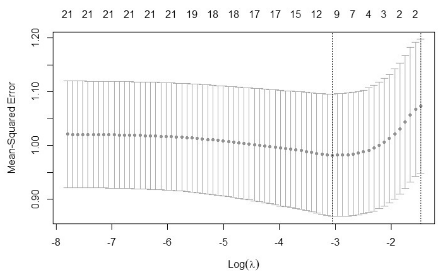


July 2020 – 0.068

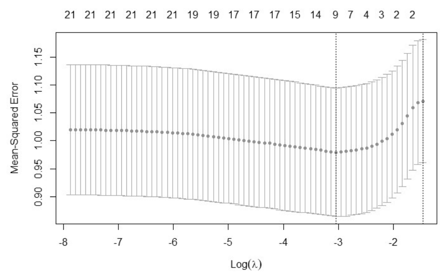


August 2020 – 0.051

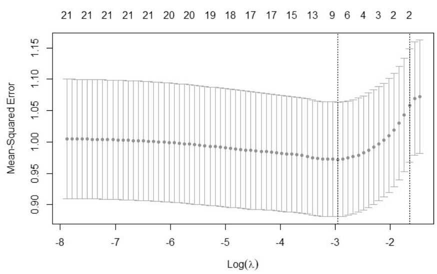
ANNEX B. Optimal shrinkage penalty via LASSO (continued)



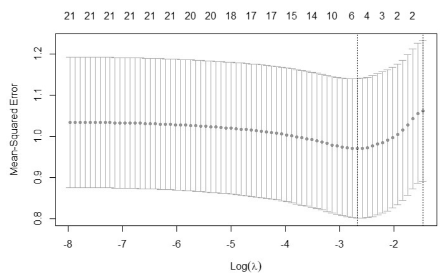
September 2020 – 0.047



October 2020 – 0.048

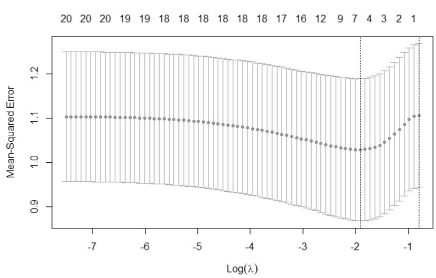


November 2020 – 0.052

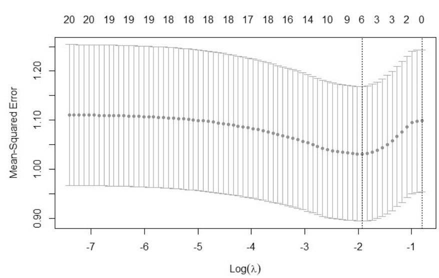


December 2020 – 0.069

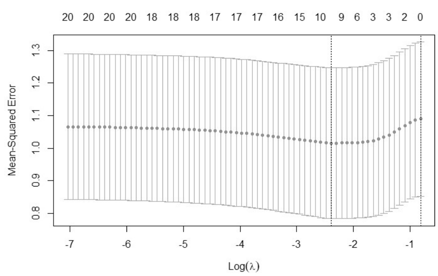
ANNEX C. Optimal shrinkage penalty via ENET



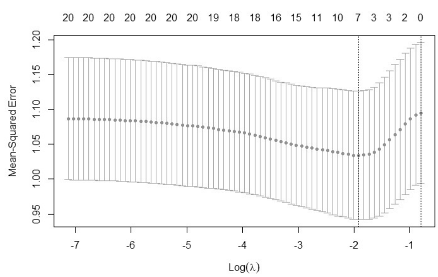
January 2020 – 0.147



February 2020 – 0.146

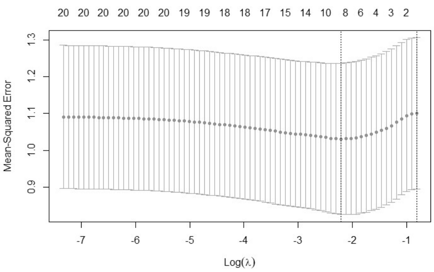


March 2020 – 0.091

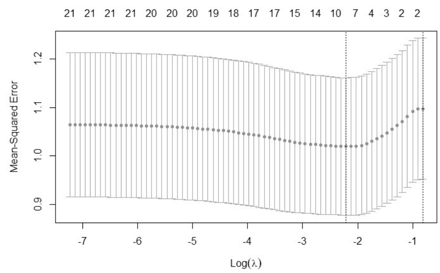


April 2020 – 0.147

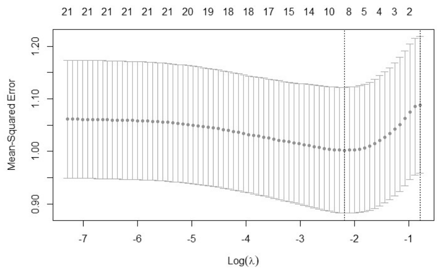
ANNEX C. Optimal shrinkage penalty via ENET (continued)



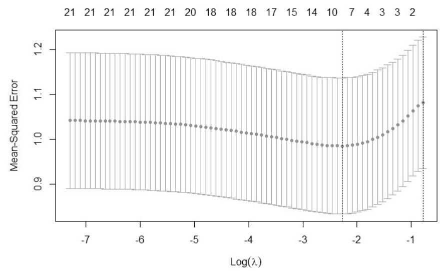
May 2020 – 0.110



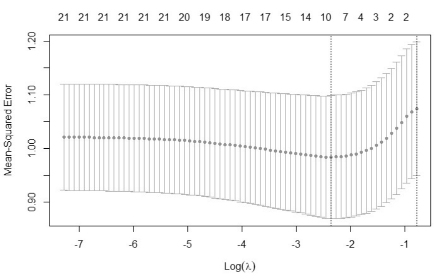
June 2020 – 0.110



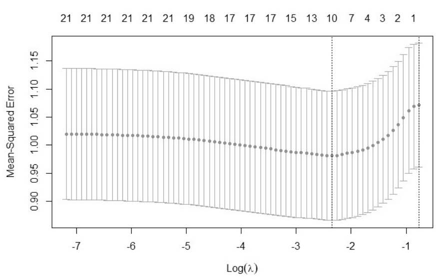
July 2020 – 0.112



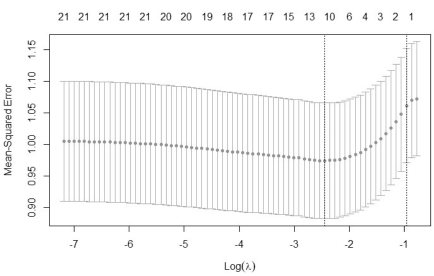
August 2020 – 0.103



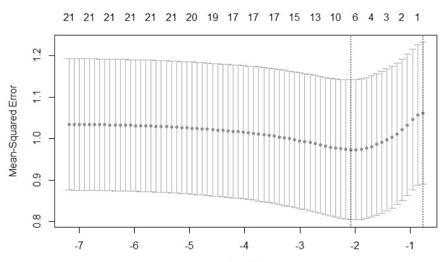
September 2020 – 0.095



October 2020 – 0.095

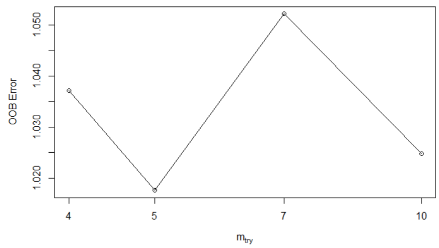


November 2020 – 0.087

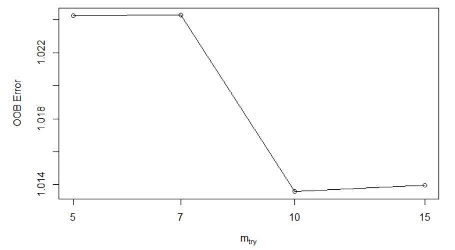


December 2020 – 0.126

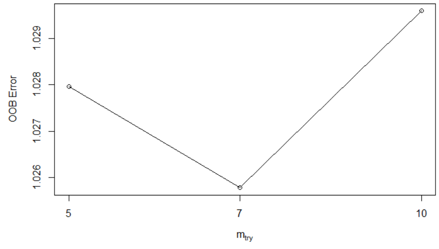
ANNEX D. OOB error of training datasets via random forest



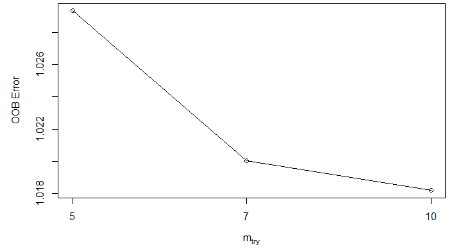
January 2020 – 5 Variables (1.018)



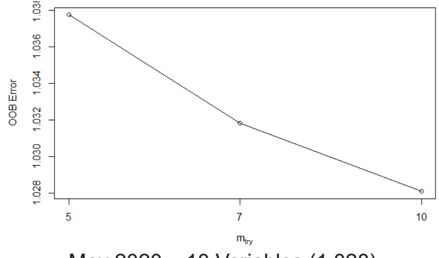
February 2020 – 10 Variables (1.014)



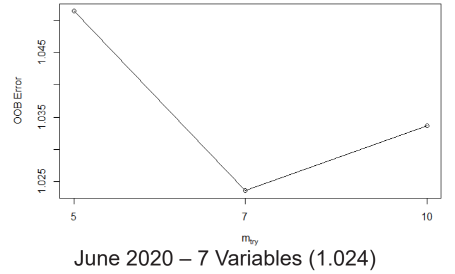
March 2020 – 7 Variables (1.026)



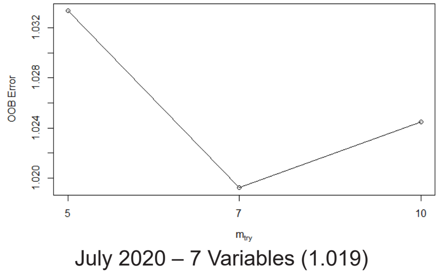
April 2020 – 10 Variables (1.018)



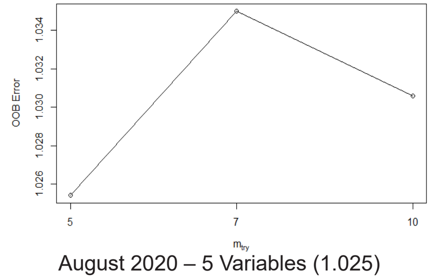
May 2020 – 10 Variables (1.028)



June 2020 – 7 Variables (1.024)

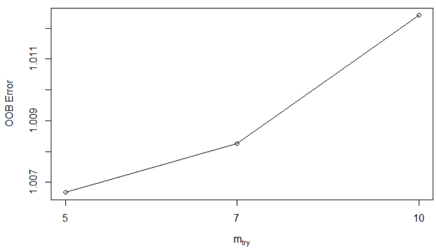


July 2020 – 7 Variables (1.019)

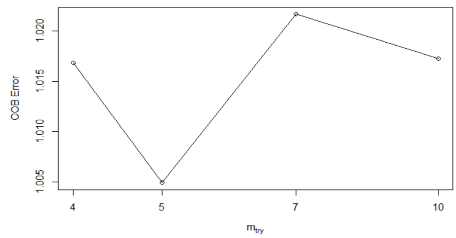


August 2020 – 5 Variables (1.025)

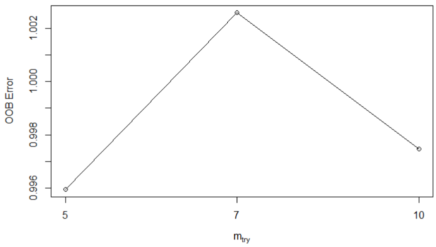
ANNEX D. OOB error of training datasets via random forest (continued)



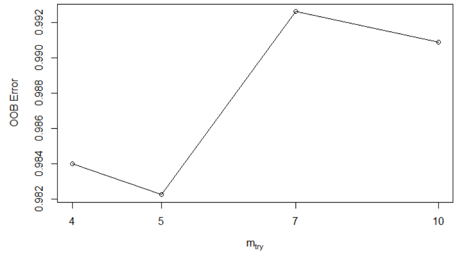
September 2020 – 5 Variables (1.007)



February 2020 – 10 Variables (1.014)

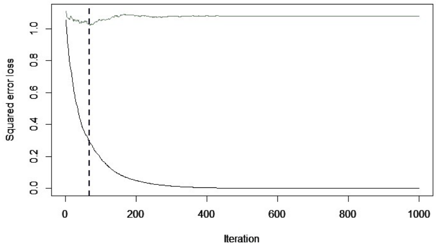


January 2020 – 5 Variables (1.018)

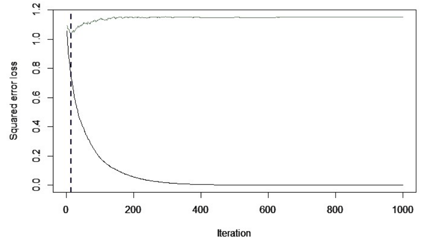


February 2020 – 10 Variables (1.014)

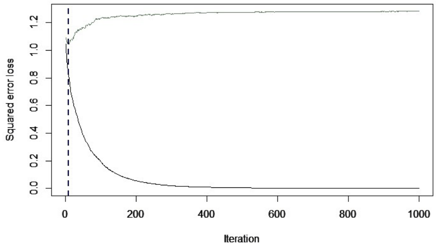
ANNEX E. Optimal number of trees via gradient boosted trees



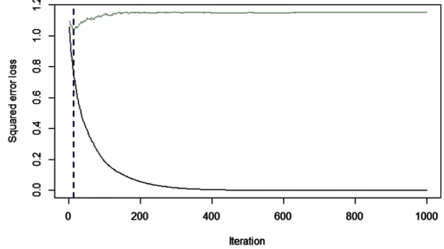
January 2020 – 67 Iterations



February 2020 – 15 Iterations

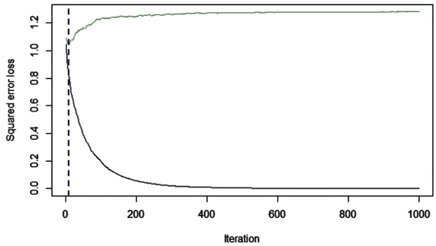


March 2020 – 8 Iterations

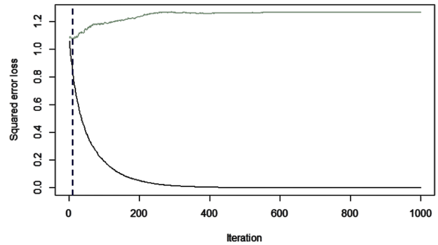


April 2020 – 10 Iterations

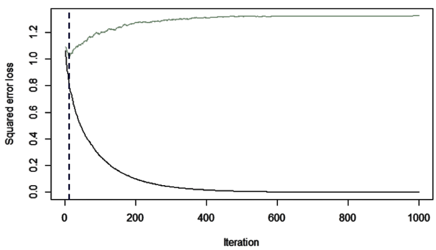
ANNEX E. Optimal number of trees via gradient boosted trees (continued)



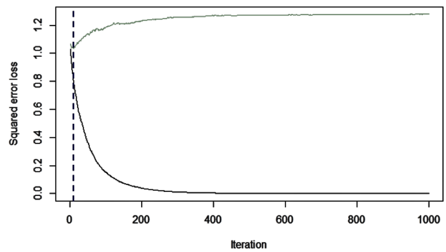
May 2020 – 2 Iterations



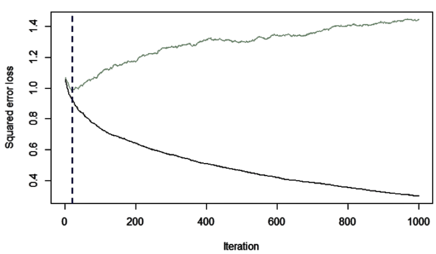
June 2020 – 4 Iterations



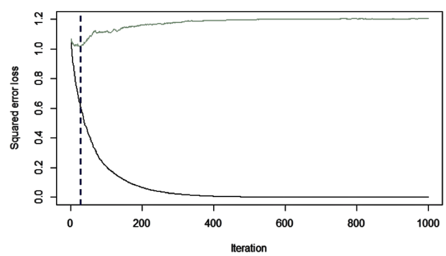
July 2020 – 13 Iterations



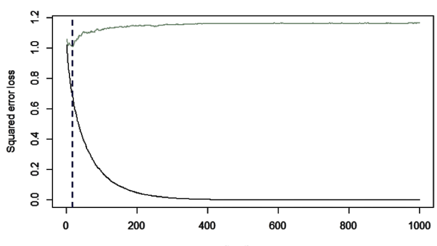
August 2020 – 10 Iterations



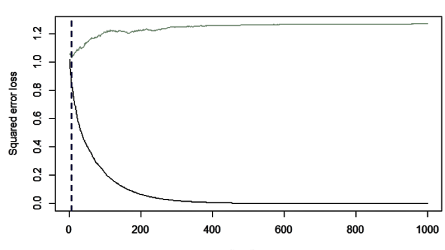
September 2020 – 22 Iterations



October 2020 – 28 Iterations



November 2020 – 17 Iterations



December 2020 – 7 Iterations

ANNEX F. Variable coefficients via LASSO (January to December 2020)

No.	Variable	1/2020	2/2020	3/2020	4/2020	5/2020	6/2020	7/2020	8/2020	9/2020	10/2020	11/2020	12/2020
-	Intercept	0.016	0.015	0.010	0.020	0.020	0.021	0.022	0.017	0.017	0.013	0.016	0.020
1	M3 Growth (T-1)	-	-	-	-	-	-	-	-	-	-	-	-
2	BSP Liabilities on NG	-0.015	-0.015	-0.017	-0.014	-0.017	-0.017	-0.016	-0.018	-0.018	-0.018	-0.017	-0.015
3	BSP Claims on Other Sectors	0.235	0.235	0.257	0.226	0.265	0.265	0.255	0.284	0.291	0.294	0.284	0.254
4	Foreign Portfolio Investment (In)	-0.003	-0.004	-0.042	-0.003	-0.050	-0.047	-0.018	-0.064	-0.070	-0.063	-0.026	-
5	Foreign Portfolio Investment (Out)	-	-	-	-	-	-	-	-	-	-	-	-
6	Available Reserves	-	-	-	-	-	-	-	-	-	-	-	-
7	Reserve Money	-	-	-	-	-	-	-	-	-	-	-	-
8	CBOE Volatility Index	-	-	-	-	-	-	-	-	-	-	-	-
9	Credit Default Swap	-	-	-	-	-	-	-	-	-	-	-	-
10	LIBOR	0.111	0.114	0.203	0.013	0.116	0.115	0.052	0.182	0.219	0.220	0.184	0.043
11	SIBOR	-	-	-	-	-	-	-	-	-0.013	-	-	-
12	PHIREF	-	-	-	-	-	-	-	-	-	-	-	-
13	Philippine Government Bond Rate	-	-	-	-	-	-	-	-	-	-	-	-
14	BSP Discount Rate	-	-	0.039	-	0.023	0.020	-	0.086	0.108	0.102	0.064	-
15	Bank Savings Rate	-0.103	-0.110	-0.396	-	-	-	-	-0.178	-0.243	-0.247	-0.157	-
16	Bank Prime Rate	-	-	-	-	-	-	-	-	-	-	-	-
17	Money Market Rate (Prom. Note)	-	-	-	-	-	-	-	-	-	-	-	-
18	Treasury Bill Rate	-	-	-	-	-	-	-	-	-	-	-	-
19	Interbank Call Rate	-	-	-	-	-0.062	-0.061	-0.036	-0.050	-0.049	-0.040	-0.038	-0.024
20	PHP per USD (FOREX)	0.124	0.124	0.149	0.106	0.134	0.133	0.121	0.155	0.160	0.158	0.147	0.110
21	WMOR	-	-	-	-0.052	-0.844	-0.817	-0.645	-0.935	-1.030	-1.019	-0.920	-0.557

ANNEX G. Variable coefficients via ENET (January to December 2020)

No.	Variable	1/2020	2/2020	3/2020	4/2020	5/2020	6/2020	7/2020	8/2020	9/2020	10/2020	11/2020	12/2020
-	Intercept	0.016	0.015	0.007	0.019	0.019	0.020	0.020	0.017	0.017	0.014	0.014	0.019
1	M3 Growth (T-1)	-	-	-	-	-	-	-	-	-	-	-	-
2	BSP Liabilities on NG	-0.014	-0.014	-0.017	-0.014	-0.016	-0.016	-0.016	-0.017	-0.017	-0.017	-0.017	-0.015
3	BSP Claims on Other Sectors	0.216	0.216	0.268	0.218	0.257	0.257	0.257	0.267	0.274	0.277	0.283	0.246
4	Foreign Portfolio Investment (In)	-0.010	-0.010	-0.086	-0.026	-0.068	-0.065	-0.053	-0.067	-0.072	-0.065	-0.056	-0.001
5	Foreign Portfolio Investment (Out)	-	-	-	-	-	-	-	-	-	-	-	-
6	Available Reserves	-	-	-	-	-	-	-	-	-	-	-	-
7	Reserve Money	-	-	-	-	-	-	-	-	-	-	-	-
8	CBOE Volatility Index	-	-	-	-	-	-	-	-	-	-	-	-
9	Credit Default Swap	-	-	-	-	-	-	-	-	-	-	-	-
10	LIBOR	0.097	0.100	0.301	0.054	0.142	0.141	0.127	0.161	0.201	0.199	0.249	0.074
11	SIBOR	-	-	-	-	-	-	-	-	-0.033	-0.007	-0.053	-
12	PHIREF	-	-	-	-	-	-	-	-	-	-	-	-
13	Philippine Government Bond Rate	-	-	-	-	-	-	-	-	-	-	-	-
14	BSP Discount Rate	-	-	0.142	-	0.053	0.050	0.041	0.074	0.094	0.089	0.115	-
15	Bank Savings Rate	-0.080	-0.087	-0.617	-	-0.079	-0.082	-0.065	-0.164	-0.229	-0.231	-0.309	-
16	Bank Prime Rate	-	-	-	-	-	-	-	-	-	-	-	-
17	Money Market Rate (Prom. Note)	-	-	-	-	-	-	-	-	-	-	-	-
18	Treasury Bill Rate	-	-	-	-	-	-	-	-	-	-	-	-
19	Interbank Call Rate	-	-	-0.015	-0.012	-0.0823	-0.081	-0.075	-0.070	-0.069	-0.061	-0.061	-0.056
20	PHP per USD (FOREX)	0.111	0.119	0.177	0.115	0.142	0.141	0.139	0.151	0.156	0.153	0.162	0.119
21	WMOR	-	-	-0.285	-0.151	-0.877	-0.851	-0.795	-0.847	-0.936	-0.929	-1.012	-0.590