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Nowcasting Domestic Liquidity in the Philippines Using Machine Learning Algorithms

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Abstract

This study utilized different machine learning algorithms to nowcast the domestic liquidity growth in the Philippines. In particular, different types of regularization (i.e., Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO), Elastic Net) and tree-based (i.e., Random Forest, Gradient Boosted Trees) methods were employed to support the BSP's suite of macroeconomic models used to forecast and analyze the said monetary indicator. These models are then evaluated and compared against the traditional time series models (e.g., Autoregressive Models, Dynamic Factor Model) using an expanding window process.

The results indicate that machine learning algorithms relatively provide better estimates than the traditional time series models utilized in this study due to their consistent month-ahead nowcasts with low Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). In addition, the models provide nowcasts with low forecast errors on the months where domestic liquidity suddenly expanded due to the impact of Coronavirus Disease 2019 (COVID-19) in the Philippines. This study also established that machine learning algorithms filter out or identify important indicators to stipulate parsimonious nowcasting models.

JEL Classification: E40, E47, E50

Keywords: Nowcasting, Domestic Liquidity, Time Series, ARIMA, Dynamic Factor Model, Machine Learning, Ridge Regression, LASSO, Elastic Net, Random Forest, Gradient Boosted Trees

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Acronyms

ACF	Autocorrelation Function
ADB	Asian Development Bank
ADF	Augmented Dickey-Fuller Test
AIC	Akaike Information Criterion
ARC	Advance Release Calendar
ARIMA	Autoregressive Integrated Moving Average
BOP	Balance of Payments
BSP	Bangko Sentral ng Pilipinas
CBS	Central Bank Survey
CDS	Credit Default Swap
COVID-19	Coronavirus Disease 2019
CPI	Consumer Price Index
DCS	Depository Corporations Survey
DES	Department of Economic Statistics
DFM	Dynamic Factor Model
ENET	Elastic Net
EWS	Early Warning System
FOREX	Foreign Exchange Rate
FPI	Foreign Portfolio Investment
GBT	Gradient Boosted Trees
GDP	Gross Domestic Product
HQ	Hannan-Quinn Information Criterion
IFI	International Financial Institutions
IMF	International Monetary Fund
LASSO	Least Absolute Shrinkage and Selection Operator
LIBOR	London Interbank Offered Rates
LSM	Large-Scale Manufacturing
M1	Monetary Base
M2	M1 and Savings/Time Deposits
M3	Domestic Liquidity
MAE	Mean Absolute Error
MAFE	Mean Absolute Forecast Error
MFSM	Monetary and Financial Statistics Manual
MSFE	Mean Squared Forecast Error
NG	National Government
NGA	National Government Agencies
ODC	Other Depository Corporations
OLS	Ordinary Least Squares
OOB	Out-of-Bag Error
PACF	Partial Autocorrelation Function
PBS	Philippine Banking System
PHIREF	Philippine Interbank Reference Rate
PP	Philipps-Perron Test
RF	Random Forest
RMSE	Root Mean Square Error

RSS	Residual Sum of Squares
RW	Random Walk
SARIMA	Seasonal Autoregressive Integrated Moving Average
SIBOR	Singapore Interbank Offered Rates
VAR	Vector Autoregression
WB	World Bank Group
WEO	World Economic Outlook
WMOR	Weighted Monetary Operations Rate
YOY	Year-on-Year

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Using Machine Learning Algorithms

Juan Rufino M. Reyes[1,2,3]

1. Introduction

1.1. Background of the Study

Timely announcements of different macro and socioeconomic indicators are essential to comprehensively monitor the developments of numerous sectors in the economy (e.g., households, other depository corporations) and formulate strong policy (e.g., fiscal, monetary) responses. Proponents of high-quality public data management, such as the International Monetary Fund (IMF), argued that having reliable and sensible datasets is essential to depict an economy's overall condition and strictly monitor the negative externalities that could cause a financial crisis. Hence, numerous government offices (e.g., central banks, finance ministries) are transforming their approach to ensure that their mandate of providing data to the public is achieved in a timely and consistent manner (Carriere-Swallow and Haskar, 2019).

However, adopting these data management principles cannot be easily implemented. This is mainly due to the tedious and complicated processes that must be performed to produce a particular dataset. Among the reasons that coerced the delay in publishing data at the national level were the proper classification of accounts, changes in the overall compilation framework, and inevitable delays in receiving input documents (Dafnai and Sidi, 2010; Chikamatsu et al., 2018). Recent studies discussed that different national government agencies (NGAs) and central banks from advanced (e.g., United States (US), Japan, New Zealand) and emerging economies (e.g., Israel, Lebanon) had recently encountered this difficulty (Dafnai and Sidi, 2010; Bragoli and Modugno, 2016; Chikamatsu et al., 2018; Richardson et al., 2018). Due to this predicament, policymakers from these countries are forced to formulate policies and address several economic phenomena (e.g., inflation, business cycle) using non-related, outdated, or lagged datasets (Richardson et al., 2018).

To systematically address this concern, nowcasting was one of the recently introduced methodologies by different International Financial Institutions (IFIs), NGAs, and central banks. The said concept is similar to forecasting. However, due to the difficulty in producing official macroeconomic indicators on a real-time basis, the former has been the alternative approach used by numerous institutions to systemically estimate the official figure of a specific set of information before it becomes available (Bańbura et al., 2013; Tiffin, 2016). The IMF, World Bank (WB) Group, and Asian Development Bank (ADB) are among the IFIs that conducted

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[1] Mr. Reyes is from the Department of Economic Statistics (DES) of Monetary Policy Sub-Sector (MPSS). The usual institutional disclaimer applies. Views, errors, and omissions are the sole responsibilities of the author and not those of the institution represented.

[2] 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.

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comprehensive studies regarding the use of nowcasting in different fields of study (e.g., economics, finance). Meanwhile, the central banks of Indonesia, Israel, Japan, and New Zealand are among the well-known institutions that attempted to use the said concept to estimate the short-run growth of their respective Gross Domestic Product (GDP) and Consumer Price Index (CPI).[4]

1.1.1. Economic Nowcasting, Big Data, and Machine Learning

For the past years, estimating the overall growth of an economy, the progress of a particular economic sector, and the transmission mechanism of policies have been commonly performed through economic forecasting using time series analysis. Univariate (e.g., ARIMA) and multivariate (e.g., VAR, DFM) models, in particular, are widely used to estimate numerous macro and socioeconomic indicators or phenomena because of their straightforward approach and ability to decompose the factors that contribute to the movement of a particular target variable of interest.[5]

However, in most cases, time series models are highly dependent on the timeliness of data or information. The publication delay of the variable(s) 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, its figure as of end-Q1:2020 is strongly needed.[6] In a typical situation, the publication of GDP for Q1:2020 is not released exactly at the end of said period. Its latest figure is usually posted within one (1) or two (2) months after the reference date (e.g., GDP for Q2:2020 is published in August 2020, rather than end-June 2020).[7] Therefore, an individual or institution that aims to forecast the economic growth for Q2:2020 using an AR(1) model should wait until the GDP as of end-Q1:2020 is published.

The aforementioned concern was one of the main reasons that pushed numerous individuals and institutions to adopt the concept of nowcasting in economics. Mainly because it has the capacity to process and provide real-time information using high-frequency data (e.g., daily financial data, survey results) to estimate the development of a particular macro or socioeconomic variable (Bańbura et al., 2013; Chikamatsu et al., 2018; Richardson et al., 2018). In contrast to a typical time series model used in economic forecasting, nowcasting models such as Mixed Data Sampling (MIDAS) can 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 became an essential tool for policymakers to minimize the usual approach of addressing different economic phenomena using non-related, outdated, or lagged data (Richardson et al., 2018).

The study of Bańbura et al. (2013) supported the concept of economic nowcasting. Specifically, the authors mentioned that:

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4 See Dafnai and Sidi (2010), Chikamatsu et al. (2018), Richardson et al. (2018), and Tamara et al. (2020).

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

6 Autoregressive Model of Order 1 or AR (1) model is defined as $y_t = \alpha_0 + \alpha_1 y_{t-1} + \epsilon_t$.

7 Depending on the statistical calendar (or advance release calendar) of a specific country.

> *Nowcasting is relevant in economics because key statistics on the present state of the economy are available with a significant delay. This is particularly true for those collected on a quarterly basis, with GDP being a prominent example. For instance, the first official estimate of GDP in the United States or in the United Kingdom is published approximately one month after the end of the reference quarter. In the Euro area, the corresponding publication lag is two (2) to three (3) weeks longer. Nowcasting can also be meaningfully applied to other target variables revealing particular aspects of the state of the economy and thereby followed closely by markets (p. 2).*

Aside from the said concern, another factor contributing to the emergence of nowcasting is the recent trend in using big data and machine learning. Numerous individuals and institutions have already conducted nowcasting using these concepts in economics for the following reasons. The first reason is that the former has a solid potential to provide supplementary information regarding the macro and socioeconomic data that government offices usually publish (Baldacci et al., 2016). Meanwhile, the latter has the capacity to utilize the immense amount of data or information that the former concept could provide (Hassani and Silva, 2015; Richardson et al., 2018). In addition to economics, nowcasting through big data and machine learning are also performed by different individuals and institutions across different fields of study (e.g., energy, medicine, population dynamics). This is mainly due to the ability of the said approach to maximize high-frequency data or information (e.g., daily demand on energy consumption, patients' health record), which further improves decision-making and policy formulation, among others (Hassani and Silva, 2015).

1.1.2. The Philippines and Domestic Liquidity

Domestic liquidity (M3) is defined as the total amount of money available in an economy that is usually determined by a central bank and banking system (Mankiw, n.d. p. 623). On a similar note, as stated under the Monetary and Financial Statistics Manual (MSFM) of the IMF, the said indicator is the sum of all liquid financial instruments held by money-holding sectors, such as Other Depository Corporations (ODCs). It can be categorized as a particular commodity that is widely accepted as (1) medium of exchange and (2) close substitute for the medium of exchange with a reliable store value (IMF, 2016 p. 180).[8,9]

The change in its overall growth is one of the most important dynamics 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 in different central banks diligently observe its expansion or contraction to formulate an effective and timely monetary response, especially when there are predicaments that require them to adjust policy rates and the overall monetary base (Mankiw, n.d.).

[8] The MFSM is the official guideline of IMF member countries in compiling and presenting monetary statistics.

[9] ODCs refers to financial corporations (other than the central bank) that incur liabilities included in domestic liquidity (IMF, 2016 p. 405).

Similar to its role in every economy across regions, domestic liquidity likewise holds a critical function in the economy of the Philippines. Both level and growth of said monetary indicator are usually being monitored by the *Bangko Sentral ng Pilipinas* (BSP) because it is primarily used as the measurement of liquidity in the country, input for early warning system (EWS) models on the macroeconomy, and principal data to formulate and implement monetary policy, among others.[10]

Further, the structure of M3 in the Philippines is similar to most countries with fractional-reserve banking systems (e.g., US, Japan).[11] Mainly because the main components of this monetary aggregate are bank reserves, currency deposits (or monetary base), and other liquid financial instruments. In particular, based on the Depository Corporations Survey (DCS) conducted by the BSP, domestic liquidity in the said country 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 (BSP, 2018).[12]

The BSP announces the current level and growth of M3 in the Philippines on a monthly basis. Mainly, the Department of Economic Statistics (DES) of the said institution consolidates the balance sheet of the BSP and ODCs to calculate domestic liquidity in a given period. However, for the said monetary indicator to be released in a timely manner, the DES and Department of Supervisory Analytics (DSA) of the BSP need to strictly ensure that punctual submission of bank reports (e.g., Financial Reporting Package for Banks) is observed.

Therefore, in order for the said institution to achieve its primary mandate in having price and financial stability in the Philippines, timely and reliable data on money supply – which highly requires the overall position (e.g., assets, liabilities) of the BSP and ODCs – is critical to support the monetary policy formulation and implementation in the said country.

1.2. Statement of the Problem

As mentioned in the previous section, 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 met the deadline to announce its latest available figure based on their advance release calendar (ARC), the publicly shared data on M3 are not based on real-time position. As seen in Table 1, despite retrieving the DCS last 15 November 2021, the latest available domestic liquidity statistics was based on its level and growth as of end-September 2021 (e.g., current release has four (4) to six (6) weeks lags).

Aside from this concern, the official data on M3 also suffers from a series of revisions. Based on the publication policy of the BSP, the latest statistical reports (which includes the DCS) are treated as preliminary information (Table 1). The initial publication is revised within

[10] See BSP DCS Frequently Asked Questions (FAQs).

[11] Fractional-reserve banking system refers to a system in which banks retain a portion of their overall deposits on reserves (Mankiw, n.d. p. 620).

[12] 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.

two (2) months to reflect changes in the reports submitted by the banks under its jurisdiction.[13] This procedure is also applicable to the other key statistical indicators being 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.

Table 1.1: Depository Corporations Survey

(Date Accessed: 15 November 2021)

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 - Aug 21	Aug 21 - Aug 20	Sep 21 - Sep 20	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**	**14,443,532**	**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: Liabilities 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 financial corporations	1,170,415	1,177,373	1,163,359	1,184,593	21,234	-7,056	7,221	1.8	-0.6	0.6
Claims on state and local 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
3. LIQUIDITY AGGREGATES										
M4 (M3 + 3.e)	**15,603,502**	**15,583,711**	**16,591,084**	**16,785,106**	**194,022**	**987,582**	**1,201,395**	**1.2**	**6.3**	**7.7**
M3 (M2 + 3.d) **	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-Residen	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: Bangko Sentral ng Pilipinas

Drawing upon this background, this study aims to address these issues and concerns by investigating the use of different machine learning algorithms to estimate the growth of domestic liquidity in the Philippines. The research primarily intends to formulate a quantitative model that can be sustainably utilized to support the BSP's suite of macroeconomic models used in forecasting and policy analysis (e.g., GDP, inflation forecasting). For this reason, the study intends to answer these research questions:

a. Compared with the traditional time series model used in nowcasting (e.g., Autoregressive Models, Dynamic Factor Model), do machine learning algorithms provide better estimates in estimating domestic liquidity growth in the Philippines?
b. What are the substantial advantages of using machine learning algorithms vis-à-vis time series models in estimating domestic liquidity growth in the Philippines?
c. By using a wide range of high-frequency monetary, financial, and external sector indicators as explanatory variables, what are the critical factors that should be included in the nowcasting model to comprehensively explain and estimate the domestic liquidity growth in the Philippines?

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

1.3. Research Objectives

To comprehensively answer the abovementioned research questions, this study aims to achieve the following objectives:

a. To develop/formulate a nowcasting model that could supplement the current method of estimating domestic liquidity growth in the Philippines.
b. To utilize various key monetary, financial, and external sector indicators as input variables.
c. To conduct one-step-ahead (out-of-sample) nowcasts using time series models and machine learning algorithms.
d. To investigate the performance and accuracy of each time series model and machine learning algorithm in obtaining nowcasts.
e. To determine the advantages and disadvantages (if any) of using machine learning algorithms to assess the current state of domestic liquidity in the said country.

1.4. Significance of the Study

For the past years, an increasing number of scholars in economics have shown their interest in using nowcasting as a primary approach to determine the growth of numerous macro and socioeconomic indicators. Most of these studies, in particular, are focused on formulating quantitative models using different time series and machine learning algorithms that could provide a decent estimate of the level and growth of numerous macro and socioeconomic indicators using conventional or unconventional data.

In the case of the Philippines, the studies of Rufino (2017), Mapa (2018), and Mariano and Ozmucur (2015; 2020) already established the use of different time series models (e.g., MIDAS, DFM) and machine learning algorithms to nowcast GDP and inflation. However, none of these published studies have explored the usefulness of nowcasting in monetary policy, particularly in using different machine learning algorithms to estimate M3 growth in the said country.

Due to this observed literature gap, the researcher sees the following reasons wherein this study is considered as timely and relevant:

a. The output of this study could serve as a supplementary tool of the BSP to nowcast domestic liquidity growth, which is considered one of the most critical inputs for GDP and inflation forecasting as well as medium-term forecasting, scenario-building, and policy simulations (e.g., single equation model, multi-equation model).
b. Machine learning algorithms utilized in this study can be replicated to estimate the different key economic indicators produced by the said institution (e.g., balance of payments, financial soundness indicators) and other NGAs within the country.
c. The input variable(s) identified as a significant contributor(s) in this study could be used as a leading indicator(s) to monitor domestic liquidity growth in the Philippines.

d. Through this study, recommendations can be crafted to mainstream and integrate big data and machine learning in the monetary policy formulation and implementation of the BSP.
e. This study could also strengthen the growing body of literature regarding the application of time series and machine learning models in economic forecasting or nowcasting.

1.5. Scope and Limitations

This paper intends to provide a comprehensive analysis in establishing a model to conduct short-term forecasting or nowcasting using machine learning algorithms. However, the following are the scope and limitations of this study.

a. While the BSP directly influences the level of domestic liquidity in the said country through different monetary policy tools (e.g., open market operations, reserve requirement rate), the institution's policy direction in terms of increasing, decreasing, and/or maintaining its level is not tackled in this research. Instead, as previously mentioned in this chapter, the primary purpose of this study is to: (1) display the capacity of different machine learning algorithms in conducting economic nowcasting; and (2) formulate a model to support the BSP's suite of macroeconomic models used in forecasting and policy analysis (e.g., GDP, inflation, domestic liquidity forecasting).
b. This study only aims to nowcast domestic liquidity growth in the Philippines. Therefore, its monetary aggregate components, such as narrow money (M1) and other deposits included in broad money (M2), are not individually analyzed.
c. The benchmark models used in this study are limited to Autoregressive Integrated Moving Average (ARIMA), Random Walk (RW), Seasonal ARIMA (SARIMA), and Dynamic Factor Model (DFM).
d. The machine learning algorithms used in this study are limited to (1) Regularization Methods, such as Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO), and Elastic Net and (2) Tree-Based Methods, such as Random Forest and Gradient Boosted Trees.
e. The study initially aims to incorporate numerous variables that can represent different sectors of the economy (e.g., central bank, financial sector) in the Philippines. However, the final indicators used became limited due to (1) data confidentiality, (2) access restrictions, and (3) time constraints.
f. Due to the limited availability of data (especially data on the explanatory variables), the overall timeframe of this study is restricted from January 2008 to December 2020 (mixed of daily, weekly, monthly frequency).

2. Review of Related Literature

2.1. Regularization Methods

Regularization methods are among the prevalent machine learning algorithms used to conduct nowcasting. This is mainly due to its regression models with almost similar characteristics with the Ordinary Least Squares (OLS) (James et al., 2013; Tiffin, 2016).

Compared to the traditional linear models, however, the said method has the characteristic to constrain its coefficient estimates to significantly reduce their variance with the intention to improve the overall model fit (James et al., 2013). In other words, Ridge Regression, Least Absolute Shrinkage (LASSO), and Elastic Net (ENET) have the capacity to provide a better estimate because it reduces model complexity by incorporating penalties to its coefficient(s), which then address the issue of bias-variance tradeoff.[14] This approach is called shrinkage in machine learning literature (Tiffin, 2016; Richardson et al., 2018).

The studies of Tiffin (2016) and Dafnai and Sidi (2010) are among the well-known studies in economics that used regularization methods to conduct nowcasting. These studies attempted to formulate nowcasting models that could accurately estimate the GDP growth in Lebanon and Israel, respectively. Due to data publication lags that both countries experienced, these authors similarly agreed that there was a need to conduct an approach wherein economic growth can be immediately determined 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 aforementioned authors used high-frequency data or information as explanatory variables to their corresponding GDP nowcasting models to meet these objectives. Tiffin (2016), in particular, used nineteen (19) monthly macroeconomic variables (e.g., customs revenue, tourist arrivals) to observe economic growth in Lebanon.[15] Through the use of regularization methods, the author found that ENET is the most suitable machine learning algorithm to estimate the short-run economic development of Lebanon. Mainly because the in-sample and out-of-sample nowcasting results managed to systematically trace the cyclical movement of Lebanon's GDP with a small Root Mean Square Error (RMSE).

Dafnai and Sidi (2010), on the other hand, used one hundred forty (140) domestic indicators and fifteen (15) global indicators as input variables to nowcast the GDP in Israel.[16] The authors similarly found that ENET is the most comprehensive regularization method to forecast the country's economic growth. Furthermore, compared to other regularization methods used in their study, Dafnai and Sidi (2010) argued that ENET is the only model that successfully captured the timing and magnitude of the economic cycle in Israel while only generating a low Mean Absolute Forecast Error (MAFE).

Hussain et al. (2018) also performed nowcasting using a similar set of machine learning algorithms. This study, however, intended to predict the short-run growth of Large-Scale Manufacturing (LSM) in Pakistan. The authors decided to conduct this research because the official GDP data in the said country also encounters publication lag. Therefore, since LSM is published on a monthly basis and strongly depicts the significant economic activities in Pakistan, estimating its current state could be a valuable tool for the country's policymakers

[14] Bias-variance tradeoff is a central concept in forecasting and machine learning (Bolhuis and Rayner, 2020 p. 5). This refers to the balance between interpretability and flexibility of a (supervised) machine learning model (James et al., 2013).

[15] See Page 10 of Tiffin (2016).

[16] See Annex of Dafnai and Sidi (2010).

to immediately implement actions in the fast-changing domestic and global economic condition (Hussain et al., 2018).

Given this objective, the authors also used high-frequency data or information as explanatory variables to nowcast the said indicator. This includes monthly data regarding financial markets, confidence surveys, interest rate spreads, credit, and the external sector in Pakistan.[17] Using these as inputs to their regularization methods, Hussain et al. (2018) concluded that Ridge Regression, LASSO, and ENET methods are comprehensive quantitative tools in estimating the overall growth of LSM. Mainly because the three (3) machine learning algorithms scrupulously tracked the overall development, trends, and cyclical movement of LSM with small forecast error. The authors particularly found that even though the DFM provided the smallest forecasting error, it presented inconsistent results in estimating the overall growth and cycle of the said macroeconomic indicator. On the other hand, while among the regularization method used, LASSO rendered the most accurate result since it comprehensively traced the trends and cycle of LSM in Pakistan while having the lowest RMSE (Hussain et al., 2018).

The regularization methods were likewise used by Cepni et al. (2018) and 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).[18] 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.[19]The former authors notably used LASSO to augment the nowcasting activity done 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 concluded that these machine learning models are convenient and comprehensive quantitative approaches to accurately estimate GDP in the short run. This is because Ridge Regression and LASSO have the capacity to filter out the insignificant variables, which could provide a parsimonious set of nowcasting models with precise results (Cepni et al., 2018; Ferrara and Simoni, 2019).

The use of nowcasting is not only popular to estimate future values of different macroeconomic indicators, such as GDP. Recent studies showed that this approach could also be used to estimate firm-level and sectoral data. The paper of Fornano et al. (2017) was among the few studies that fall under this category. In particular, the authors applied the three (3) regularization methods to nowcast the turnover indices growth of the main economic sectors

[17] See Page 13 of Hussain et al. (2018).
[18] See Page 2 of Cepni et al. (2018).
[19] See Page 7 of Ferrera and Simoni (2019).

(e.g., services, manufacturing) in Finland.[20] The individual results of these methods were compared with traditional time series models, such as ARIMA to estimate their respective prediction accuracy. Using these methods, Fornano et al. (2017) found that machine learning algorithms outperformed the said univariate model in estimating the turnover indices growth of all sectors in Finland. This is due to the low Mean Square Forecast Errors (MSFE) that Ridge Regression, LASSO, and ENET registered compared to the said time series model used in their study (Fornano et al., 2017).

Aside from estimating the growth of a particular macroeconomic and firm-level indicator, nowcasting was also utilized in energy and medicine. The papers of Ziel (2020) and Lan and Subramanian (2019) were among the studies in these fields that used regularization methods to estimate the current state of electricity or power consumption and dengue occurrence in Europe as well as Puerto Rico and Peru, respectively.

Both authors mentioned that their attempt to estimate these circumstances was due to the increasing concerns regarding publication lag on the official data of electricity consumption and dengue occurrence in Europe as well as Puerto Rico and Peru. In addition, their studies were prompted by the high volume of different stakeholders' requests that use the two (2) indicators for economic and public health reasons (Ziel, 2020; Lan and Subramanian, 2019).

Likewise, the authors use high-frequency data or information to perform their corresponding nowcasting exercise. Ziel (2020) used daily energy load values provided by the European Transmission System Operators (TSO) from 2014 to 2019, while Lan and Subramanian (2019) employed climatic variables and data from Google Trends as explanatory variables.[21,22] Based on their analysis, both authors concluded that regularization methods could accurately nowcast the two (2) aforementioned circumstances with ease. This is mainly due to the capacity of regularization methods to handle and incorporate a large number of predictors with low levels of MAE and RMSE. Ziel (2020), as well as Lan and Subramanian (2019), similarly found that Ridge Regression and LASSO are the most accurate regularization models to nowcast electricity consumption in Europe and dengue occurrence in Puerto Rico and Peru, respectively.

2.2. Tree-Based Methods

Aside from regularization methods, numerous studies also introduced the use of tree-based methods in nowcasting. The said approach is one of the well-known options to perform nowcasting through machine learning algorithms because of its strong capacity, similar to regularization methods, in being flexible and interpretable.[23] However, in contrast to Ridge Regression, LASSO, and ENET, tree-based methods strongly involve stratifying or segmenting the predictor space into a number of simple regions. To estimate a given observation, the

[20] See Page 5 of Fornano et al. (2017).
[21] See Page 8 of Ziel (2020).
[22] See Page 5 of Lan and Subramanian (2019).
[23] Similar to regularization methods, tree-based methods in machine learning also address the issue of bias-variance tradeoff.

mean or mode of the training observation is typically used in the region it belongs to (James et al., 2013 p. 303).

The study of Biau and D'Elia (2010) was the most recognized study that used tree-based methods to estimate economic growth. These authors, in particular, utilized Random Forest (RF) algorithm to forecast the short-term GDP growth in Europe. Furthermore, the analysis of said authors was complemented by the numerous datasets – under the European Union Business and Consumer Survey – to strongly utilize the capacity of said machine learning model in handling a large number of input variables with robust prediction accuracy.[24]

Using the aforementioned data through RF, Biau and D'Elia (2010) concluded that the said approach is a well-performing machine learning algorithm to predict the short-term growth of GDP in Europe. RF provided more accurate estimates than the projections registered by the traditional time series model, such as ARIMA, to forecast the said macroeconomic indicator. In particular, forecasting the GDP in Europe using the said tree-based approach only generated an MSE of 0.43 while the AR produced 0.64. The authors also cited that RF is an effective tool to create a parsimonious model. Since the aforementioned had identified which predictive variables included in their model are the most significant (Biau and D'Elia, 2010).

This approach was similarly performed under the study of Adriansson and Mattson (2015). The authors, in particular, used the methodology of Biau and D'Elia (2010) to investigate the use of RF in forecasting the quarterly economic growth of Sweden. To attain this objective, these authors similarly used a large amount of survey datasets to estimate the GDP of said country. The data under the Economic Tendency Survey conducted by the National Institute of Economic Research (NIER) were mainly used as explanatory variables in their forecasting model using RF.[25] This survey consists of different confidence indicators and questions to private firms and households regarding their economic outlook and perception of economic activity in Sweden (Adriansson and Mattson, 2015).

Using these data as inputs for their tree-based method nowcasting, Adriansson and Mattson (2015) found that RF provides a better prediction performance against the ad hoc linear model and ARIMA in forecasting the GDP growth of Sweden. Furthermore, RF registered the lowest RMSE of 0.75 compared to the 0.79 and 0.95 of the two (2) time series benchmark models, respectively (Adriansson and Mattson, 2015). Therefore, similar to the recommendation of Biau and D'Elia (2010), the study of Adriansson and Mattson (2015) proposed that RF is a valuable quantitative approach that could improve forecasting when applied to economic time series data.

Aside from RF, Adaptive Trees (AT) – which is highly based on Gradient Boosted Trees (GBT) – was also utilized as a primary machine learning model to conduct forecasting. This is because of its strong capacity to deal with non-linearities 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 three (3)- to twelve (12)-months ahead GDP growth forecast to the Group of Seven (G7) countries.[26] In this study, the author employed

[24] See Page 6 of Biau and D'Elia (2010).
[25] See Page 5 of Adriansson and Mattson (2015).
[26] Canada, however, was not included in the analysis of Woloszko (2020).

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.[27]

Based on the conducted forecast simulations, Woloszko (2020) similarly concluded that the said machine learning algorithm is a valuable tool in economic forecasting. This was attributable to the accurate prediction results compared to the traditional time series models. In contrast to univariate models, the 3- and 6-months ahead GDP growth forecast for the US, United Kingdom (UK), France, and Japan using AT displayed lower RMSEs. The authors, however, found that this level of accuracy was only applicable in short-run forecasting because the forecasting results of AT became uninformative after they used it to conduct the one (1)-year-ahead forecast. Due to this reason, Woloszko (2020) argued that despite having the advantage to handle a large number of variables in economic forecasting, AT might not be a suitable model to predict long-run effects.

Other empirical studies utilized RF and GBT as machine learning algorithms 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 aim to determine the most optimal tree-based method to estimate economic growth using high-frequency data or information. In particular, the study of Boluis and Rayner (2020) used two hundred thirty-four (234) country-specific and global indicators from Haver Analytics. This includes macroeconomic indicators regarding the financial, labor, and external sectors.[28] Meanwhile, Soybilgen and Yazgan (2021) utilized more than one hundred (100) financial and macroeconomic variables, including data on the labor market, money and credit, and stock market.[29]

Using these input variables, Boluis and Rayner (2020) and Soybilgen and Yazgan (2021) concluded that the tree-based methods provide superior forecasts compared to the benchmark models used. 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.[30] Aside from their outstanding individual accuracy, these authors also cited that the tree-based methods have the strength to predict economic volatility and the capacity to determine which among the variables included in the forecasting model are the most essential.

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 because they intended to distinguish the accuracy of each machine learning method

[27] See Page 11 of Woloszko (2020).
[28] See Tables A5.1 and A5.2, Pages 24-25 of Boluis and Rayner (2020).
[29] See Appendix 1, Page 23 of Soybilgen and Yazgan (2021).
[30] See Table 1 and 2, Page 13 of Soybilgen and Yazgan (2021).

to estimate the growth of a specific macroeconomic indicator or phenomenon and assess the overall fit (e.g., linear, non-linear) of the variables in a particular model (Richardson et al., 2018; Aguilar et al., 2019; Tamara et al., 2020).

One of the studies that fall under this category is the research produced by Richardson et al. (2018). In particular, the authors attempted to use regularization and tree-based methods to formulate a model that could strongly estimate the movement of GDP growth in New Zealand. The objective of this study was drawn from the difficulty of their policymakers in addressing various economic vulnerabilities because policy formulations in the said country are highly dependent on the non-related, outdated, or lagged data (Richardson et al., 2018).

Given this scenario, Richardson et al. (2018) used a number of real-time vintages of macroeconomic and financial market statistics as explanatory variables to their simulated nowcasting models. This includes data from business surveys, consumer and producer prices, and general domestic activity production, among others.[31]

By using these as regressors for the different machine learning algorithms, Richardson et al. (2018) concluded that regularization and tree-based methods could be both used as a primary methodology to nowcast the economic growth in New Zealand. This is mainly due to the consistent low forecast errors that these models registered compared to the traditional time series methods, such as ARIMA, DFM, and Bayesian VAR, to estimate the GDP in the said country. In particular, the authors found that LASSO, GBT, and Ridge Regression provided lower RMSE compared to the aforementioned time series models, with 0.45, 0.47, and 0.57, respectively.

This research methodology is also utilized under the study of Tamara et al. (2020). These authors used regularization and tree-based methods to nowcast the GDP growth in Indonesia. Similar to the objective of Richardson et al. (2018), Tamara et al. (2020) conducted this research to provide accurate estimates on the output growth of the said country. This is because Indonesia's quarterly data for GDP is released with five (5) weeks lag after the end of reference (Tamara et al., 2020).

Based on this objective, Tamara et al. (2020) used eighteen (18) predictor variables in their model. These data are comprised of quarterly macroeconomic (e.g., consumption expenditure, current account) and financial market statistics (e.g., change in stocks).[32] Using these indicators as explanatory variables, the authors concluded that regularization and tree-based methods provide better estimates for the short-run GDP growth in Indonesia. This is mainly due to said machine learning algorithms' RMSE and Mean Average Deviation (MAD). The results also demonstrate that the forecasted values of these methods produce a similar pattern close to the actual values. Furthermore, the authors found that regularization and tree-based methods reduced the average forecast errors at thirty-eight (38) to sixty-three (63) percent relative to ARIMA. Further, Tamara et al. (2020) cited that RF and ENET have the lowest average forecast errors of 1.27 and 1.31, respectively.

[31] See Page 8 of Richardson et al. (2018).
[32] See Appendix of Tamara et al. (2020).

The potential of regularization and tree-based methods was also utilized to estimate global poverty. The paper of Aguilar et al. (2019) used these machine learning algorithms to formulate a quantitative model to improve the accuracy of the current poverty nowcasting model of the World Bank (WB). Remarkably, the authors applied LASSO, RF, and GBT to nowcast the mean welfare and back out poverty rates. This study was drawn to have a more reliable and cost-effective method to predict the current state of poverty across regions (Aguilar et al., 2019).

Considering this, Aguilar et al. (2019) used similar datasets under the current forecasting model of WB to estimate the current level and growth of global poverty. These datasets include macroeconomic and social indicators extracted from the World Economic Outlook (WEO) database and World Development Indicators (WDI).[33] Using these as inputs, the authors found that regularization and tree-based methods – as a primary nowcasting model – decreased the overall nowcast error by 5.7 percent from 2.8 percentage points (Aguilar et al., 2019). However, the author argued that despite having accurate estimates, LASSO, RF, and GBT only provide minor improvement vis-à-vis the current method used by the WB to nowcast global poverty.

3. Research Methodology

3.1. Models

Time series models and machine learning algorithms are utilized to systematically support the main objective of this research. The former models are used as benchmarks since these are the most commonly used quantitative models to estimate the current and future growth of a particular macroeconomic indicator or economic phenomenon. Meanwhile, machine learning algorithms are used as the alternative methods to nowcast domestic liquidity growth in the Philippines. This approach is conducted for two main reasons: (1) to establish which quantitative models could accurately estimate the real-time growth of said monetary indicator; and (2) to determine the strength of machine learning algorithms to precisely nowcast vis-à-vis traditional time series models.

Drawing upon this background, the properties of the time series and machine learning models utilized in this study are comprehensively discussed in this chapter. The former includes traditional forecasting models such as univariate (e.g., ARIMA and Random Walk) and multivariate (i.e., VAR, DFM) models. On the other hand, the latter models are comprised of regularization (i.e., Ridge, LASSO, ENET) and tree-based (i.e., RF, GBT) methods.

3.1.1. Benchmark Models

3.1.1.1. Univariate Models

Univariate models are the most frequently used approach to predict the growth and development of a particular macroeconomic indicator or scenario. Mainly because of its strong ability to perform forecasting despite using a single time series. Numerous studies argued that

[33] See Page 6 of Aguilar et al. (2019).

univariate models are highly utilized in time series forecasting because of their simple but powerful method of using past values to identify a particular indicator's future growth and development (Meyler et al. 1998; Medel and Pincheira, 2015).

3.1.1.2. Autoregressive Integrated Moving Average

Various univariate models are specifically used depending on the nature of a time series. The Autoregressive Integrated Moving Average (ARIMA) is one of the general models under this approach. This time series model is frequently used in most forecasting studies when a specific time series data is non-stationary, previous values are significant to predict its current state, or errors are autocorrelated. Mainly because ARIMA can be interpreted as a filter that aims to separate the signal from the noise, and the signal is then generalized into the future to acquire forecasts (Nau, 2014). The general forecasting equation using ARIMA is structured as follows:

$$\hat{y}_t = \mu + \phi_0 + \phi_1 y_{t-1} + \ldots + \phi_2 y_{t-p} \ldots + \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q} \quad (3.1)$$

Under equation 3.1, p represents the order of the autoregression, which includes the overall effect(s) of past values into 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 pp. 10-11).

3.1.1.2.1. Random Walk

Another popular univariate model used in economic forecasting is the Random Walk. The property of this time series model is quite similar to ARIMA. Mainly because these models similarly use the previous data points as a reference of the future trend of a specific time series. This univariate model is also utilized if a particular time series is non-stationary.[34,35] However, compared to ARIMA, the Random Walk model assumes that the next step is decided by the last data point and takes an independent random step away (Fan, 2019 p. 11-12). The general forecasting equation using Random Walk is written below:

$$\hat{y}_t = \epsilon_t + y_{t-1} \quad (3.2)$$

In equation 3.2, the y_t and y_{t-1} represents the observations of the time series and ϵ_t is the white noise with zero mean and constant variance (Fan, 2019 p.12).

3.1.1.3. Vector Autoregression

Using univariate models as a principal approach to estimate a particular time series has limitations. This is their characteristic to rely on previous data points to forecast a particular indicator heavily. In other words, when ARIMA or Random Walk are used, other determinants that could influence the growth and development of an indicator are not being strongly considered.

[34] Random walk is similar with ARIMA(0,1,0).

[35] Random walk is a prevalent forecasting model for non-stationary time series data such as foreign exchange rates.

Most economic forecasting studies used multivariate time series models such as Vector Autoregression (VAR) to address this concern. The superiority of this algorithm against univariate time series models has been proven and established over time. Mainly because it has the capability to create structural equations with other influential features and incorporate two (2) or more time series to forecast the growth and development of a particular indicator. Therefore, VAR can be considered a comprehensive forecasting model compared to ARIMA or Random Walk. The general form of VAR model with deterministic term and exogenous variable can be expressed as:

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_p y_{t-p} + \pi d_t + \gamma x_t + \epsilon_t \tag{3.3}$$

Under equation 3.3, d_t denotes $(l \times 1)$ matrix of other deterministic terms as such linear time trend or seasonal dummy variables and x_t represents $(m \times 1)$ matrix of stochastic exogenous components. The notations π and γ are the parameter matrices (Fan, 2019 p. 12-13).

3.1.1.4. Dynamic Factor Model

The Dynamic Factor Model (DFM) is also a prevalent method to estimate the future growth of a particular variable with numerous explanatory variables. This is mainly due to its capacity to handle large datasets with no practical or computational limits (Stock and Watson, 2016). Mariano and Ozmucur (2020) also mentioned that DFM is a valuable tool to forecast a specific indicator with numerous explanatory variables because it addresses the difficulty of getting convergence in a state-space framework.

Compared to VAR, where the set of variables is immediately included in the model, a DFM reduces the dimension of these datasets by summarizing the information available into a small number of common factors. Then, each variable is represented as the common and idiosyncratic components. The former is constructed with a linear combination of the common factors that could explain the main part of the variance of the time series, while the latter contains the remaining variable-specific information (Fan, 2019 p. 13). The DFM is expressed as:

$$X_t = \lambda(L) f_t + \epsilon_t \tag{3.4}$$

Under Equation 3.4, notation X_t represents the vector of observed time series variables depending on a reduced number of latent factors f_t and 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).

3.1.2. Machine Learning Models

3.1.2.1. Regularization Methods

As discussed in the previous chapter, regularization methods are among the well-known machine learning algorithms used to conduct nowcasting. This is because their individual properties strongly resemble OLS characteristics in fitting a linear model (James et al., 2013; Tiffin, 2016). However, in contrast with the said linear model, regularization methods constrain its coefficient estimates to significantly reduce their variance with the intention to improve the overall model fit (James et al., 2013).

3.1.2.1.1. Ridge Regression

One of the regularization methods used in nowcasting is Ridge Regression. This regularization method is very similar to least squares. It also aims to obtain coefficients that fit the data well by making the residual sum of squares (RSS) as small as possible. However, the said approach seeks to minimize a second term – called shrinkage penalty – which is small when the regression coefficients are close to zero (Tiffin, 2016 p. 7) (Equation 3.5).

$$\sum_{t=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j\, x_{ij}\right)^2 + \lambda\sum_{j=1}^{p}\beta_j^2 \tag{3.5}$$

Equation 3.5 depicts the RSS and penalty term of the said regularization method. 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 p. 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 shrinkage penalty increases, and the coefficient estimates approach to zero (0) (Tiffin, 2016).

3.1.2.1.2. Least Absolute Shrinkage and Selection Operator

Another form of regularization method is the Least Absolute Shrinkage and Selection Operator (LASSO). Similar to Ridge Regression, LASSO also includes a penalty term to its RSS (Equation 3.6).

$$\sum_{t=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j\, x_{ij}\right)^2 + \lambda\sum_{j=1}^{p}\left|\beta_j\right| \tag{3.6}$$

In contrast with the former regularization method, which only shrinks all of its coefficients towards zero (0) but does not set any of them exactly to zero (0), LASSO forces its coefficients to be precisely equal to zero (0) when tuning the parameter λ is adequately large (James et al., 2016).[36] Therefore, due to its substantial penalty, the main advantage of LASSO over Ridge Regression is its ability to select important variables and produce a parsimonious model with fewer predictors.

[36] Except if the penalty of Ridge Regression is $\lambda = \infty$.

3.1.2.1.3. Elastic Net

Numerous studies also used Elastic Net (ENET) as their primary approach to perform nowcasting in order to maximize the strengths of the two (2) aforementioned methods.[37]. ENET is a regularization method containing both properties of Ridge Regression and LASSO (Equation 3.7).

$$\sum_{t=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j\, x_{ij}\right)^2 + \lambda\sum_{j=1}^{p}[(1-\alpha)(\beta\,_j^2) + \alpha|\beta_j|] \tag{3.7}$$

In particular, this model utilizes the penalty strength 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 (2) penalties are determined through the additional tuning parameter α (Richardson et al., 2018).

3.1.2.2. Tree-Based Methods

Other studies also utilized tree-based methods as a primary approach to conduct nowcasting. These studies notably used Random Forest and Gradient Boosting Trees because it has a strong resemblance with regularization methods, which are popular for their capacity to address bias-variance tradeoff that provides an intuitive and easy-to-implement way of modeling non-linear relationships.

However, in contrast with Ridge Regression, LASSO, and ENET, these methods are considered non-parametric models that do not require the underlying relationship between the dependent and independent variables (Fan, 2019). Instead, tree-based methods involve stratifying or segmenting the predictor space into a number of simple regions. Therefore, in order to estimate for a given observation, tree-based methods utilize the mean or mode of training observation in the region to which it belongs (James et al., 2013 p. 303).

3.1.2.2.1. Decision Tree

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 (2) classes in a systematic manner in order 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 (Figure 3.1). The algorithm, afterward, makes the estimation by using the mean or mode of training observation in that particular region (James et al., 2013).

3.1.2.2.2. Random Forest

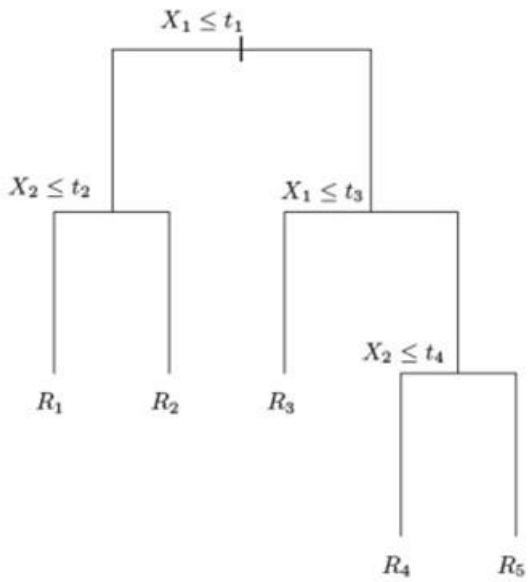
One of the most well-known tree-based machine learning algorithms is the Random Forest (RF). This particular model is computationally simple to use, does not require tuning of

[37] See the studies of Tiffin (2016), Richardson et al. (2018), and Tamara et al. (2020).

model parameters, and is ideal for forecasting time series data with relatively few observations (James et al., 2013).

RF is a machine learning algorithm that uses combinations of multiple decision trees to formulate a comprehensive forecast. Notably, it modifies the approach of a decision tree in order to minimize the problem of overfitting and maximize the information content of the data by using subsamples of observations and predictions (Tiffin, 2016; Bolhuis and Rayner, 2020). To perform this, 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. Using these approaches, RF generates an accurate and robust aggregate prediction (Tiffin, 2016; Bolhuis and Rayner, 2020).

Figure 3.1: Decision Tree Growing Process
(Recursive Binary Splitting of Two-Dimensional Feature Space)



Source: James et al. (2013)

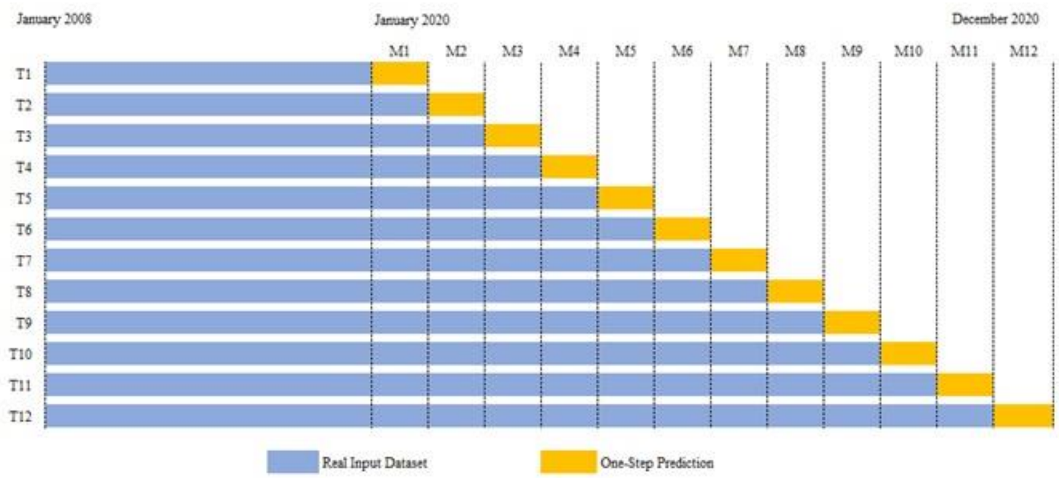
3.1.2.2.3. Gradient Boosted Trees

Gradient Boosted Trees (GBT) is another tree-based model often used by studies that aim to perform nowcasting. This is because of its powerful capability to capture complex non-linear functions (Fan, 2019). Compared with RF, GBT is a machine learning algorithm that formulates sequential decision trees rather than combinations to construct an aggregate forecast. This tree-based model does not involve bootstrap sampling that RF conducts. GBT, instead, train 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).

3.2. Nowcast Evaluation Methodology

This study evaluates the performance of time series and machine learning algorithms based on their one-step-ahead (out-of-sample) nowcast. The models are trained over an expanding window (also called recursive method) to estimate domestic liquidity growth from January to December 2020 (Figure 3.2). For instance, for the first nowcast in January 2020, the dataset used is 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. Overall, there are twenty-four (24) generated nowcasts for each time series and machine learning algorithms used in this research, with the end-month nowcast being the principal prediction result.[38]

Figure 3.2: Expanding Window Process



After the individual performance is evaluated, the accuracy of each model is gauged through their respective forecast errors such as RMSE (Equation 3.8) and MAE (Equation 3.9). The forecast errors of each machine learning algorithm are compared against benchmark models (e.g., AR, DFM). This comparison method is performed to determine whether the nowcast results obtained from the former are significantly superior to the latter methods or vice versa.

$$RMSE = \frac{\sqrt{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}}{n} \tag{3.8}$$

$$MAE = \frac{\sum_{t=1}^{n}|y_t - \hat{y}_t|}{n} \tag{3.9}$$

3.3. Research Tool

R is the primary statistical software used in this study. It is a well-known environment for statistical computations, mathematical equations, and data visualizations. In particular, this

[38] Since the data of target and input variables are unbalanced (e.g., monthly for target variable, daily/weekly for input variable) problem. Averaging and interpolation are conducted to align of the data properly. This is further discussed in Chapter 4: Data and Diagnostics.

study highly utilized the capacity of R Studio to perform the whole process of this research. This includes data integration, data cleaning, model building, and statistical validation.[39]

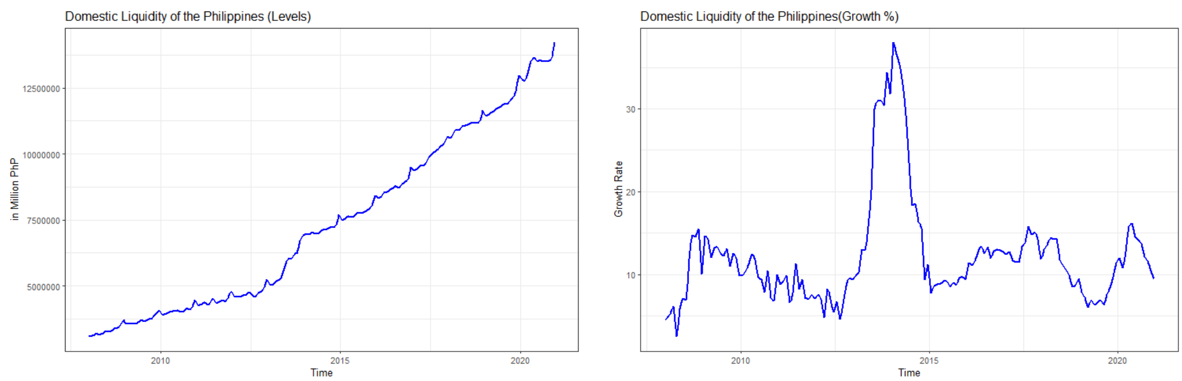
4. Data and Diagnostics

4.1. Data

4.1.1. Target Variable

Driven by the objective and nature of this study, the dependent variable utilized is the domestic liquidity in the Philippines. This monetary indicator represents the total amount of money available in the economy of said country. The numerical figures (i.e., level, growth rate) of domestic liquidity are acquired from the monthly Depository Corporations Survey (DCS) that the BSP published on its official website from January 2008 to December 2020.[40,41] Figure 4.1 depicts the level (in million PHP) and year-on-year (YOY) growth rate (in percent), while Table 4.1 presents the summary statistics of domestic liquidity in the Philippines.

Figure 4.1: Domestic Liquidity in the Philippines (January 2008-December 2020)
(a) Levels (in Million PHP); (b) Growth Rate (in Percent)



(a) (b)

Table 4.1: Summary Statistics of Domestic Liquidity in the Philippines

	MIN.	1ST QU.	MEDIAN	MEAN	3RD QU.	MAX
M3 (Level in PHP)	3,101,926	4,357,222	7,118,632	7,395,092	10,203,734	14,211,479
M3 (Growth %)	2.550	8.615	11.200	12.292	13.365	37.970

4.1.2. Input Variables

Similar to previous studies that intend to formulate nowcasting models of different macro and socioeconomic indicators and transmission mechanisms of policies through machine learning algorithms, high-frequency data are also used as independent variables in

39 The R packages used in this study are listed in Annex A.
40 Official BSP Website: https://www.bsp.gov.ph.
41 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.

this study. These are comprised of numerous monetary, financial, and external sector indicators, which are used as conventional components to monitor domestic liquidity growth.

4.1.2.1. Monetary Indicators

The numerical data of monetary variables used in this study are formally requested from the DES and obtained from the official website of the BSP.[42] A formal request is made because daily figures of these variables are not published nor shared publicly. Therefore, monetary indicators that are requested from the DES are the daily (1) available reserves (i.e., required reserves, excess reserves) and (2) reserve money (i.e., currency-in-circulation, central bank liabilities). Meanwhile, (3) central bank claims on National Government (NG) and (4) claims on other sectors are obtained from the monthly Central Bank Survey (CBS) posted on the BSP's website. The data of these indicators covers January 2008 to December 2020.

4.1.2.2. Financial Indicators

The financial indicators used in this study are sourced from the BSP's website and Bloomberg. These are comprised of daily (1) Weighted Monetary Operations Rate (WMOR), (2) BSP Discount Rate, (3) CBOE Volatility Index, (4) Credit Default Swap (CDS) (5) London Interbank Offered Rates (LIBOR), (6) Singapore Interbank Offered Rates (SIBOR), (7) Philippine Interbank Reference Rate (PHIREF), (8) Government Bond Rate, (9) Interbank Call Loan Rate, (10) Bank Prime Rate, (11) Treasury Bill Rate, and (12) Promissory Note Rate from January 2008 to December 2020.

4.1.2.3. External Indicators

Statistics for external sector indicators are also obtained from Bloomberg. However, the weekly figures of Foreign Portfolio Investment (FPI) are formally requested from the International Operations Department (IOD) of the BSP.[43] Similar to the case of available reserves and reserve money, its daily historical values are not published nor shared publicly. Other than the (1) FPI, (2) daily foreign exchange rate (i.e., Philippine Peso per US Dollar) is also used as an external sector indicator in this study. The coverage of these data is from January 2008 to December 2020.

4.1.2.4. Lagged Values of Domestic Liquidity [44]

Although this study captures numerous monetary, financial, and external indicators as input variables to predict the future movement of domestic liquidity in the Philippines, other determinants that could also influence its growth are not included in the dataset. To address this concern, the lagged value of the domestic liquidity is also considered an input variable. Therefore, the lagged values used in this study are $t - 1$ of the target variable.

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[42] The DES is the technical arm of the BSP that generates monetary and economic statistics needed in the formulation and implementation of monetary policy (2020 BSP Organization Primer, p. 25).

[43] The IOD supports the BSP in maintaining the monetary stability and external sustainability through the management of external debt, foreign investments, and other foreign exchange transactions (2020 BSP Organization Primer, p. 25).

[44] Lagged values of domestic liquidity are only utilized under machine learning algorithms.

Table 4.2: List of Data

NO.	VARIABLE	TYPE	FREQ.	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

4.2. Averaging and Interpolation

Given that one of the main objectives of this study is to formulate a model to minimize the usual approach in formulating policies based on outdated or lagged data, this study aims to nowcast domestic liquidity in the said country on a bi-monthly basis, with the second nowcast being the principal prediction result. This is to maximize the capability of each high-frequency input variable (i.e., variables with daily frequency) in explaining the variability of the target variable. Aside from this, utilizing regressors with high-frequency data typically solves the overfitting problem caused by the "curse of dimensionality" or fat regression (i.e., various input variables with limited observations).

However, based on the data publication release of each indicator (Table 4.2), it can be observed that there is an unbalanced frequency problem. Standard regression models require that the datasets should have the same granularity level. Therefore, to align all of the data correctly, averaging and interpolation are conducted in this study.

4.2.1. Averaging of High-Frequency Variables

Data averaging is performed on variables with a daily and weekly frequency. The input variables (e.g., monetary, financial indicators) with daily frequency are aggregated and averaged into two (2) numerical values in a month. The first value is the average of 1st until the 15th day of the month, while the other half is the mean of 16th until the last day of the month (e.g., available reserves data from 1 to 15 January and 16 to 31 January are averaged, respectively). On the other hand, explanatory variables with weekly frequency are averaged based on the first and second week as well as third and fourth-week data release, respectively (e.g., first- and second-week data of foreign portfolio investment are averaged).

4.2.2. Interpolation of Low-Frequency Variables

Data interpolation is conducted on the variables with low frequency (i.e., monthly), such as domestic liquidity, BSP liabilities on NG, and BSP claims on other sectors. Since these are published on a monthly basis, their official data are categorized as the month-end growth rate. 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 non-linear data estimation.

4.3. Diagnostics

The raw dataset is refined to improve the performance of time series and machine learning algorithms used in this study. Data of target and input variables are (1) seasonally adjusted, (2) log-transformed, and (3) individually assessed if they are stationary.[45]

4.3.1. Seasonal Adjustment

Since most published data in the Philippines are not seasonally adjusted, the numerical figures of domestic liquidity and most input variables used in this study are deseasonalized accordingly. This includes data requested from the DES and IOD and the other statistics obtained from the official website of the BSP and Bloomberg (e.g., BSP liabilities to NG, BSP discount rate). Hence, the aforementioned correction was performed to ensure that estimates from the time series and machine learning models are accurate since seasonal components (e.g., holidays) are absent in each model simulation.

4.3.2. Logarithmic Transformation

The normality of data is also important in economic and statistical modeling. However, since most real-life datasets do not always follow a normal distribution, they are often skewed, making the empirical results or analysis spurious. Therefore, to address this concern, the numerical figures of target and input variables in this study are transformed based on their respective logarithmic equivalent.

4.3.3. Stationarity

To develop an accurate or precise nowcasting model, it is crucial to establish that the time series data of each indicator is stationary. This is to ensure that the statistical properties of each time series do not change over time. In this study, the stationarity of target and input variables are verified through the Augmented Dickey-Fuller (ADF) and Philipps-Perron (PP) tests.

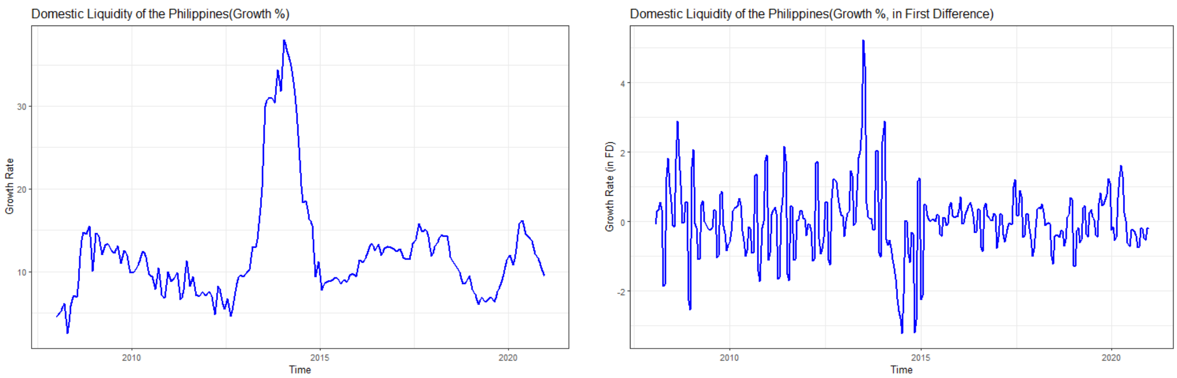
[45] To equally compare the performance of each model, seasonally adjusted, logarithmic transformed, and stationary data are also used under the machine learning algorithms utilized in this study.

Based on the unit root tests conducted, the level, the growth rate, and/or the logarithmic equivalent of domestic liquidity and input variables are non-stationary (Table 4.3).[46] This is mainly due to their p-value, which is greater than the five (5) percent significance level (except for BSP liabilities to NG). However, ADF and PP tests showed that these variables are stationary when transformed in their respective first difference. Therefore, in this study, the simulated nowcasting models used the first difference values of target and input variables (except for BSP Liabilities to NG).[47]

Table 4.3: Unit Root Tests for Domestic Liquidity in the Philippines

VARIABLE	TEST	LEVEL OF SIG.	P-VALUE (LEVEL/GROWTH/LOG)	P-VALUE (FIRST DIFF.)
M3	ADF PP	0.05	0.14 0.61	0.01 0.01

Figure 4.2: Domestic Liquidity in the Philippines (January 2008 – December 2020)
(a) Growth Rate (in %); (b) Growth Rate (in %, First Difference)



(a) (b)

5. Results and Analysis

5.1. Calibration and Nowcast Results

5.1.1. One-Step-Ahead (Out-of-Sample) via Expanding Window

Considering that one of the main objectives of this study is to estimate domestic liquidity growth in the short-run, one-step-ahead (out-of-sample) nowcasts are performed. This particular approach is preferred over multi-step-ahead (out-of-sample) estimates because of two (2) primary underlying reasons. The first reason is to ensure that the recent numerical figures of target and input variables are part of the structure and characteristics of the training datasets. The second reason is to maximize the forecasting ability of time series models, specifically ARIMA and Random Walk. These univariate models place heavier emphasis on the recent past than the distant past in conducting a forecast. Therefore, to appropriately compare

[46] See Annex B for the individual ADF and PP test result of input variables.

[47] For univariate models, the process of obtaining the first difference values of target variable is conducted within the ARIMA and RW process. For DFM and machine learning models (i.e., regularization, tree-based methods), data of target and input variables are transformed by their first difference prior model simulation.

the accuracy of benchmark models vis-à-vis machine learning algorithms, their respective one-step-ahead (out-of-sample) nowcasts should be considered one of the bases of evaluation.

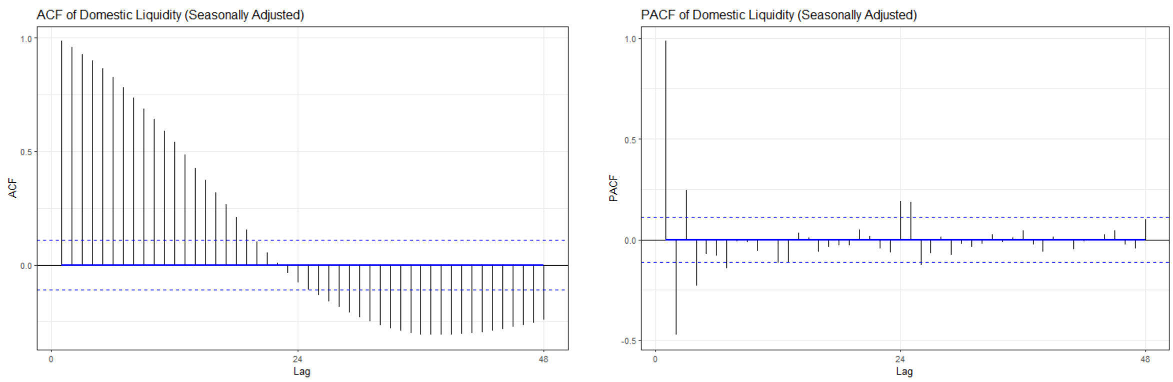
Aside from the two (2) reasons mentioned, it is also crucial to determine the precision consistency of simulated nowcasting models. Therefore, the benchmark and machine learning models are trained over an expanding window (also known as recursive method) to provide a series of one-step-ahead (out-of-sample) nowcast. The bi-monthly dataset covering thirteen (13) years from 2008 to 2020 is divided into twelve (12) different 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. Overall, there are twenty-four (24) generated nowcasts for each time series model and machine learning algorithm, with the end-month one-step-ahead (out-of-sample) nowcast being the principal prediction result. The estimates of benchmark models and machine learning algorithms under the said approach are then individually and collectively evaluated based on their Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

5.1.2. Univariate Models

5.1.2.1. Model Calibration

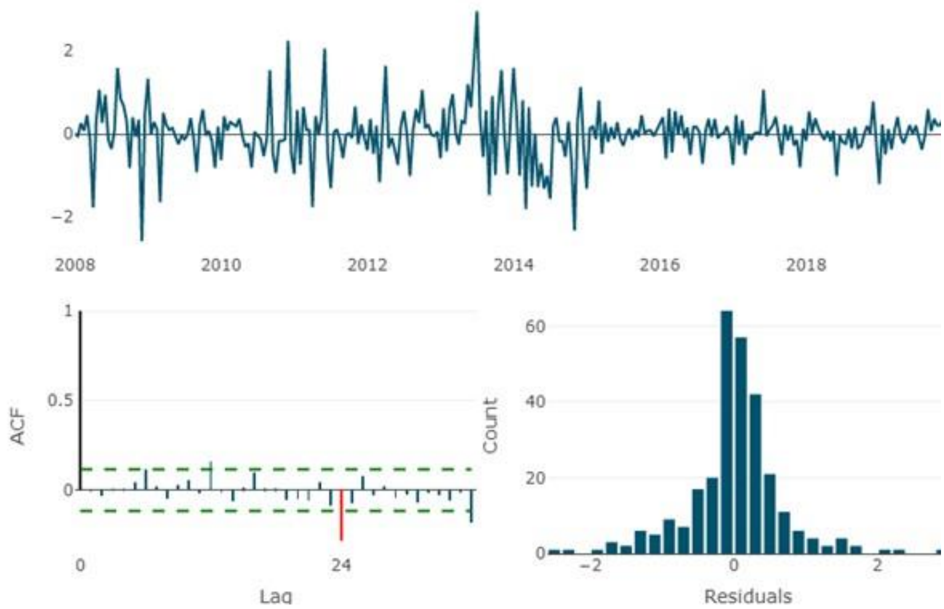
In this study, the trained models under univariate models are simulated based on three (3) different approaches. The first simulated model has the parameters (0,1,0) of an ARIMA structure, otherwise known as Random Walk because the time series data of domestic liquidity shows an irregular growth as found in the Augmented Dickey-Fuller (ADF) and Philipps-Perron (PP) tests. Therefore, one of the best strategies is to estimate the change that occurs from one period to the next rather than directly determining the level of the series at each period to address this concern. In other words, it is essential to observe the first difference of the time series to monitor if there are predictable patterns that can be determined (Nau, 2014).

Figure 5.1: ACF and PACF of Domestic Liquidity Growth in the Philippines (Seasonally Adjusted)
(a) ACF of M3 (Seasonally Adjusted); (b) PACF of M3 (Seasonally Adjusted)



(a) (b)

Figure 5.2: Residual Plot for ARIMA (4,1,1)[48]



The second univariate model simulated has the parameters (4,1,1) of an ARIMA Model. This is formulated since the Partial Autocorrelation Function (PACF) as well as Akaike Information Criterion (AIC) suggest that four (4) autoregressive (AR) lags should be considered to estimate domestic liquidity growth in the Philippines (Figure 5.1). Aside from this, the data of said monetary indicator was found to be non-stationary. Hence, in some non-stationary time series data cases, it is essential to use the average of the last few observations to filter out the noise and accurately estimate the local mean (Nau, 2014).

Lastly, the third univariate model parameters are established based on the built-in function of the statistical software, R Studio. The decision to use this automated process is due to the seasonal lag that was found to be relevant under the Autocorrelation Function (ACF) of ARIMA (4,1,1) (Figure 5.2). For this reason, a Seasonal ARIMA (SARIMA) with parameters based on the characteristics of the twelve (12) training datasets is utilized in this study.[49]

5.1.2.2. Nowcast Results

Based on the three (3) univariate models conducted, results indicate that their respective one-step-ahead (out-of-sample) nowcasts from January to December 2020 strongly depict the overall trend of domestic liquidity growth in the Philippines (Figure 5.3). Furthermore, the ARIMA, RW, and SARIMA models provided reasonable estimates in the months where the growth of said monetary indicator (i.e., March, April, May) suddenly expanded due to the increase in the borrowings of the National Government (NG) to minimize

[48] The red-colored line under the ACF of ARIMA(4,1,1) indicates that a seasonal lag should be included in overall model.

[49] The parameters under auto-SARIMA models can be different from January to December 2020. This is because R Studio selects the optimal lag orders to forecast domestic liquidity in each time period. For example, univariate model to nowcast January 2020 has the parameters ARIMA(2,1,4)(1,0,1) while for February 2020 the model has the parameters of ARIMA(5,1,1)(1,0,1).

the negative impact of Coronavirus Disease 2019 (COVID-19) pandemic in the economy of said country.

Figure 5.3: 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 there is no superior univariate model that estimates the domestic liquidity growth throughout the expanding window timeframe. In particular, Tables 5.1 and 5.2 displayed that SARIMA has provided the highest number of months with low RMSE and MAE (i.e., March, May, September, November, December). This was followed by RW (i.e., January, February, June, July) and ARIMA (i.e., April, August, October), respectively. Further, SARIMA provides estimates with relatively higher precision since the statistical software designates its parameters.

Table 5.1: RMSE of Autoregressive Models [50]

	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
R. Walk	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 5.2: 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
R. Walk	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

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

The overall forecast errors of the three (3) univariate models, on the other hand, provided different results to the aforementioned statement. Based on their overall RMSE and MAE, it can be observed that ARIMA (4,1,1) is the most appropriate univariate model to estimate domestic liquidity growth because it registered the most accurate overall nowcasts with RMSE of 0.917 and MAE of 0.688. Both of these indicators are relatively lower in comparison to the forecast errors registered by RW (1.016 and 0.766) and SARIMA (1.066 and 0.739), respectively (Tables 5.1 and 5.2).

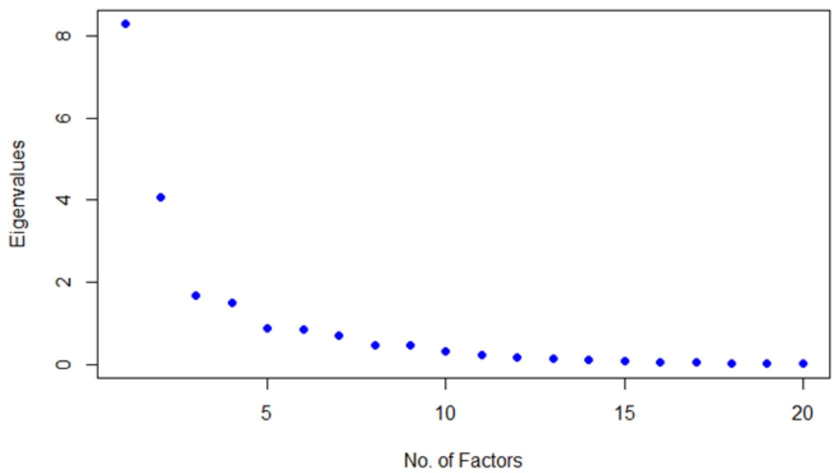
5.1.3. Dynamic Factor Model

5.1.3.1. Model Calibration

This study also utilizes the Dynamic Factor Model (DFM) to systematically include the wide range of high-frequency monetary, financial, and external sector indicators as input variables. Hence, this study followed the methodology used by Mariano and Ozmucur (2020) in implementing the said approach, wherein: (1) the number of indicators is reduced through factor analysis; (2) factors identified are applied under a Vector Autoregressive (VAR) framework; and (3) predicted values from those mentioned above are then used to nowcast the target variable.

Three (3) determinants were extracted from the initial twenty (20) input variables using the method of maximum likelihood by performing factor analysis. The decision to use these number of factors was based on each indicator's eigenvalues and cumulative variance.[51] Figure 5.4 indicates that factors one (1) to three (3) (i.e., first three (3) blue points) have larger eigenvalues in contrast to the remaining seventeen (17) factors. Although using a higher number of factors is still acceptable, the first three (3) factors already explain the sixty-four (64) percent of the variance in the twenty (20) different monetary, financial, and external sector indicators used in this study.[52]

Figure 5.4: Eigenvalues of Input Variables via Factor Analysis



[51] Eigenvalues refers to the total amount of variance that can be explained by a given principal component/factor.
[52] Sixty (60) to sixty-five (65) percent of variance is the common figure used in economic analysis (Mariano and Ozmucur, 2020).

After the aforementioned process, the three (3) factors identified are then utilized under a VAR framework to complete the method of estimating the domestic liquidity growth in the Philippines. The optimal lags for this model are selected based on the AIC and Hannan-Quinn (HQ) Information Criterion. Based on these selection criteria, five (5) autoregressive lags are considered under the twelve (12) training models to determine the estimates from January to December 2020.

5.1.3.2. Nowcast Results

Compared with the three (3) univariate models conducted, DFM provides inconsistent estimates on the overall movement of domestic liquidity in the first semester of 2020. The one-step-ahead (out-of-sample) nowcasts of said model, in particular, did not correctly estimate the expansion of domestic liquidity due to the sharp increase in the borrowings and deposits of NG to the central bank that took effect last March to May 2020 (Figure 5.5).

Figure 5.5: DFM Nowcasts vs. Actual M3 Growth (January to December 2020)
(In Percent Difference, Seasonally Adjusted)

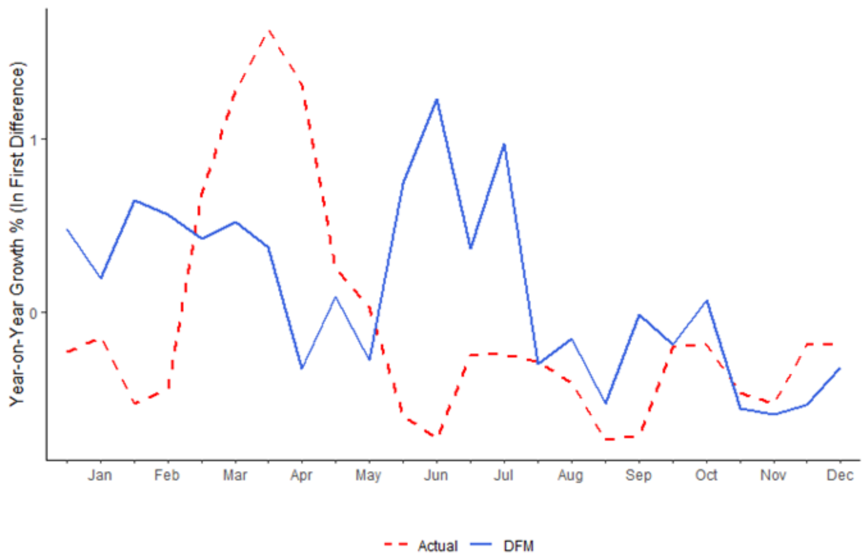


Table 5.3: RMSE of DFM

	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

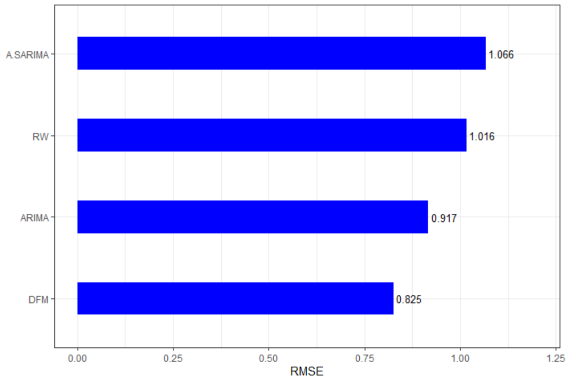
Table 5.4: MAE of DFM

	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

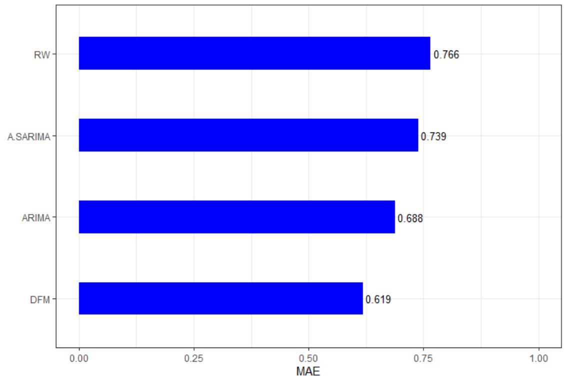
On the contrary, the model provides more accurate results in the latter half of the year. It can be observed in Tables 5.3 and 5.4 that the monthly forecast errors of the said model are relatively lower than those under ARIMA, Random Walk, and auto-SARIMA, particularly from

August to December 2020. In addition, this particular outcome can also be noticed from the overall forecast errors of DFM. The said multivariate model only conveyed an overall RMSE and MAE of 0.825 and 0.619, respectively. These forecast errors are relatively lower than the overall RMSE and MAE displayed by the univariate models (Figure 5.6).

Figure 5.6: Overall (a) RMSE and (b) MAE of Autoregressive Models and DFM



(a)



(b)

5.1.4. Machine Learning Algorithms

The machine learning algorithms used in this study are calibrated using the cross-validation method. This ensures that these models strongly regulate the bias-variance tradeoff and provide estimates based on the training or historical data (James et al., 2013). Therefore, in this study, the aforementioned approach is performed before conducting a series of recursive nowcasts on domestic liquidity growth in the Philippines via regularization (i.e., Ridge Regression, LASSO, Elastic Net) and tree-based (i.e., Random Forest, Gradient Boosted Trees) methods.

Although there are various methods to cross-validate machine learning algorithms (e.g., holdout method, stratified K-Fold cross-validation), this study mainly utilized (1) K-Fold cross-validation and (2) leave-one-out cross-validation methods for the twelve (12) training datasets of target and input variables. Specifically, training datasets under Ridge Regression, LASSO, Elastic Net (ENET), and Gradient Boosted Trees (GBT) are tuned based on a Ten (10)-Fold cross-validation. On the other hand, training datasets under Random Forest (RF) are calibrated based on their out-of-bag (OOB) scores.[53,54]

5.1.4.1. Regularization Methods

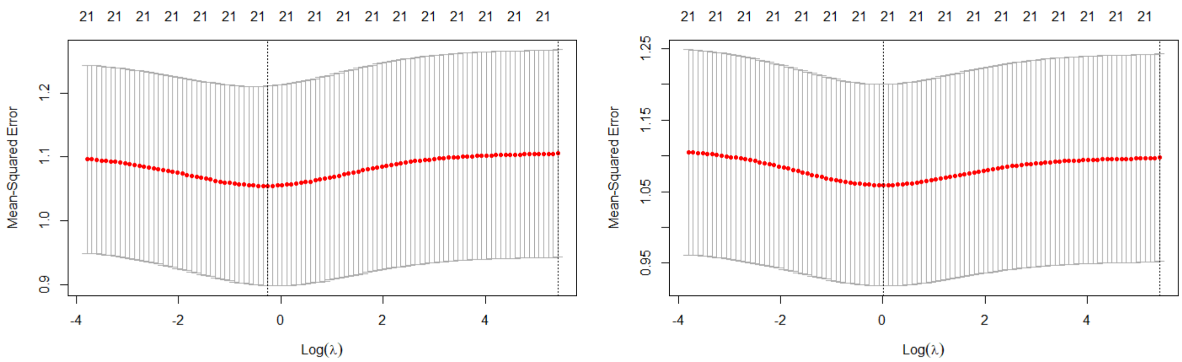
5.1.4.1.1. Model Calibration

The optimal shrinkage penalty for each algorithm under regularization methods is determined based on a ten (10) fold cross-validation method. Under this approach, twelve (12) different parameter values are determined since there are twelve (12) training datasets used in each regularization algorithm. In order words, the value of shrinkage penalty is specifically

[53] 10-Fold cross-validation is the standard cross-validation technique used in machine learning exercises.
[54] OOB is virtually equivalent to leave-one-out cross validation (James et al., 2013).

tailored based on the attributes of the training datasets and the norm of regularization (i.e., Ridge Regression, LASSO, ENET). Figure 5.6 presents this scenario. It shows that the optimal shrinkage penalty for estimating the domestic liquidity growth for January 2020 has a different value than the optimal shrinkage penalty to predict the said monetary indicator for February 2020. In particular, Panel A shows that the former has an optimal shrinkage penalty value of 0.772, while Panel B presents that the latter has an optimal shrinkage penalty value of 1.012.[55]

Figure 5.7: Optimal Shrinkage Penalty via Ridge Regularization (January and February 2020)
(a) Training Dataset to Estimate M3 Jan. 2020; (b) Training Dataset to Estimate M3 Feb. 2020



(a) (b)

5.1.4.1.2. Nowcast Results

After the calibration based on their specific shrinkage penalty, models under regularization methods then estimate domestic liquidity growth using the test datasets from January to December 2020. The result from recursive nowcasts displayed that Ridge Regression, LASSO, and ENET are able to provide estimates with relatively higher precision compared to the estimates registered by the benchmark models. In particular, the monthly nowcasts of these models have significantly lower forecast errors than the individual estimates stipulated by ARIMA, RW, SARIMA, and DFM (Tables 5.5 and 5.6), except for September and October 2020 (Figure 5.8). In addition, the Ridge Regression, LASSO, and ENET estimate domestic liquidity growth with the lowest forecast error on its unexpected growth due to the increase in NG borrowings and deposits to BSP from March to May 2020 (Tables 5.5 and 5.6).

A similar result can also be observed from the overall forecast errors of the three (3) machine learning algorithms. Mainly because Ridge Regression, LASSO, and ENET have provided low overall RMSE and MAE in comparison with the overall forecast errors of 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 5.9).

By comparing the three (3) models under the regularization method, it can be seen that LASSO is the most accurate because it provided the highest number of months with low RMSE and MAE from January to December 2020. Meanwhile, Ridge Regression and ENET

[55] See Annex C to E for the complete list of optimal shrinkage penalty for each training dataset via regularization methods.

registered precise overall estimates due to their low forecast errors compared to LASSO (Figure 5.9).

Figure 5.8: Regularization Method Nowcasts vs. Actual M3 Growth (January to December 2020)
(In Percent Difference, Seasonally Adjusted)

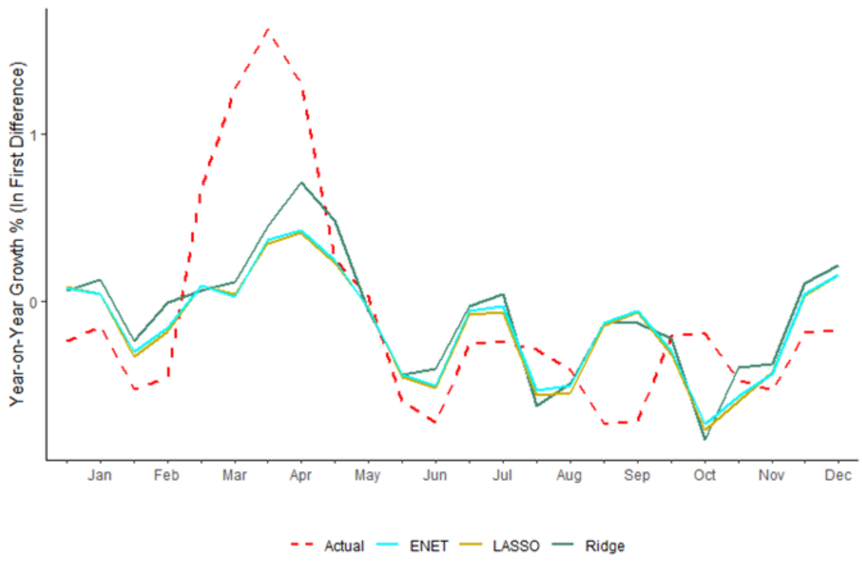


Table 5.5: RMSE of Ridge Regression, LASSO, and ENET

	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 5.6: MAE of Ridge Regression, LASSO, and ENET

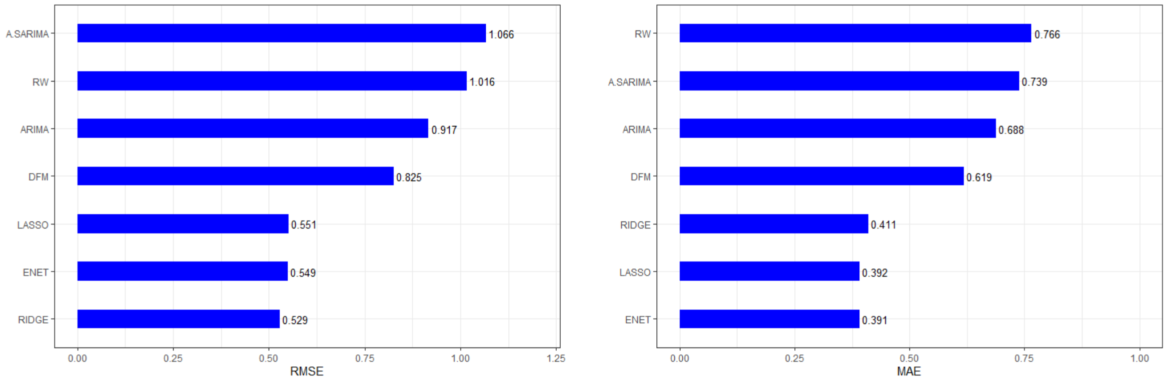
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
Ridge	0.292	0.364	0.887	1.136	0.156	0.245	0.259	0.209	0.596	0.325	0.116	0.345	0.411
LASSO	0.257	0.234	0.909	1.340	0.040	0.182	0.179	0.202	0.620	0.345	0.114	0.281	0.392
ENET	0.255	0.257	0.916	1.321	0.036	0.196	0.206	0.171	0.631	0.318	0.099	0.286	0.391

5.1.4.2. Tree-Based Methods

5.1.4.2.1. Model Calibration

Similar to regularization methods, RF and GBT are tuned via the cross-validation method to provide correct estimates on domestic liquidity growth from January to 2020. The methods used to calibrate these two (2) algorithms are OOB scores and 10-Fold cross-validation, respectively. Further, the twelve (12) training datasets under RF and GBT individually have an optimal number of variables randomly sampled as candidates at each split and the number of trees to grow.

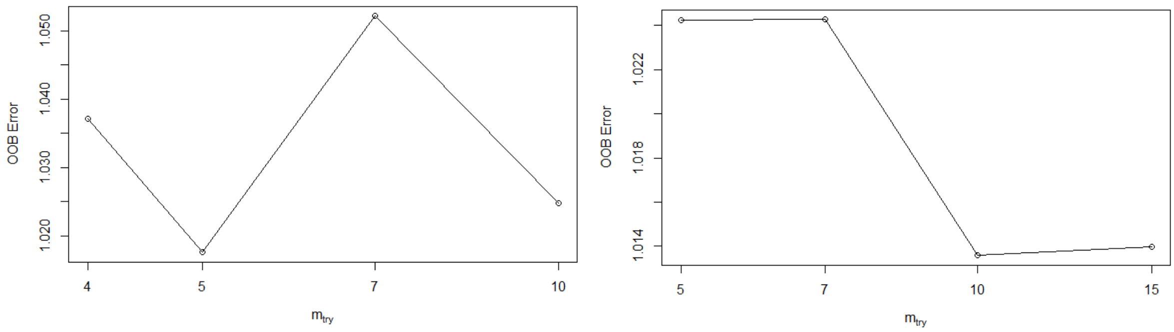
Figure 5.9: Overall (a) RMSE and (b) MAE of Benchmark Models and Regularization Methods



(a) (b)

Figure 5.10: OOB Error of Training Datasets via Random Forest [56]

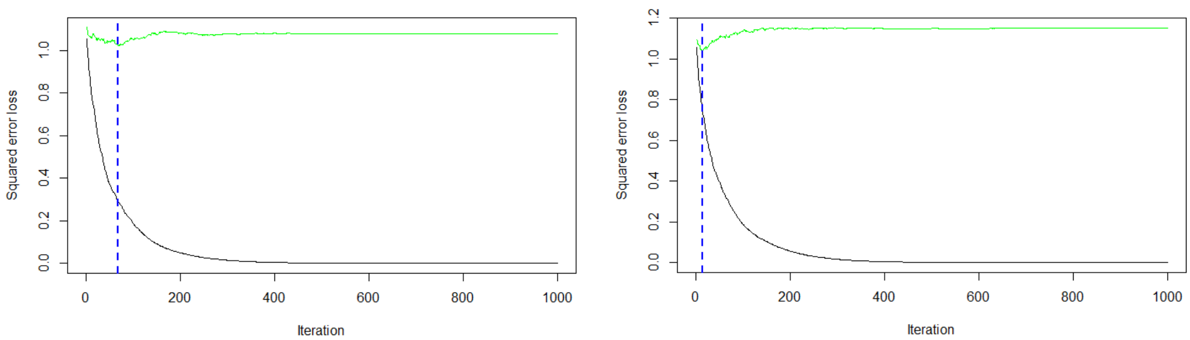
(a) Training Dataset to Estimate M3 Jan. 2020; (b) Training Dataset to Estimate M3 Feb. 2020



(a) (b)

Figure 5.11: Optimal Number of Trees via Gradient Boosted Trees [57]

(a) Training Dataset to Estimate M3 Jan. 2020; (b) Training Dataset to Estimate M3 Feb. 2020



(a) (b)

[56] See Annex F for the complete list of OOB errors for each training dataset via Random Forest.

[57] See Annex G for the complete list of the optimal number of trees for each training dataset via Gradient Boosted Trees.

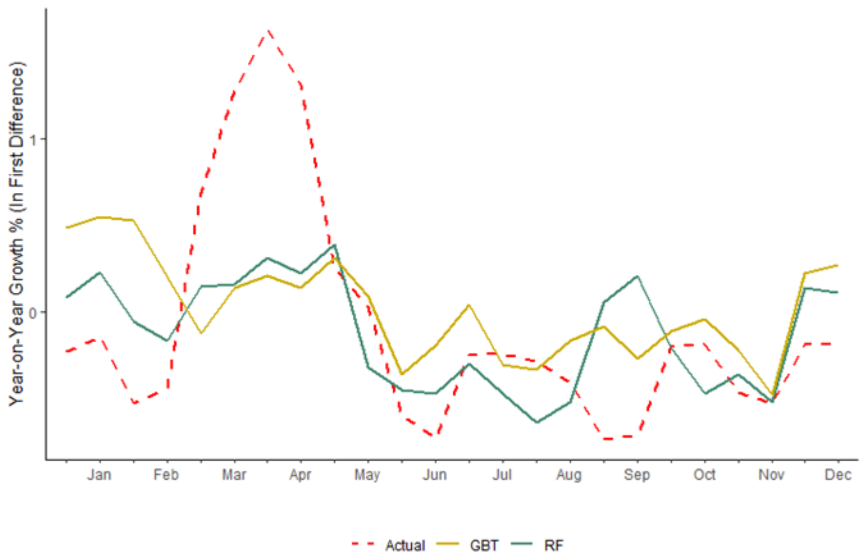
The results of these calibration techniques further elaborate this discussion. Figure 5.10 depicts the OOB errors of the training datasets under RF for January and February 2020. Panel A shows that five (5) indicators are sufficient to estimate domestic liquidity growth for January 2020 because it has the lowest OOB error of 1.018. On the other hand, Panel B indicates that ten (10) indicators are necessary to accurately nowcast the growth of said monetary indicator for February 2020 since it registered the lowest OOB error of 1.014.

Meanwhile, Figure 5.11 illustrates the optimal number of trees that are considered to nowcast the growth of domestic liquidity under GBT. Panel A presents that sixty-seven (67) iterations are taken into account in order to estimate domestic liquidity growth for January 2020. On the other hand, Panel B depicts that fifteen (15) iterations are sufficient for the GBT model to nowcast the growth of said monetary indicator for February 2020.

5.1.4.2.2. Nowcast Results

Similar to the results under regularization methods, utilizing RF and GBT as nowcasting models also stipulate more consistent estimates with relatively higher precision in contrast with the benchmark models used in this study. The monthly forecast errors of the two (2) machine learning models are also significantly lower than those under ARIMA, RW, SARIMA, and DFM, except for the nowcast result of RF in September 2020. Based on the recursive nowcasts, it is found that RF and GBT estimate the variable with low forecast error on the months where domestic liquidity growth unexpectedly expanded due to the increased borrowings of NG (i.e., March, April, May) (Tables 5.7 and 5.8).

Figure 5.12: 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 based on the timeline of expanding window also registered lower forecast errors. The result indicates that RF only displayed an RMSE of 0.595 and MAE of 0.432. Meanwhile, GBT provided RMSE of 0.632 and MAE of 0.469. The figures mentioned are significantly lower than the overall forecast errors registered under the univariate and multivariate models performed in this study (Figure 5.13).

In addition, among the tree-based method used in this study, it can also be established that RF provided the lowest forecast errors. Despite having an imprecise estimate in September 2020, the said model provided the highest number of months with higher precision from January to December 2020. This includes the nowcasts for January, February, March, April, June, July, November, and December 2020 (Tables 5.7 and 5.8).

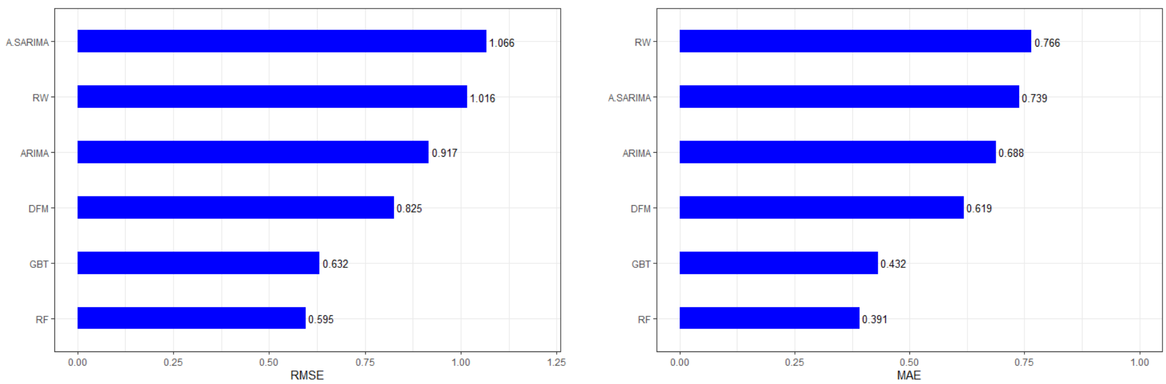
Table 5.7: RMSE of RF and GBT

	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 5.8: MAE of RF and GBT

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
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

Figure 5.13: Overall (a) RMSE and (b) MAE of Benchmark Models vs. Tree-Based Methods



(a) (b)

5.2. Further Analysis

5.2.1. Variable Importance

One of the main advantages of using machine learning algorithms in economic nowcasting is their strong capability to identify critical factors that could comprehensively explain the movement or growth of a particular macroeconomic indicator and scenario. In addition, numerous studies have already established that these algorithms can formulate quantitative models with accurate estimates despite using a limited number of indicators.[58]

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

The machine learning models that specifically have this ability are regularization and tree-based methods, such as LASSO, ENET, RF, and GBT.[59]

5.2.1.1. LASSO and ENET

The recursive nowcasts conducted by LASSO and ENET from January and December 2020 indicate that (1) foreign exchange rate (FOREX), (2) inflow of FPI, (3) LIBOR, (4) bank savings rate, (5) NG 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 twenty-one (21) indicators used as input variables, these are the consistent determinants under LASSO and ENET that do not stipulate zero coefficients in January to December 2020 (Table 5.9).[60]

Table 5.9: Variable Coefficients via LASSO and ENET (January-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	-	-	-	-

5.2.1.2. Random Forest and Gradient Boosted Trees

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 values $(t-1)$ of the target variable, as an input variable, are also crucial to estimate domestic liquidity growth in the Philippines. In particular, Figures 5.14 and 5.15 indicate that (1) M3 $(t-1)$, (2) liabilities of other sectors to the central bank (OSC), and (3) NG deposits to the central bank (NGD) are by far the three (3)

[59] See Chapter 3 for the comprehensive discussion on these models.

[60] Other months identified BSP Discount Rate, Bank Savings Rate, and WMOR as important indicators (See Annex H and I).

most significant variables that should be considered in estimating the growth of said monetary indicator.

Figure 5.14: Node Impurity via Random Forest

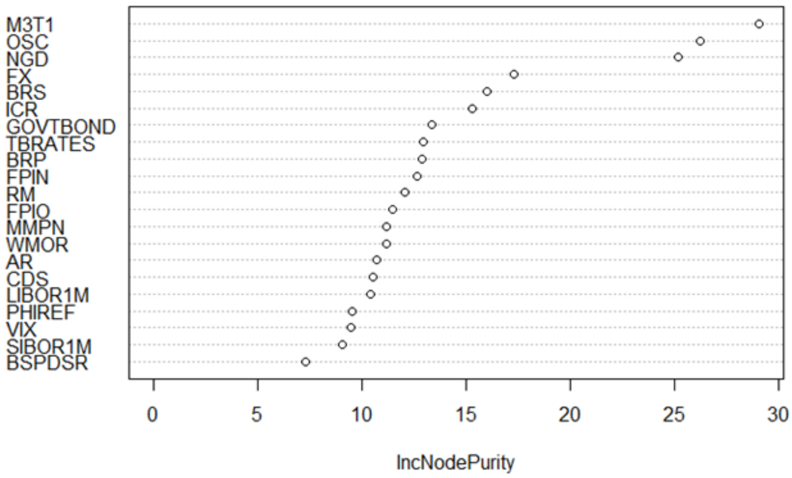
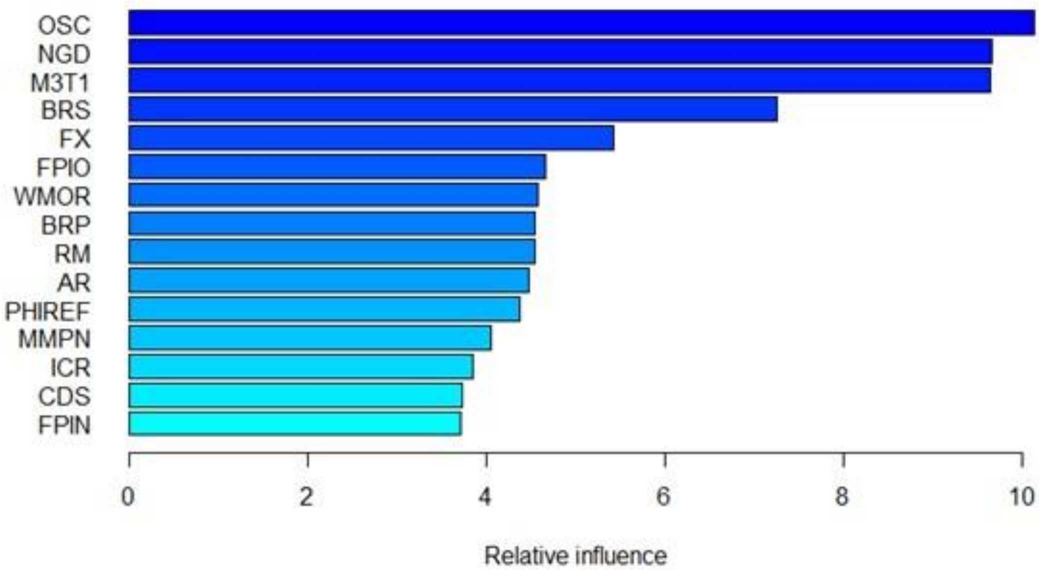


Figure 5.15: Variable Importance Plot via Gradient Boosted Trees



6. Conclusion

Domestic liquidity is defined as the sum of all liquid financial instruments held by money-holding sectors used as a medium of exchange in an economy (IMF, 2016). The changes in the overall growth of this monetary indicator are among the most critical dynamics that numerous central banks are closely monitoring because of its property of being an essential element to the overall transmission mechanism of monetary policy, particularly the impact on aggregate demand, interest rates, inflation, and overall economic growth (Mankiw, n.d.).

In the Philippines, data on domestic liquidity is used as one of the primary components to adjust monetary policy and utilized as a leading indicator to observe price and financial stability. However, similar to the delayed publication of different statistical indicators encountered by most government offices, data on domestic liquidity in the said country also suffers from a series of lags and revisions. Due to this predicament, policymakers in the BSP typically formulate monetary policies and address different economic phenomena (e.g., inflation, business cycle) using its outdated or lagged values.

The concept of short-term forecasting or "nowcasting" is one of the contemporary methodologies utilized by numerous institutions (e.g., International Financial Institutions (IFIs), central banks) to address the aforementioned issues in data publication. This approach, at present, also became prevalent because of the emergence of the use of big data and machine learning. These approaches augment the overall process in providing a solution for the difficulty in producing data on a real-time basis. Mainly because the two (2) methodologies provide complementary information concerning the macroeconomic data that government offices usually publish and stipulate accurate estimates using an immense amount of data or information, respectively (Hassani and Silva, 2015; Richardson et al., 2018).

Drawing upon this background, the concept of nowcasting using different machine learning algorithms is utilized in this study to address the aforementioned issues, particularly to support the BSP's suite of macroeconomic models used in forecasting and policy analysis (e.g., GDP, inflation, domestic liquidity forecasting). Hence, to support this objective, regularization methods (i.e., Ridge Regression, LASSO, ENET) and tree-based method (i.e., RF, GBT) using different high-frequency monetary, financial, and external sector indicators from January 2008 to December 2020 are performed. These algorithms are compared against traditional time series models such as ARIMA, Random Walk, and Dynamic Factor Models (DFM). In particular, 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 demonstrate that machine learning algorithms provide relatively higher precision estimates than traditional time series models due to their consistent monthly nowcasts with low forecast errors, especially in the months where domestic liquidity suddenly expanded (i.e., increased NG borrowings and deposits) due to the impact of COVID-19 in the Philippines (Tables 6.1 and 6.2). It can also be observed that these models estimate the said monetary indicator with the lowest overall RMSE and MAE. Furthermore, it can be concluded that regularization and tree-based machine learning algorithms could be alternative models to estimate domestic liquidity growth in the Philippines.

However, among these models, LASSO and RF provided the highest number of months with low forecast errors from January to December 2020. The Ridge Regression and ENET, on the other hand, registered the lowest overall RMSE and MAE with 0.529 and 0.391, respectively (Figure 6.1). These results provide a shred of solid evidence that nowcasting through regularization methods is the most appropriate approach to nowcast the said monetary indicator among the machine learning algorithms used in this study.

Using machine learning algorithms as a primary nowcasting approach also provides substantial advantages against traditional time series models because these models can filter out or identify important indicators that could stipulate parsimonious nowcasting models with precise results. Hence, nowcasts based on LASSO, ENET, RF, and GBT indicate that (1) BSP

Liabilities on NG, (2) BSP Claims on Other Sectors, (3) FOREX, and (4) Lagged Values of M3 are among the critical indicators that should be considered in estimating the growth of domestic liquidity in the Philippines.

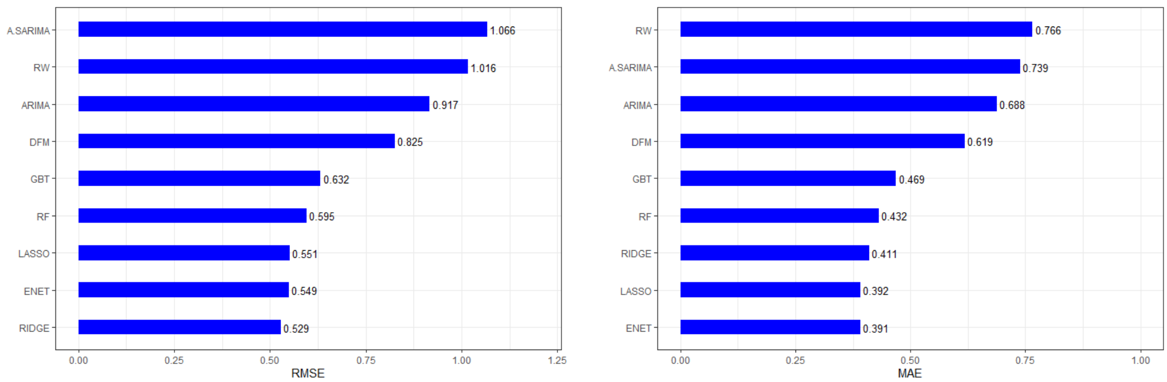
Table 6.1: RMSE of Benchmark and Machine Learning Models (Summary)[61]

	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
R.Walk	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
A. 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 6.2: 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
R. Walk	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
A. 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

Figure 6.1: Overall Forecast Errors of Benchmark and Machine Learning Models



(a) (b)

7. Recommendation

This study highly recommends these models as supplementary tools of the BSP to nowcast domestic liquidity growth, which is considered one of the most critical inputs for GDP and inflation forecasting as well as medium-term forecasting, scenario-building, and policy simulations (e.g., single equation model, multi-equation model). Implementing these concepts could also support the objective of the BSP in conveying data-based monetary policy in the

[61] The red-colored cells represent high forecast errors, while yellow- and green-colored cells are moderate to low forecast errors.

country. Furthermore, the additional data or information that can be gathered by the different departments in the said institution could further improve the individual and overall accuracy of each machine learning algorithm used in this study. However, although this cannot be guaranteed, it is always better to calibrate models using an immense amount of data than operating with a limited number of indicators.

Among the possible determinants that could be explored and collected over time are high-frequency (e.g., daily, weekly) unconventional data or information regarding the credit condition of the Philippine Banking System (PBS). Mainly because domestic credit – which is composed of loans outstanding for production and household consumption – is considered a significant contributor to the monthly change in domestic liquidity in the Philippines.

The study also recommends a regular and sustainable way of accumulating other statistics related to the critical indicators identified in this study. For example, this could include high-frequency data or information regarding (1) debt securities issued by the NG and the BSP, (2) amount of loans granted by the BSP ODCs, (3) amount of loans granted by the BSP to Other Sectors (e.g., Other Financial Corporations), and (4) New Effective Exchange Rate (NEER) Indices of Philippine Peso.

8. Suggestions for Future Research

As mentioned in the previous chapters, this study has limitations in formulating the different nowcasting models using time series and machine learning algorithms. Therefore, the following are suggested to enhance the results and comprehensiveness of this research:

a. It is recommended to conduct encompassing tests (e.g., Diebold-Mariano tests) to formally determine the advantage of machine learning models against the benchmark models used in this study. In addition, this test may also establish the need to combine the different machine learning algorithms with low monthly and overall forecast errors. Combining the models is performed to have a single model that contains the strength of each algorithm. Studies of Tiffin (2016), Richardson et al. (2018), Mariano and Ozmucur (2020), and Tamara et al. (2020) have already utilized this approach.
b. Other robust econometric approaches such as Mixed Data Sampling (MIDAS) Regression and Mixed Frequency-Vector Autoregression (MF-VAR) are recommended to be part of the benchmark models. These methods, in particular, are mainly used for models with target and input variables with a large number of observations and data with different levels of granularity.
c. Supplementary machine learning algorithms, such as Artificial Neural Networks (ANN), Long-Short Term Memory (LTSM), and Support Vector Machines (SVM), could be included in the nowcasting exercise conducted in this study.
d. The use of more granular data or information regarding the critical indicators identified in this study is recommended to be part of input variables under the machine learning algorithms used in this study. In particular, the daily volume or amount of (1) BSP Liabilities on NG, (2) BSP Claims on Other Sectors, and (3) Other Foreign Exchange Rates (e.g., PHP per JPY) are useful to enhance the result of this research.

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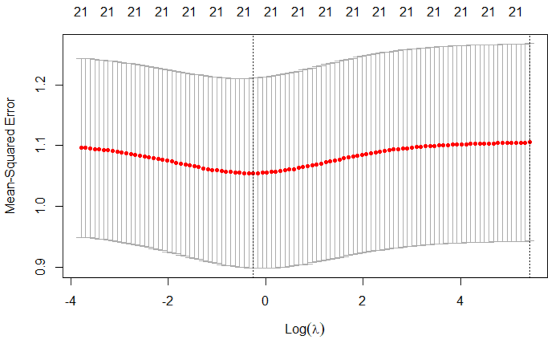
Annex 1: R Studio Packages

PACKAGE	AUTHOR/S	SOURCE URLs
caret	Kuhn et al.	https://cran.r-project.org/web/packages/caret/vignettes/caret.html
dplyr	-	https://cran.r-project.org/web/packages/dplyr/dplyr.pdf
forecast	Hyndman et al.	https://cran.r-project.org/web/packages/forecast/forecast.pdf
gbm	Greenwell et al.	https://cran.r-project.org/web/packages/gbm/gbm.pdf
ggplot2	Wickham et al.	https://cran.r-project.org/web/packages/ggplot2/ggplot2.pdf
glmnet	Friedman et al.	https://cran.r-project.org/web/packages/glmnet/glmnet.pdf
hrbrthemes	Rudis et al.	https://cran.r-project.org/web/packages/hrbrthemes/hrbrthemes.pdf
leaps	Lumely, T.	https://cran.r-project.org/web/packages/leaps/leaps.pdf
lubridate	Spinu et al.	https://cran.r-project.org/web/packages/lubridate/lubridate.pdf
maptree	White and Gramacy	https://cran.r-project.org/web/packages/maptree/maptree.pdf
Metrics	Hamner et al.	https://cran.r-project.org/web/packages/Metrics/Metrics.pdf
mFilter	Balcilar, M.	https://cran.r-project.org/web/packages/mFilter/mFilter.pdf
pls	Mevik et al.	https://cran.r-project.org/web/packages/pls/pls.pdf
psych	Revelle, W.	https://cran.r-project.org/web/packages/psych/psych.pdf
randomForest	Breiman et al.	https://cran.r-project.org/web/packages/randomForest/randomForest.pdf
repr	Angerer P.	https://cran.r-project.org/web/packages/repr/repr.pdf
tidyverse	Wickham, H.	https://cran.r-project.org/web/packages/tidyverse/tidyverse.pdf
tree	Ripley, B.	https://cran.r-project.org/web/packages/tree/tree.pdf
tsDyn	Di Narzo et al.	https://cran.r-project.org/web/packages/tsDyn/tsDyn.pdf
tseries	Trapletti et al.	https://cran.r-project.org/web/packages/tseries/tseries.pdf
TStudio	Krispin, R.	https://cran.r-project.org/web/packages/TSstudio/TSstudio.pdf
urca	Pfaff et al.	https://cran.r-project.org/web/packages/urca/urca.pdf
vars	Pfaff and Stigler	https://cran.r-project.org/web/packages/vars/vars.pdf
xgboost	Chen et al.	https://cran.r-project.org/web/packages/xgboost/xgboost.pdf

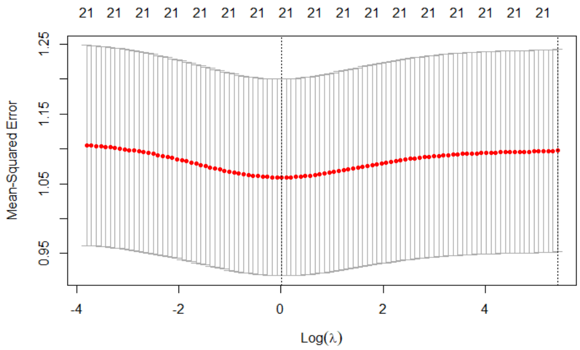
Annex 2: Unit Root Test for Input Variables

VARIABLE	TEST	LEVEL OF SIGNIF.	P-VALUE (LEVEL/GROWTH /LOG)	P-VALUE (FIRST DIFF.)
BSP Liabilities on NG	ADF PP	0.05	0.01 0.01	0.01 0.01
BSP Claims on Other Sectors	ADF PP	0.05	0.80 0.79	0.01 0.01
FPI (In)	ADF PP	0.05	0.32 0.01	0.01 0.01
FPI (Out)	ADF PP	0.05	0.17 0.01	0.01 0.01
Available Reserves	ADF PP	0.05	0.99 0.97	0.01 0.01
Reserve Money	ADF PP	0.05	0.99 0.98	0.01 0.01
CBOE Volatility Index	ADF PP	0.05	0.07 0.01	0.01 0.01
Credit Default Swap	ADF PP	0.05	0.22 0.05	0.01 0.01
LIBOR	ADF PP	0.05	0.26 0.34	0.01 0.01
SIBOR	ADF PP	0.05	0.73 0.66	0.01 0.01
PHIREF	ADF PP	0.05	0.22 0.01	0.01 0.01
Phil. Government Bond Rate	ADF PP	0.05	0.34 0.66	0.01 0.01
BSP Discount Rate	ADF PP	0.05	0.16 0.28	0.01 0.01
Bank Savings Rate	ADF PP	0.05	0.28 0.97	0.01 0.01
Bank Prime Rate	ADF PP	0.05	0.92 0.93	0.01 0.01
Money Market Rate (P. Note)	ADF PP	0.05	0.10 0.01	0.01 0.01
Treasury Bill Rate	ADF PP	0.05	0.60 0.67	0.01 0.01
Interbank Call Rate	ADF PP	0.05	0.56 0.88	0.01 0.01
PHP per USD (FOREX)	ADF PP	0.05	0.77 0.82	0.01 0.01
WMOR	ADF PP	0.05	0.48 0.87	0.01 0.01

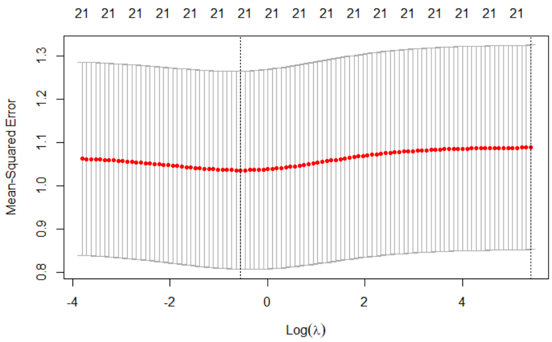
Annex 3: Optimal Shrinkage Penalty via Ridge Regression



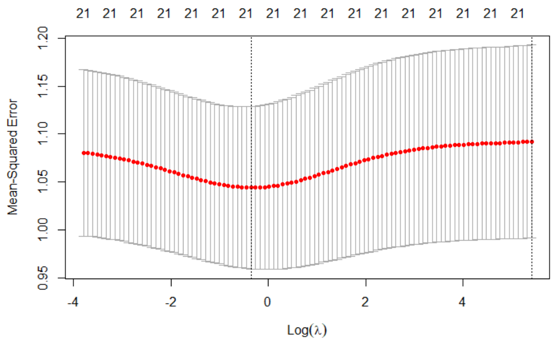
January 2020 – 0.772



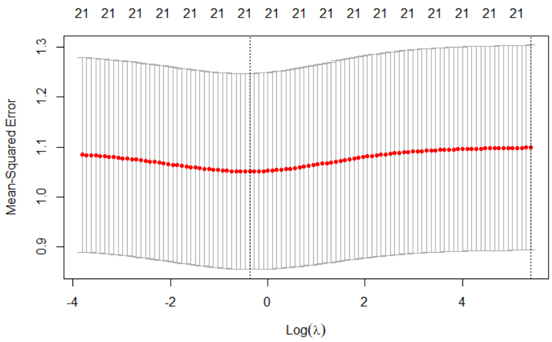
February 2020 – 1.012



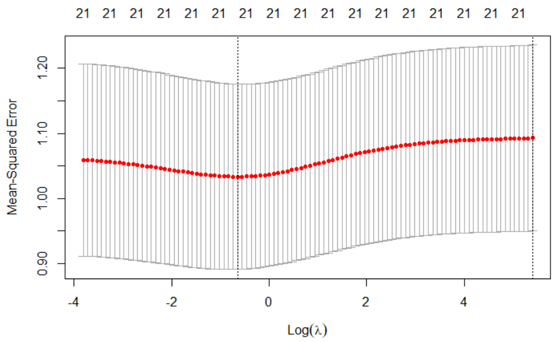
March 2020 – 0.577



April 2020 – 0.700

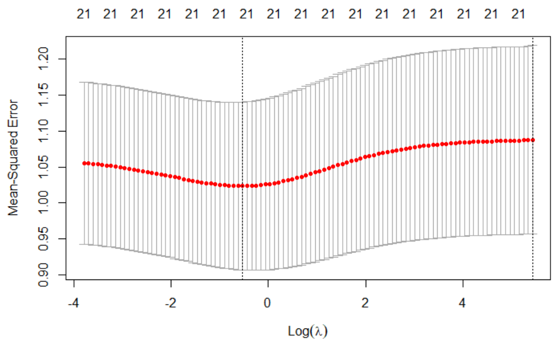


May 2020 – 0.691

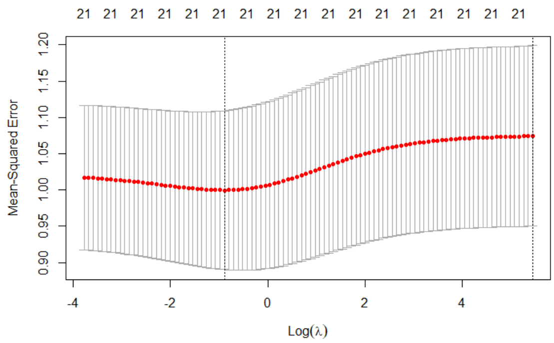


June 2020 – 0.523

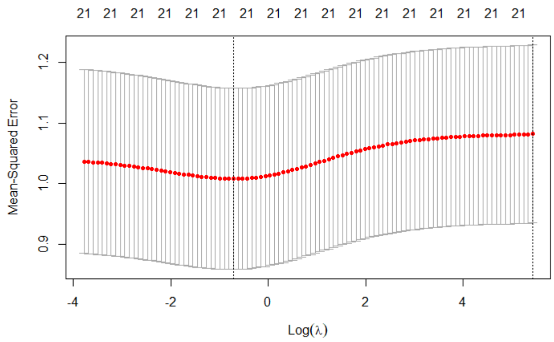
Annex 3: Optimal Shrinkage Penalty via Ridge Regression – Cont.



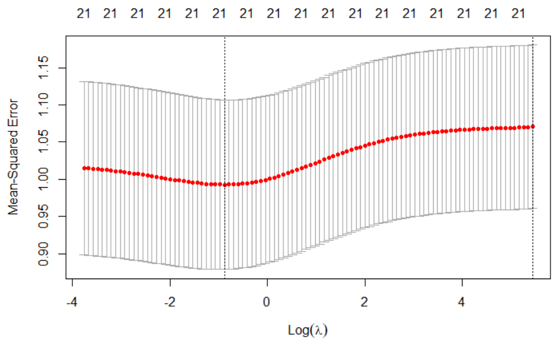
July 2020 – 0.589



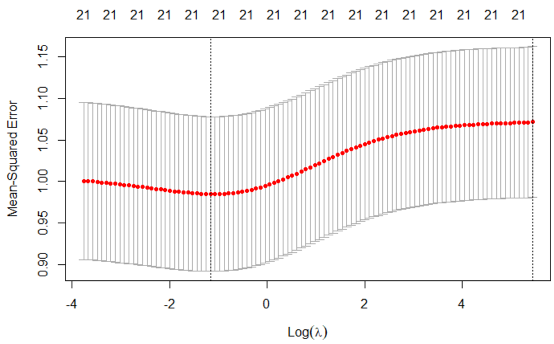
August 2020 – 0.491



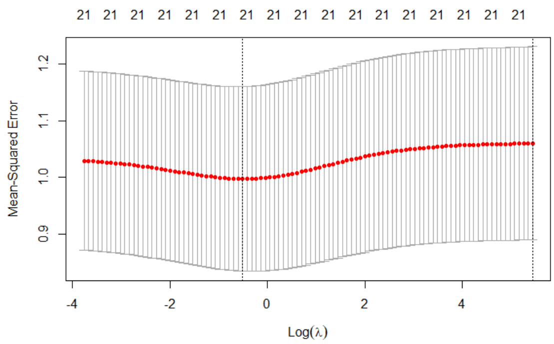
September 2020 – 0.411



October 2020 – 0.415

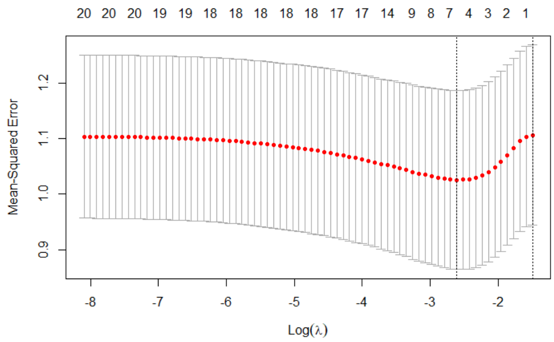


November 2020 – 0.313

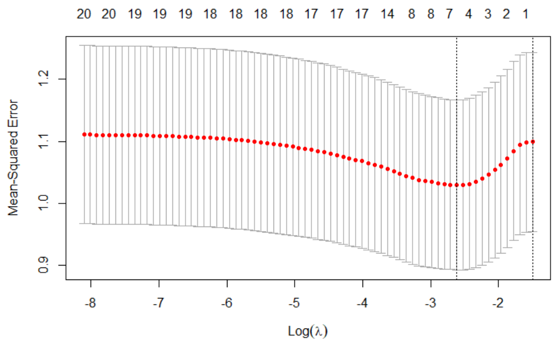


December 2020 – 0.600

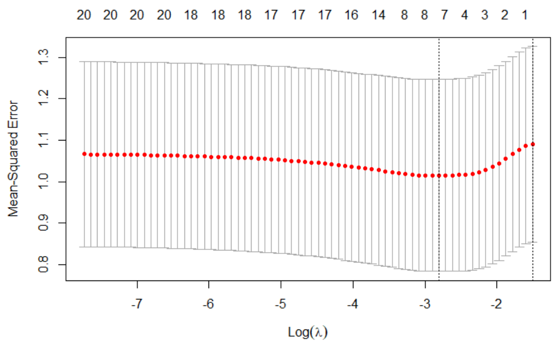
Annex 4: Optimal Shrinkage Penalty via LASSO



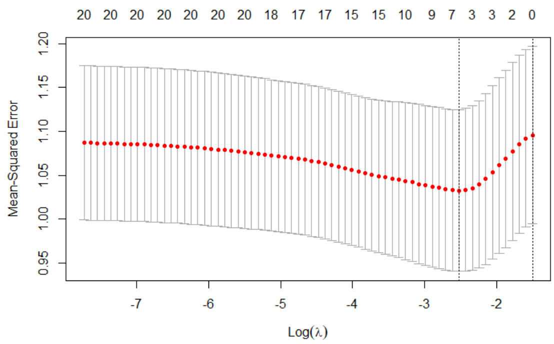
January 2020 – 0.737



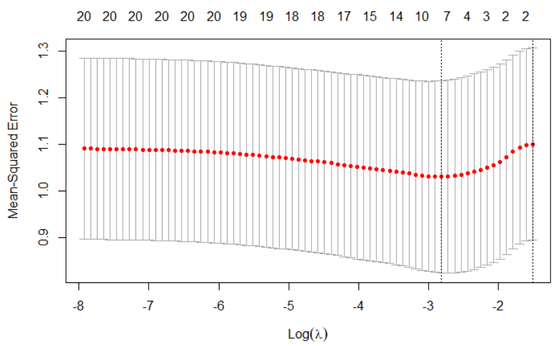
February 2020 – 0.073



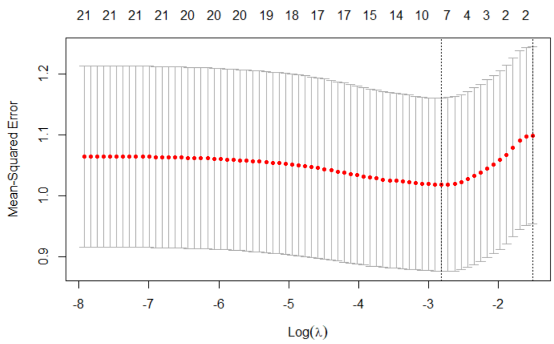
March 2020 – 0.060



April 2020 – 0.080

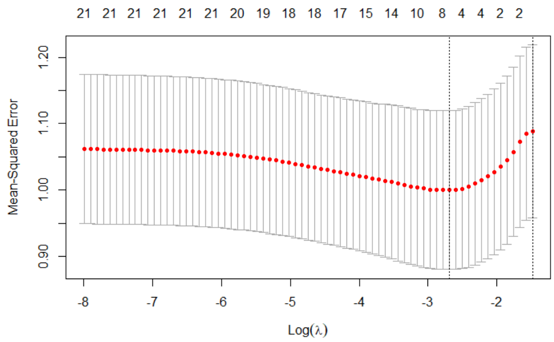


May 2020 – 0.060

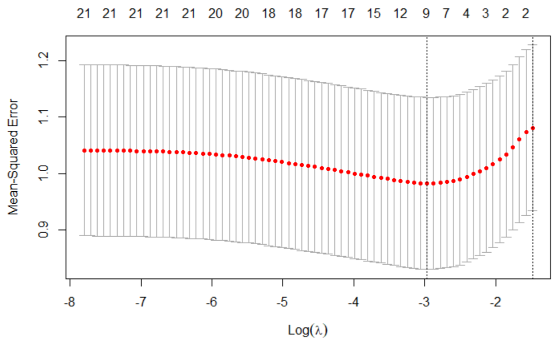


June 2020 – 0.060

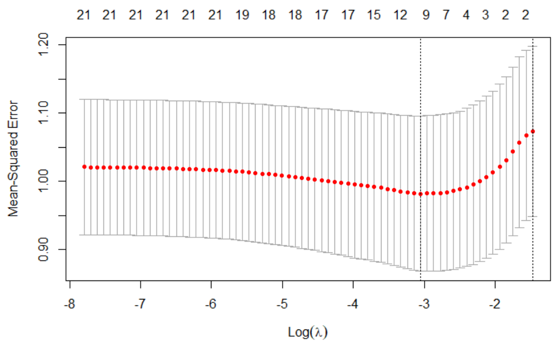
Annex 4: Optimal Shrinkage Penalty via LASSO – Cont.



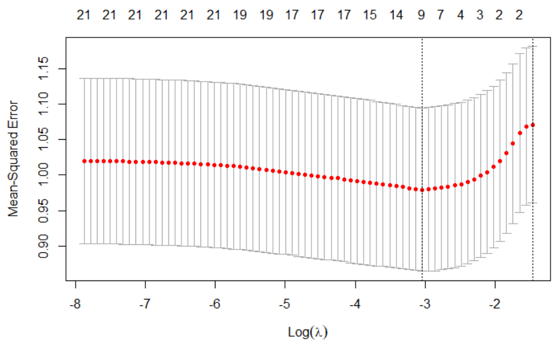
July 2020 – 0.068



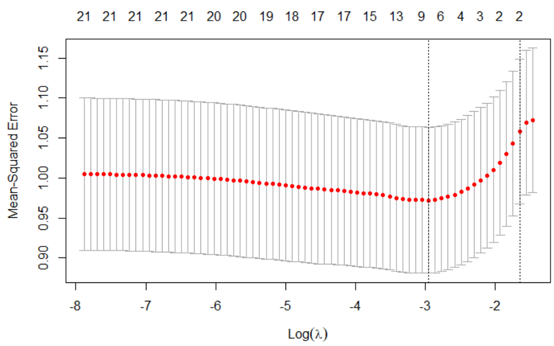
August 2020 – 0.051



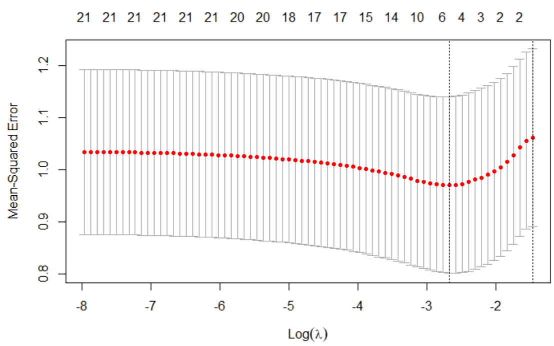
September 2020 – 0.047



October 2020 – 0.048

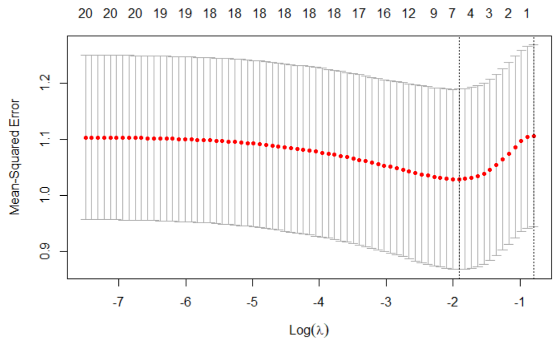


November 2020 – 0.052

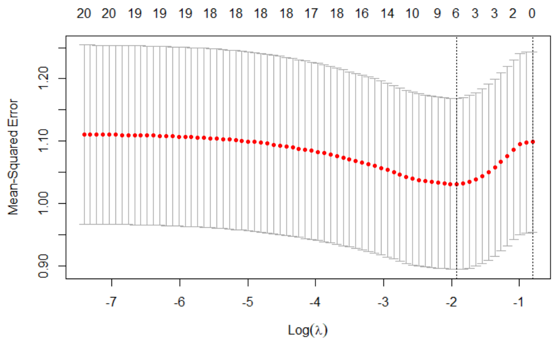


December 2020 – 0.069

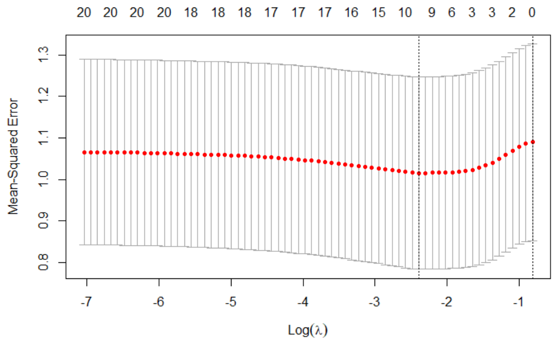
Annex 5: Optimal Shrinkage Penalty via ENET



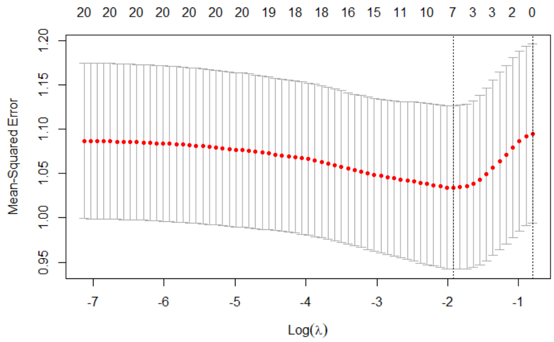
January 2020 – 0.147



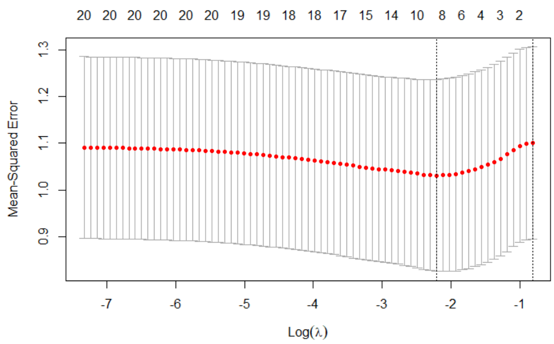
February 2020 – 0.146



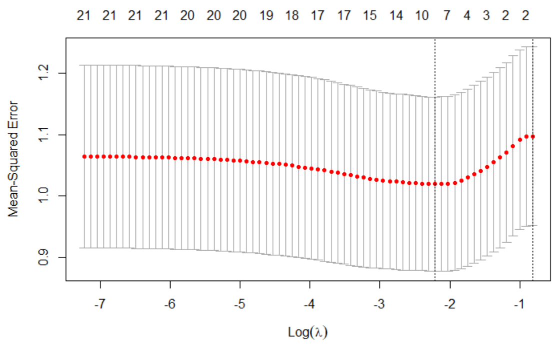
March 2020 – 0.091



April 2020 – 0.147

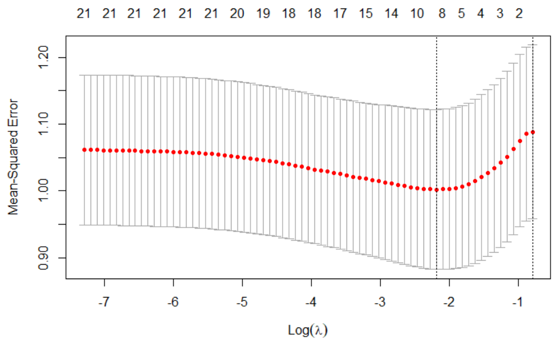


May 2020 – 0.110

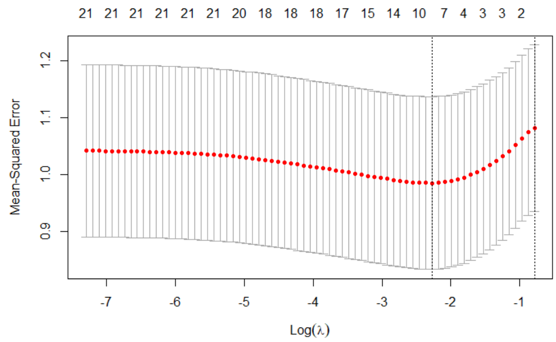


June 2020 – 0.110

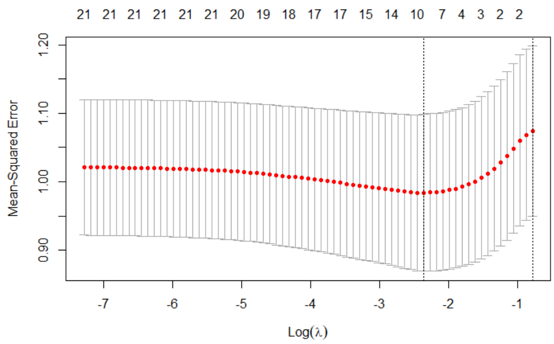
Annex 5: Optimal Shrinkage Penalty via ENET – Cont.



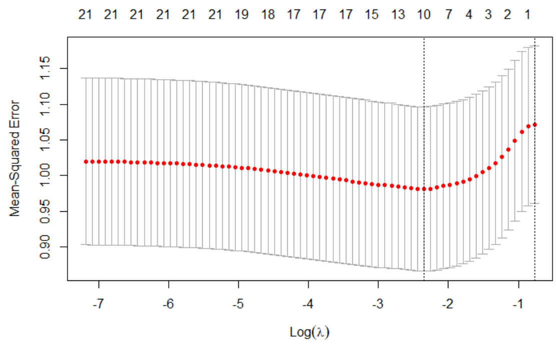
July 2020 – 0.112



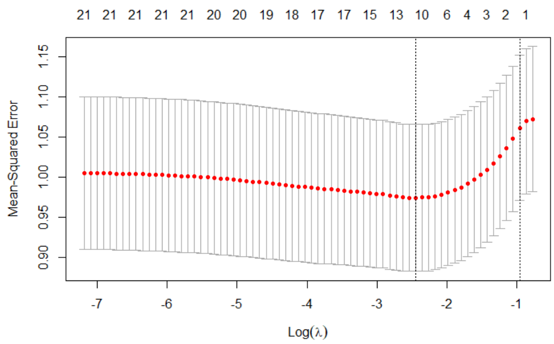
August 2020 – 0.103



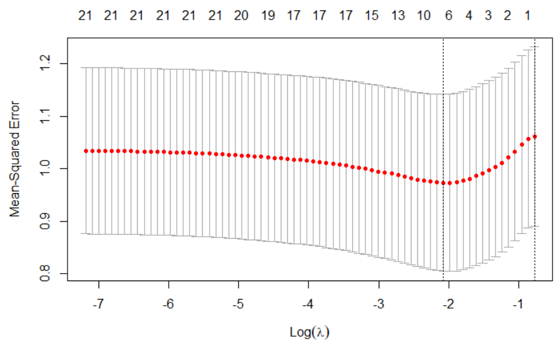
September 2020 – 0.095



October 2020 – 0.095

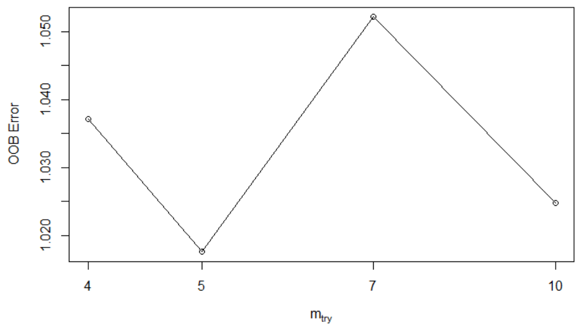


November 2020 – 0.087

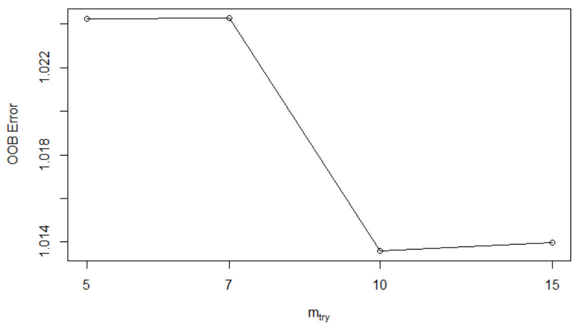


December 2020 – 0.126

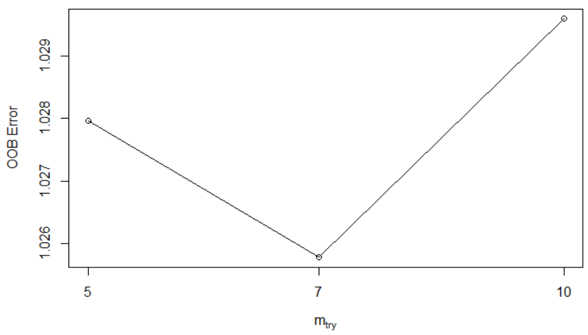
Annex 6: OOB Error of Training Datasets via Random Forest



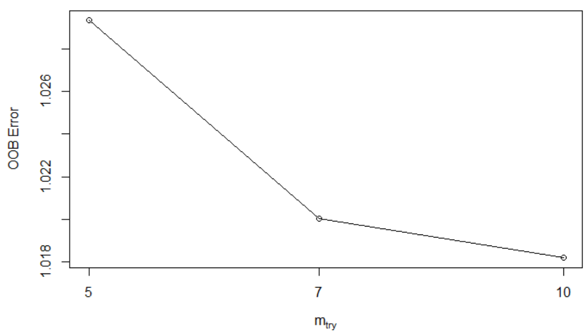
January 2020 – 5 Variables (1.018)



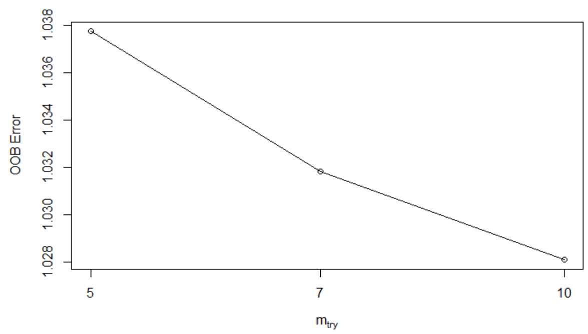
February 2020 – 10 Variables (1.014)



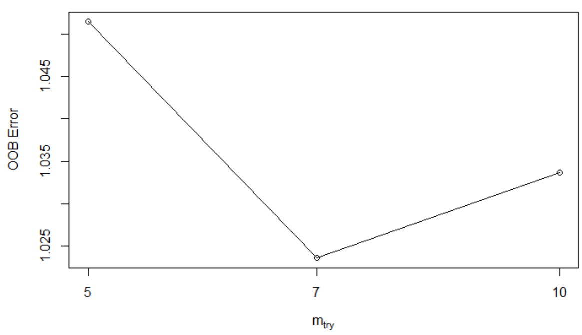
March 2020 – 7 Variables (1.026)



April 2020 – 10 Variables (1.018)

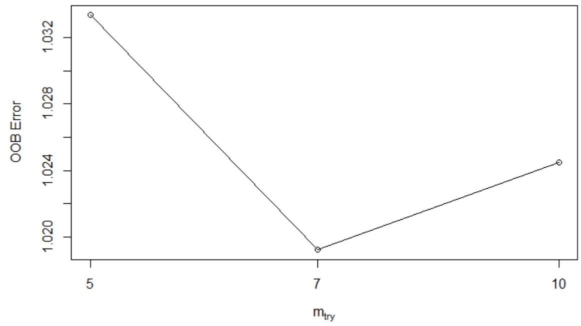


May 2020 – 10 Variables (1.028)

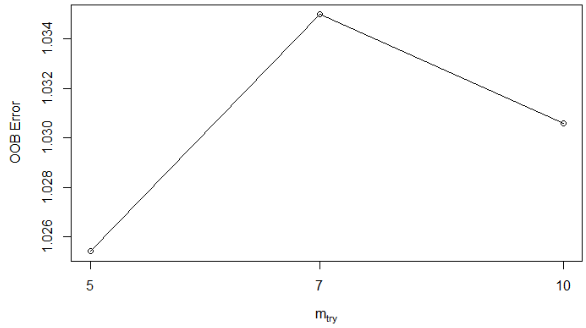


June 2020 – 7 Variables (1.024)

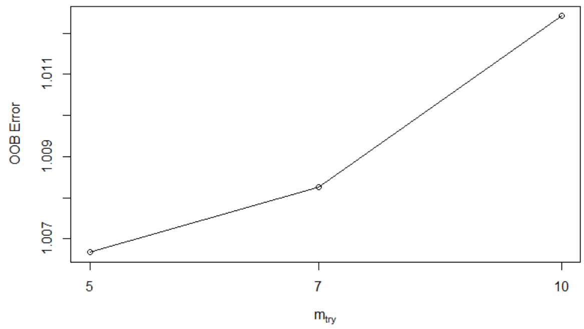
Annex 6: OOB Error of Training Datasets via Random Forest – Cont.



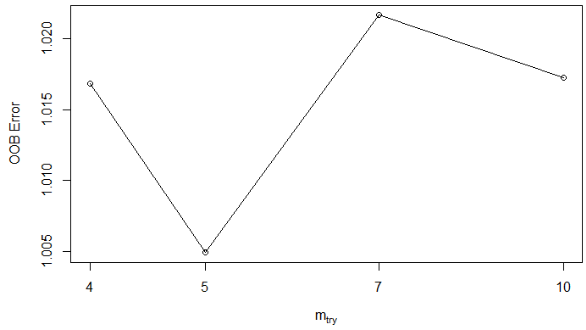
July 2020 – 7 Variables (1.019)



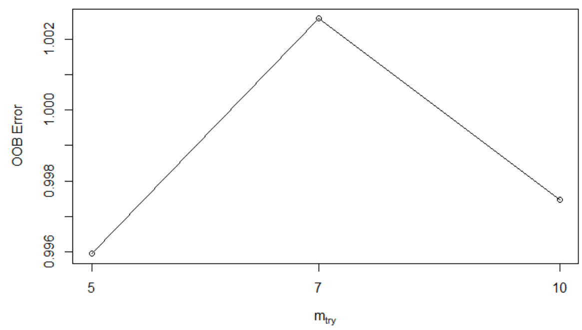
August 2020 – 5 Variables (1.025)



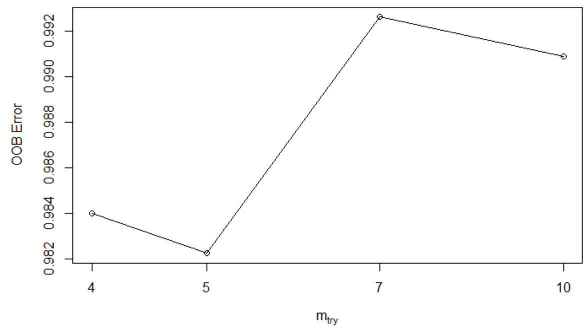
September 2020 – 5 Variables (1.007)



October 2020 – 5 Variables (1.004)

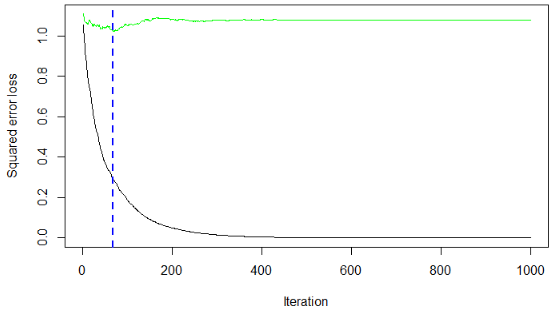


November 2020 – 5 Variables (0.996)

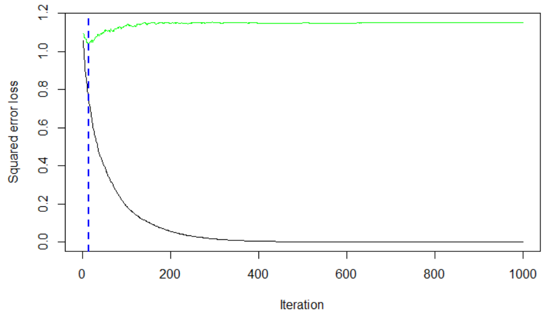


December 2020 – 5 Variables (0.982)

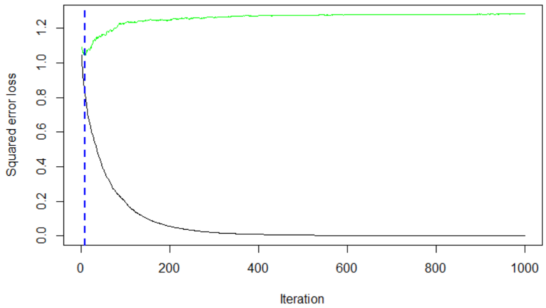
Annex 7: Optimal Number of Trees via Gradient Boosted Trees



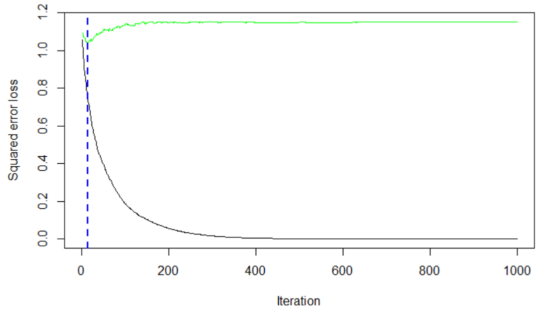
January 2020 – 67 Iterations



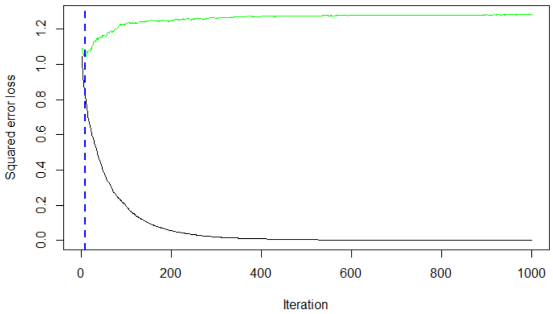
February 2020 – 15 Iterations



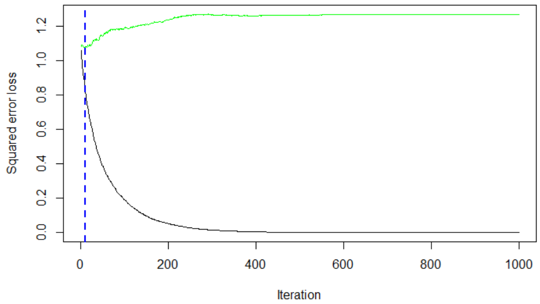
March 2020 – 8 Iterations



April 2020 – 10 Iterations

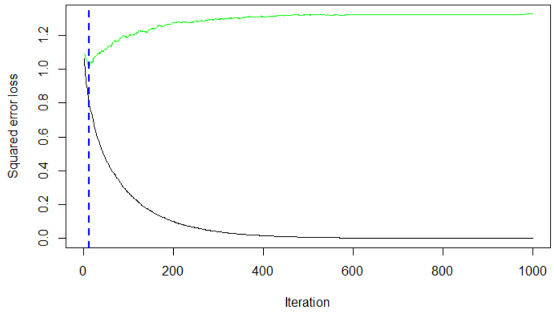


May 2020 – 2 Iterations

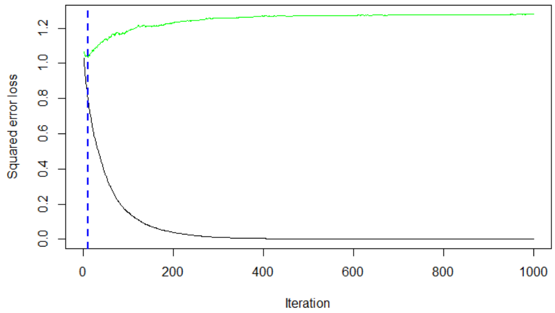


June 2020 – 4 Iterations

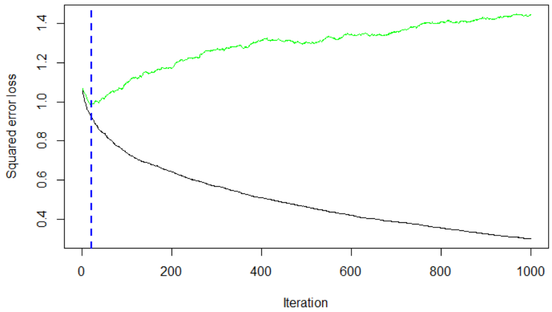
Annex 7: Optimal Number of Trees via Gradient Boosted Trees – Cont.



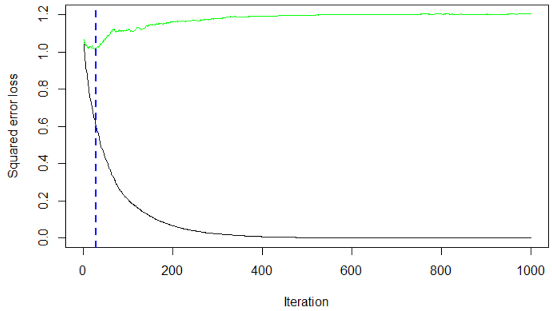
July 2020 – 13 Iterations



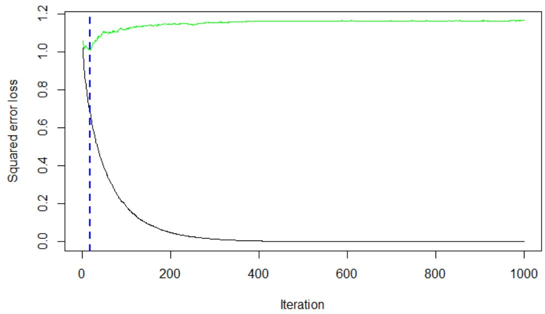
August 2020 – 10 Iterations



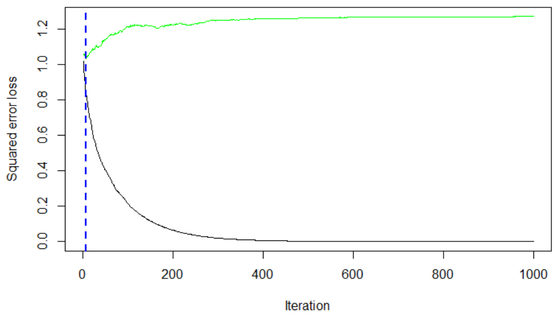
September 2020 – 22 Iterations



October 2020 – 28 Iterations



November 2020 – 17 Iterations



December 2020 – 7 Iterations

Annex 8: 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

Annex 8: Variable Coefficients via LASSO: January to December 2020 – Cont.

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
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 9: 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

Annex 9: Variable Coefficients via ENET: January to December 2020 – Cont.

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
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

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