NOWCASTING DOMESTIC LIQUIDITY IN THE PHILIPPINES USING MACHINE LEARNING ALGORITHMS

A Thesis By

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DECLARATION

I hereby declare that this thesis is my original work, and I have written it in its entirety. I have duly acknowledged all the sources of information that have been used in this research.

In addition, this study has not been submitted for any degree or university previously.

(Sgd.)

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ABSTRACT[1,2]

Domestic liquidity (also known as broad money) is defined as the sum of all liquid financial instruments held by money-holding sectors that are 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 important dynamics that numerous central banks are closely monitoring. This is because of its property of being an essential element to the overall transmission mechanism of monetary policy, particularly the impact of money supply expansion or contraction on aggregate demand, interest rates, inflation, and overall economic growth (Mankiw, n.d.).

In the Philippines, data on domestic liquidity is used as a primary component to formulate monetary policy and utilized as a leading indicator to observe price and financial stability. However, similar to the concerns regarding the delayed publication of data or statistical indicators generated by most government offices, data on domestic liquidity in the said country also suffers from series of lags and revisions. Due to this predicament, policymakers in the Central Bank of the Philippines or *Bangko Sentral ng Pilipinas* (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formulate monetary policies and address different economic phenomena (e.g., inflation, business cycle) using its outdated or lagged values.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 big data and machine learning which augment its overall process (Hassani and Silva, 2015; Richardson et al., 2018).

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[2] The results expressed herein do not represent the views nor opinions of GraSPP, UTokyo, as well as the BSP. Errors and omissions are sole responsibility of the author.

That being said, this study aims to utilize machine learning algorithms to provide an optimal model to nowcast the growth of domestic liquidity in the Philippines. In particular, the following steps are performed to support this objective: (1) perform one-step-ahead (out-of-sample) nowcasts through regularization (i.e., Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO), Elastic Net (ENET)) and tree-based methods (i.e., Random Forest (RF), Gradient Boosted Trees (GBT)); (2) recognize and compare the accuracy of each algorithm vis-à-vis traditional time series models used in economic forecasting, such as Autoregressive (AR) Models and Dynamic Factor Model (DFM); and (3) systematically identify important high-frequency variables (i.e., monetary, financial, external sector) that could accurately nowcast domestic liquidity in the Philippines.

Based on the conducted recursive nowcasts from January to December 2020, it was found that machine learning algorithms provide more accurate estimates than the traditional time series models utilized in this study. This is due from the consistent monthly estimates with low forecast errors (i.e., Root Mean Square Error, Mean Absolute Error) that the machine learning algorithms registered. The said quantitative models also registered precise nowcasts on the months where domestic liquidity growth suddenly expand (e.g., increased borrowings and deposits of National Government to BSP) due to the impact of Coronavirus Disease 2019 (COVID-19) in the Philippines. Further, the results indicate that regularization methods are the most optimal machine learning algorithms to nowcast the aforementioned monetary indicator.

This study also concludes that using regularization methods, such as LASSO and ENET, as well as tree-based methods, such as RF and GBT, are useful in filtering out or identifying important indicators that stipulate parsimonious nowcasting models with precise results.

Keywords: Domestic Liquidity, Machine Learning, Nowcasting, Philippines

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
AT	Adaptive Trees
BOP	Balance of Payments
BSP	Bangko Sentral ng Pilipinas
BVAR	Bayesian Vector Autoregression
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
FOF	Flow of Funds
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
IOD	International Operations Department

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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PART ONE

RESEARCH FRAMEWORK:
BACKGROUND, THEORY, AND
METHODOLOGY OF THE STUDY

CHAPTER I: INTRODUCTION

CHAPTER II: REVIEW OF RELATED LITERATURE

CHAPTER III: RESEARCH METHODOLOGY

Chapter I:
INTRODUCTION

1.1. Background of the Study

Understanding the current condition of their respective economy is essential for every policymaker around the world. Therefore, timely announcements of various macroeconomic indicators (e.g., monetary, national accounts) are important for them to be able to monitor the current growth of different economic sectors comprehensively (e.g., households, other depository corporations) as well as to formulate and implement 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 are essential to depict the overall condition of an economy and to strictly monitor if any negative externalities could cause a financial crisis. Hence, numerous government offices (e.g., central banks, finance ministries) are transforming their approach to ensure that macroeconomic indicators are published in a timely and consistent manner (Carriere-Swallow and Haskar, 2019).

Adopting these data management principles, however, cannot be easily implemented in every country. This is because of the tedious and complicated processes that each government office must perform to produce numerous macroeconomic indicators promptly. The proper classification of accounts, changes in the overall compilation framework, and inevitable delays in receiving input documents are among the few reasons that coerced the delay in publishing data at the national level (Dafnai and Sidi, 2010; Chikamatsu et al., 2018). Recent studies discussed that national government agencies (NGAs) and central banks from different advanced (e.g., United States (US), Japan, New Zealand) and emerging economies (e.g., Israel, Lebanon) had 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, short-term forecasting or "nowcasting" was one of the recently introduced methodologies by different International Financial Institutions (IFIs), NGAs, and central banks. This is because of its strong capacity to observe the overall state of an economy or any target variable of interest using conventional and unconventional data as well as high-frequency indicators that are usually published at an earlier date (Tiffin, 2016). Due to the difficulty in producing official macroeconomic indicators on a real-time basis, nowcasting has been the alternative approach used by said institutions to systemically estimate the official figure of a specific set of information before it becomes available (Bańbura et al., 2013). The IMF, World Bank (WB), and Asian Development Bank (ADB) are among the IFIs that conducted comprehensive studies regarding the use of nowcasting in different fields of study (e.g., economics, finance). Meanwhile, 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).[3]

1.1.1. Economic Nowcasting, Big Data, and Machine Learning

For the past years, predicting the overall growth of an economy, the progress of a particular economic sector, and the transmission mechanism of policies are commonly performed through economic forecasting using time series analysis. This approach has been the traditional forecasting methodology under the field of economics (or econometrics) because numerous studies have already established its capacity to provide a clear and substantial outlook of different macro and socioeconomic indicators, such as GDP, CPI, and poverty incidence, among others. Aside from this, the said approach is frequently used by various well-known institutions to estimate the dynamic effects of policy implementation on the overall economic growth of their

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

respective country. Among the numerous time series models used in economic forecasting are Autoregressive (AR), Vector Autoregressive (VAR), and Dynamic Factor Models (DFM).[4]

However, in most cases, time series models used in economic forecasting are highly dependent on the timeliness of data or information. Therefore, any delay in the publication process of the explanatory variable(s) included in a particular forecasting model could hamper the attempt to predict the future condition of the target output. For instance, to predict the GDP for Q2:2020 using a simple AR(1) model, its figure as of end-Q1:2020 is strongly needed.[5] However, in a typical situation, the publication of GDP for Q1:2020 is not released exactly at the end of said period. The latest figures are typically posted 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).[6] 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.

This concern was one of the main reasons that pushed numerous individuals and institutions to adopt the concept of nowcasting in the field of economics. This is because of its capacity to exploit multiple real-time data or information (e.g., daily financial data, survey results) to accurately estimate the present, near future, and recent past of a particular macro or socioeconomic variable (Bańbura et al., 2013, Chikamatsu et al., 2018; Richardson et al., 2018). For example, to predict the current state of an economy, high-frequency data or information (e.g., trade balances, financial data) that signals the current GDP can be utilized before associated official GDP figures are published (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).

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4 See Hang (2010), Ikoku (2014), Doguwa and Alade (2015), and Rajapov and Axmadjonov (2018).

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

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

The study of Bańbura et al. (2013) supported the aforementioned statement. In particular, the authors mentioned that:

> *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 institutional concern, another factor that contributed to the emergence of nowcasting is the recent trend in the use of big data and machine learning.[7,8] The rise of these concepts improved the overall effectiveness of nowcasting in the field of economics because of two (2) particular reasons. The first reason is that the former has a strong potential to provide complementary information with respect to the macroeconomic data that government offices usually published (Baldacci et al., 2016). Meanwhile, the latter has the capacity to utilize the immense amount of data or information that the former concept provided (Hassani and Silva, 2015; Richardson et al., 2018). In addition to economics, conducting nowcasting through big data and machine learning is also performed by different individuals and institutions in the fields of energy, medicine, and population dynamics. This is because the said approach was found to be an essential tool to have an accurate short-term forecast,

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[7] Big data is defined as large datasets that can be examined computationally to observe different patterns, trends, among others .

[8] Machine learning refers to the use of computer system, algorithms, and/or statistical models to analyze and draw conclusions from patterns in data.

which further improves the decision-making as well as policy formulation and implementation of individuals or institutions under these fields (Hassani and Silva, 2015).

1.1.2. The Philippines and Domestic Liquidity

Domestic liquidity 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).[9] In particular, as stated under the Monetary and Financial Statistics Manual (MSFM) of the IMF, the said monetary 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 that has a reliable store value (IMF, 2016 p. 180).[10,11]

The change in the overall growth of this monetary indicator is one of the most important dynamics that most central banks are closely monitoring. Mainly because it is an essential element to the transmission mechanism of monetary policy, particularly the impact of money supply expansion or contraction on aggregate demand, interest rates, inflation, and overall economic growth. For this reason, policymakers in different central banks passionately observe its current and future development to formulate an effective and timely monetary policy response, especially when there are seen predicaments that require them to adjust policy rates and the overall monetary base (Mankiw, n.d.).

Similar to its role in every economy across regions, domestic liquidity likewise holds a critical function in the economy of the Philippines. Both the level and growth of said monetary indicator are usually being monitored by its central bank – otherwise known as the

[9] The words domestic liquidity, broad money, money supply, money demand, and M3 are interchangeably used in this paper.

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

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

Bangko Sentral ng Pilipinas (BSP) – because it is also 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. [12]

Money supply in the Philippines has a similar structure with most countries with fractional-reserve banking systems (e.g., US, Japan).[13] Mainly because bank reserves, currency deposits (or monetary base), and other liquid financial instruments are likewise its main components. In particular, based on the Depository Corporations Survey (DCS) conducted by the BSP, broad money 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).[14]

On a monthly basis, the BSP announces the current level and growth of broad money in the Philippines. However, for the said monetary indicator to be released in a timely manner, the said institution needs to strictly ensure that the monthly submission of bank reports (e.g., balance sheets, income statements) is observed promptly. Since the Philippine Banking System (PBS) is characterized as a fractional-reserve banking system, the balance sheets of the BSP together with the ODCs are necessary to be consolidated to calculate M3 in a given period.

Therefore, in order for the BSP 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 overall monetary policy formulation and implementation in the said country.

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

[13] 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).

[14] 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.

1.2. Statement of the Problem

As mentioned in the previous section, delay in data publication is one of the most common difficulties that 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 10 April 2021, the latest available domestic liquidity statistics was based on its level and growth as of end-February 2021 (e.g., current release has four (4) to six (6) weeks lags).

Table 1.1: Depository Corporations Survey

(Date Accessed: 10 April 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	
	Jan-20	Feb-20	Jan-21 p,r	Feb-21 p	Feb 21 - Jan 21	Jan 21 - Jan 20	Feb 21 - Feb 20	Feb-21 p	Jan-21 p,r	Feb-21 p
1. NET FOREIGN ASSETS	**4,978,882**	**5,037,698**	**6,066,252**	**6,136,265**	**70,013**	**1,087,370**	**1,098,567**	**1.2**	**21.8**	**21.8**
A. Central Bank	4,353,952	4,424,681	5,237,544	5,289,482 a	51,938	883,592	864,801	1.0	20.3	19.5
Claims on Non-residents	4,434,971	4,505,219	5,314,224	5,367,164	52,940	879,253	861,945	1.0	19.8	19.1
Less: Liabilities to Non-residents	81,019	80,538	76,680	77,682	1,002	-4,339	-2,856	1.3	-5.4	-3.5
B. Other Depository Corporation	624,930	613,017	828,708	846,783	18,075	203,778	233,766	2.2	32.6	38.1
Claims on Non-residents	1,690,081	1,639,692	1,745,763	1,714,495	-31,268	55,681	74,802	-1.8	3.3	4.6
Less: Liabilities to Non-residents	1,065,152	1,026,676	917,055	867,712	-49,343	-148,097	-158,964	-5.4	-13.9	-15.5
2. DOMESTIC CLAIMS	**13,109,403**	**13,031,485**	**13,754,915**	**13,757,122**	**2,207**	**645,513**	**725,637**	**0.0**	**4.9**	**5.6**
A. Net Claims on Central Government	2,268,389	2,149,613	3,152,491	3,161,671	9,180	884,102	1,012,058	0.3	39.0	47.1
Claims on Central Government	2,942,573	3,134,239	4,996,636	4,991,800	-4,835	2,054,063	1,857,562	-0.1	69.8	59.3
Less: Liabilities to central government	674,184	984,625	1,844,145	1,830,129	-14,016	1,169,961	845,503	-0.8	173.5	85.9
B. Claims on Other Sectors	10,841,013	10,881,872	10,602,424	10,595,450	-6,974	-238,589	-286,421	-0.1	-2.2	-2.6
Claims on other financial corporations	1,152,117	1,175,436	1,100,365	1,098,802	-1,563	-51,752	-76,634	-0.1	-4.5	-6.5
Claims on state and local government	98,737	98,650	102,484	103,317	834	3,747	4,667	0.8	3.8	4.7
Claims on public nonfinancial corporations	258,401	255,636	267,424	261,793	-5,631	9,022	6,157	-2.1	3.5	2.4
Claims on private sector	9,331,758	9,352,149	9,132,152	9,131,538	-614	-199,606	-220,612	0.0	-2.1	-2.4
3. LIQUIDITY AGGREGATES										
M4 (M3 + 3.e)	**14,828,756**	**14,792,993**	**15,962,300**	**15,983,317**	**21,016**	**1,133,544**	**1,190,324**	0.1	**7.6**	**8.0**
M3 (M2 + 3.d) **	12,805,426	12,764,857	13,945,474	13,963,382	17,907	1,140,048	1,198,525	0.1	8.9	9.4
M2 (M1 + 3.c)	12,084,372	12,017,031	13,310,555	13,316,155	5,600	1,226,183	1,299,124	0.0	10.1	10.8
M1 (3.a + 3.b)	4,435,647	4,448,628	5,372,029	5,376,988	4,959	936,382	928,360	0.1	21.1	20.9
3.a Currency outside depository corporations	1,292,606	1,296,646	1,632,147	1,617,498	-14,649	339,541	320,853	-0.9	26.3	24.7
3.b Transferable deposits included in broad money	3,143,041	3,151,982	3,739,882	3,759,490	19,608	596,841	607,507	0.5	19.0	19.3
3.c Other deposits included in broad money	7,648,725	7,568,403	7,938,526	7,939,167	641	289,801	370,764	0.0	3.8	4.9
Savings deposits	4,952,449	4,965,844	5,660,937	5,752,661	91,724	708,488	786,817	1.6	14.3	15.8
Time deposits	2,696,276	2,602,559	2,277,589	2,186,506	-91,083	-418,687	-416,053	-4.0	-15.5	-16.0
3.d Securities other than shares included in broad money	721,054	747,826	634,919	647,227	12,307	-86,135	-100,599	1.9	-11.9	-13.5
3.e Transferable and other deposits in foreign currency	2,023,330	2,028,136	2,016,826	2,019,935	3,109	-6,504	-8,201	0.2	-0.3	-0.4
4. LIABILITIES EXCLUDED FROM BROAD MONEY	**3,259,528**	**3,276,190**	**3,858,867**	**3,910,070**	**51,203**	**599,338**	**633,880**	**1.3**	**18.4**	**19.3**

* Based on the Standardized Report Forms (SRFs), a unified framework for reporting monetary and financial statistics to the International Monetary Fund (IMF).
p Preliminary
r Revised
a Based on revised Central Bank Survey
** M3 may also be derived as Net Foreign Assets + Domestic Claims, net of Liabilities excluded from broad money and transferable and other deposits in foreign currency(FCDs-Residents)
. Growth rate rounds off to zero

Source: BSP

Aside from this concern, the official data on money supply also suffers from 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 two (2) months to reflect changes (if any) on the reports submitted by the banks under its jurisdiction.[15] 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, in some cases, the preliminary and revised data have significant numerical discrepancies.

Drawing upon this background, this study aims to address these issues and concerns by investigating the use of different machine learning algorithms to predict the real-time growth of broad money in the Philippines. This approach particularly intends to formulate an accurate quantitative model that the BSP can sustainably use to estimate domestic liquidity in the said country using regularization and tree-based methods. For this reason, the overarching research question for this study is:

WHAT IS THE OPTIMAL MACHINE LEARNING ALGORITHM TO ACCURATELY NOWCAST THE GROWTH OF DOMESTIC LIQUIDITY IN THE PHILIPPINES?

The study also intends to answer these sub-research questions that could further strengthen the overall finding(s):

a. Does the use of machine learning algorithms improve the overall accuracy in predicting the real-time growth of domestic liquidity in the Philippines?
b. What are the substantial advantages of using machine learning algorithms vis-à-vis traditional time series models (e.g., Autoregressive Models, Dynamic Factor Model) in predicting the current growth of domestic liquidity 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 predict the real-time growth of domestic liquidity in the Philippines?

[15] See DCS revision policy – 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 an accurate nowcasting model that could be used as a primary method in predicting the real-time growth of money supply in the Philippines.
b. To strongly 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 determine the current state of domestic liquidity in the said country.

1.4. Significance of the Study

For the past years, there was an increasing number of scholars in the field of economics that showed their interest in using nowcasting as a primary approach to determine the real-time growth of numerous macroeconomic indicators. Most of these studies are focused on formulating quantitative models using different time series and machine learning algorithms that could accurately estimate the movement of numerous macro and socioeconomic indicators using conventional and unconventional data or information.

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 mixed frequency models 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 the growth of broad money in the said country.

Due to this 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 primary tool of the BSP to accurately nowcast the growth of domestic liquidity, which is considered one of the most critical inputs for monetary policy formulation (e.g., reserve requirements, open market operations) in the Philippines.
b. Machine learning algorithms utilized in this study can be replicated to nowcast 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 result of this study could be a valuable input to the current nowcasting initiatives performed by the BSP, such as GDP and inflation nowcasting, among others.
d. The determinants identified as principal components in this study could be used as additional leading indicators of domestic liquidity growth in the Philippines.
e. 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.
f. This study could also strengthen the growing body of literature regarding the application of time series and machine learning models in economic forecasting.

1.5. Scope and Limitations

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

a. The main objective of this study is to nowcast the growth of domestic liquidity (M3) 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.
b. The benchmark models used in this study are limited to (1) Autoregressive (AR) such as Autoregressive Integrated Moving Average (ARIMA) and Random Walk Models as well as (2) Dynamic Factor Model (DFM).[16]
c. To conduct domestic liquidity nowcasting using machine learning algorithms, the models 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.
d. 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 in the different nowcasting models became limited due to (1) data confidentiality, (2) access restrictions, and (3) time constraints.
e. 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).

1.6. Definition of Terms

The following terms, which are frequently cited in this study, are defined operationally or derived from official or technical sources:

Autoregressive (AR) Model – a time series model whose current value strongly depends linearly on its current value and an unpredictable disturbance (Wooldridge, 2012 p. 844).

[16] Vector Autoregression (VAR) is used as part of DFM.

Big Data – large datasets that can be examined computationally to observe different patterns, trends, among others.

Central Bank – an institution responsible for the conduct of monetary policy (Mankiw, n.d. p.618).

Domestic Liquidity – 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).

Liquidity – refers to the assets that can be exchanged in a rapid manner without affecting its overall price (IMF, 2016).

Machine Learning – use of computer systems, algorithms, and statistical models to analyze and conclusions from patterns in data.

Monetary Policy – refers to the management of money supply and interest rates (Mishkin, n.d. p. 10).

Other Depository Corporations (ODCs) – financial corporations (other than the central bank) that incurs liabilities included in domestic liquidity (IMF, 2016 p. 405).

Time Series Data – refers to any data or information that is collected over time (Wooldridge, 2012 p. 859).

Vector Autoregressive (VAR) Model – a model for two (2) or more time series. Each variable is modeled as a linear function of past values of all variables, plus disturbances that have zero (0) means given all past values of the observed variables (Wooldridge, 2012 p. 860).

Chapter II:
REVIEW OF RELATED LITERATURE

2.1. Primer

Nowcasting became one of the alternative methodologies used by numerous institutions to predict the recent developments of various macroeconomic indicators (e.g., Gross Domestic Product (GDP), inflation) and potential transmission mechanisms of fiscal or monetary policies. This quantitative approach transpired because most economic indicators published by government offices (e.g., national government agencies (NGAs), central banks) tend to suffer from lags and revisions. Hence, numerous nowcasting exercises are recently conducted to eliminate the practice of using non-related, outdated, or lagged datasets in addressing different predicaments in an economy, such as hyperinflation, unemployment, among others (Richardson et al., 2018).

Aside from this concern, the popularity of nowcasting is strongly enhanced by the recent emergence of big data and machine learning. This is due to the potential of the former concept to provide complementary information, such as high-frequency data concerning the macroeconomic data that government offices usually published (Baldacci et al., 2016). In contrast, the latter concept has the capacity to accurately provide estimates despite having an immense amount of data or information in a nowcasting model (Hassani and Silva, 2015; Richardson et al., 2018).

That being said, to strengthen the foundation of this research, previous studies that conducted nowcasting through the use of big data (or high-frequency data) and different machine learning algorithms are discussed in this chapter. However, this literature review mainly focuses on the studies that used (1) regularization methods (i.e., Ridge Regression, Least Absolute Shrinkage and Selection Operator, Elastic Net) and (2) tree-based methods (i.e., Random Forest, Gradient Boosted Trees) as their primary or secondary approach to nowcast different macroeconomic variables and other statistical indicators.

2.2. Regularization Methods

Regularization methods are among the prevalent machine learning algorithms used to conduct nowcasting. This is because regression models under its purview almost have similar characteristics with the Ordinary Least Squares (OLS) to fit a linear model (James et al., 2013; Tiffin, 2016). Compared to OLS, however, each of these methods 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 better forecast output because it reduces model complexity by incorporating penalties to its coefficient(s) – which then address the issue of bias-variance tradeoff.[17] This approach is called shrinkage in machine learning literature (Tiffin, 2016; Richardson et al., 2018).

The studies of Tiffin (2016), as well as Dafnai and Sidi (2010), are among the well-known studies in the field of economics that managed to use regularization methods as an approach to conduct nowcasting. Both of these studies attempted to formulate nowcasting models that could accurately estimate the GDP growth in Lebanon and Israel, respectively. Due to the data publication lags that both countries experienced, these authors similarly agreed that there was a need to conduct an approach wherein the current status of 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., International Financial Institutions (IFIs), bilateral partners) landscape in assessing the overall economic health of their respective countries (Tiffin, 2016; Dafnai and Sidi; 2010).

[17] 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).

To meet these objectives, the aforementioned authors used high-frequency data or information as explanatory variables to their corresponding GDP nowcasting models. Tiffin (2016) used nineteen (19) monthly macroeconomic variables (e.g., customs revenue, tourist arrivals) to observe economic growth in Lebanon.[18] Using the aforementioned data through regularization methods, the author found that ENET is the most suitable machine learning algorithm to predict the short-run economic development of Lebanon. Mainly because its 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). On the other hand, Dafnai and Sidi (2010) used one hundred forty (140) domestic indicators and fifteen (15) global indicators as input variables to nowcast the GDP in Israel.[19] The authors similarly found that ENET is the most comprehensive regularization method to nowcast the economic growth in said country. Compared to other regularization methods used in their study, Dafnai and Sidi (2010) argued that ENET is the only regularization method 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 the aforementioned 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, predicting its current state could be a valuable tool for the country's policymakers to immediately implement actions in the fast-changing domestic and global economic condition (Hussain et al., 2018).

Given this objective, Hussain et al. (2018) also used high-frequency data or information as explanatory variables to nowcast the aforementioned indicator. This includes monthly indicators regarding financial markets, confidence surveys, interest rate spreads, credit,

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

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

and the external sector in Pakistan.[20] Using these data as inputs to their regularization methods, the authors concluded that Ridge Regression, LASSO, and ENET methods are comprehensive quantitative tools in predicting the overall growth of LSM. This is because all three (3) machine learning algorithms scrupulously tracked the overall growth, trends, and cyclical movement of LSM with small forecast error. Comparing each method, Hussain et al. (2018) found that LASSO rendered the most accurate nowcasting result since it comprehensively traced the trends and cycle of LSM in Pakistan while having the lowest RMSE. The Dynamic Factor Model (DFM) used in the study of said authors provided the smallest forecasting error in nowcasting the trend. However, it presented inconsistent estimates in predicting the overall growth and cycle of said macroeconomic indicator (Hussain et al., 2018).

The aforementioned machine learning algorithms were likewise used by Cepni et al. (2018) as well as Ferrara and Simoni (2019). These authors utilized the said methods to formulate models that could accurately nowcast the GDP of emerging economies (i.e., Brazil, Indonesia, Mexico, South Africa, Turkey) and the United States (US), respectively. Similar to the previous studies discussed in this section, numerous high-frequency data or information were used as explanatory variables to nowcast the economic growth of said countries. Cepni et al. (2018), in particular, utilized country-specific (1) macroeconomic indicators such as industrial production, demand, and consumption indices and (2) survey data from Market Purchasing Managers' Index (PMI).[21] 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.[22] 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 predict GDP in the short run

[20] See Page 13 of Hussain et al. (2018).

[21] See Page 2 of Cepni et al. (2018).

[22] See Page 7 of Ferrera and Simoni (2019).

accurately. This is because Ridge Regression and LASSO each 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 quantitative approach could also be used to predict 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 (e.g., services, manufacturing) in Finland.[23] Individual results of these methods were compared with traditional time series models, such as Autoregressive Integrated Moving Average (ARIMA), to estimate their respective prediction accuracy. Based on the conducted analysis, Fornano et al. (2017) found that these machine learning algorithms outperformed ARIMA in predicting the turnover indices growth of all sectors in Finland. This is because Ridge Regression, LASSO, and ENET provided low Mean Squared Forecast Errors (MSFE) compared to the said time series benchmark (Fornano et al., 2017).

Aside from predicting macroeconomic and firm-level indicators, nowcasting was also utilized in the field of energy and medicine. The papers of Ziel (2020) as well as Lan and Subramanian (2019) were among the studies in these fields that used regularization methods to conduct nowcasting. In particular, the former author used the said quantitative approach to predict the current state of electricity or power consumption in Europe. Meanwhile, the latter authors applied the said concept to formulate a nowcasting model to estimate the recent dengue occurrence in Puerto Rico and Peru. Both of the 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,

[23] See Page 5 of Fornano et al. (2017).

respectively. This is because different stakeholders strongly use the two (2) indicators for economic and public health reasons (Ziel, 2020; Lan and Subramanian, 2019).

To perform their corresponding nowcasting exercise, these authors likewise use high-frequency data or information. Ziel (2020) makes use of 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.[24,25] Based on their analysis, both authors concluded that regularization methods could accurately nowcast the two (2) aforementioned circumstances with ease. This is because the machine learning algorithms used in their respective model could handle and incorporate a large number of predictors with a low level of Mean Absolute Error (MAE) and RMSE. Ziel (2020), as well as Lan and Subramanian (2019), specifically 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.

2.3. Tree-Based Methods

Aside from regularization methods, numerous studies also introduced the use of tree-based methods to conduct nowcasting. The said approach is one of the well-known options to perform nowcasting through machine learning algorithms. This is because of its strong capacity, similar to regularization methods, in being flexible and interpretable.[26] 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. In order to make a prediction for a given observation, the mean or mode of the training observation is typically used in the region to which it belongs (James et al., 2013 p. 303).

[24] See Page 8 of Ziel (2020).

[25] See Page 5 of Lan and Subramanian (2019).

[26] Similar to regularization methods, tree-based methods in machine learning also address the issue of bias-variance tradeoff.

The study of Biau and D'Elia (2010) was considered one of the most recognized studies that used tree-based methods to predict economic growth. These authors, in particular, utilized Random Forest (RF) algorithm to forecast the short-term GDP growth in Europe. 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.[27]

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. This is because RF provided more accurate estimates than the projections registered by the traditional time series model, such as the Autoregressive (AR) Model, 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 among the 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 concept of Biau and D'Elia (2010) to investigate the use of RF in forecasting the quarterly GDP growth of Sweden. To attain this objective, these authors similarly used a large amount of survey dataset to predict the said macroeconomic variable. The data or information 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.[28] This survey consists of different confidence indicators and questions to private firms and households regarding their economic outlook and perception of economic activity in the said country (Adriansson and Mattson, 2015).

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[27] See Page 6 of Biau and D'Elia (2010).

[28] See Page 5 of 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 AR model in forecasting the GDP growth of Sweden. RF had the most precise forecasting results since it has 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 bring forecasting improvements 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 nonlinearities and structural changes, among others (James et al., 2013; Woloszko, 2020). The paper of Woloszko (2020) was one of the recent studies that specifically used AT to provide three (3)- to twelve (12)-months ahead GDP growth forecast to the Group of Seven (G7) countries.[29] In this study, the author employed country-specific information (e.g., expectation surveys, consumer confidence) and macroeconomic data (e.g., housing prices, employment rate) as explanatory variables to the tree-based forecasting model.[30]

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 it generates compared to the traditional time series models. In contrast to AR 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. This is 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

[29] Canada, however, was not included in the analysis of Woloszko (2020).

[30] See Page 11 of Woloszko (2020).

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 both 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, the studies of these authors also aim to determine the most optimal tree-based method to predict economic growth using high-frequency data or information. 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.[31] Meanwhile, Soybilgen and Yazgan (2021) utilized more than one hundred (100) financial and macroeconomic variables, which include data on the labor market, money and credit, and stock market, among others.[32]

Using the aforementioned input variables, Boluis and Rayner (2020) as well as Soybilgen and Yazgan (2021) concluded that the tree-based methods provide superior forecasts compared to benchmark models, such as DFM and linear models. This is because RF and GBT produced lower forecast errors against the benchmark models. Boluis and Rayner (2020) mentioned that the RMSE of RF was 1.26 while GBT produced 1.29. Both of these results were lower compared to the benchmark linear model, which registered an RMSE of 1.66. Likewise, Soybilgen and Yazgan (2021) discussed that, compared to the DFM, the tree-based methods provided the lowest average RMSE and MAE.[33] Aside from their outstanding individual accuracy, these authors also cited that RF and GBT 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.

[31] See Tables A5.1 and A5.2, Pages 24-25 of Boluis and Rayner (2020).

[32] See Appendix 1, Page 23 of Soybilgen and Yazgan (2021).

[33] See Table 1 and 2, Page 13 of Soybilgen and Yazgan (2021).

2.4. The Utilization of Two (2) Machine Learning Methods

Several studies also attempted to utilize the strengths of both regularization and tree-based methods to perform nowcasting. Authors of these studies have considered this research approach because most of them intended to distinguish the accuracy of each machine learning method to nowcast or forecast the growth of a specific macroeconomic indicator or the possible impact of policy implementation (Richardson et al., 2018; Tamara et al., 2020; Aguilar et al. 2019).

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 both regularization and tree-based methods to formulate a model that can precisely nowcast the GDP in New Zealand. The objective of this study was drawn from the difficulty of their policymakers in addressing various economic vulnerabilities. This is 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 a range 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.[34] By using these as inputs for the different machine learning algorithms, Richardson et al. (2018) concluded that regularization or tree-based approach could be used as a primary methodology to nowcast the economic growth in New Zealand. Mainly because the RMSE and Mean Absolute Deviation (MAD) of these machine learning algorithms are lower than the traditional time series models used to forecast the GDP in the said country. However, comparing these methods, Richardson et al. (2018) argued that LASSO (0.45) had the lowest average forecast errors.[35]

[34] See Page 8 of Richardson et al. (2018).

[35] Richardson et al. (2018) also found that Support Vector Machines (SVM) and Neural Network (NN) both have low forecast errors compared to AR and BVAR.

The authors also found that GBT (0.47) and Ridge Regression (0.57) provided lower RMSE compared to Bayesian VAR (BVAR) model (0.61).

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 the quarterly data of GDP for Indonesia 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).[36] Using these indicators as explanatory variables, the authors concluded that regularization and tree-based methods precisely estimate the short-run growth of GDP in Indonesia. Mainly because these machine learning algorithms reduce the average forecast errors at thirty-eight (38) to sixty-three (63) percent (on average) relative to the AR benchmark. Tamara et al. (2020) also found that the forecasted values using these methods could produce a similar pattern close to the actual values. However, comparing these methods, the authors cited that RF (1.27) and ENET (1.31) have the lowest average forecast errors.

The potential of regularization and tree-based methods was also used to provide estimates on global poverty. The paper of Aguilar et al. (2019) utilized 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 predict 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).

[36] See Appendix of Tamara et al. (2020).

Taking this into consideration, Aguilar et al. (2019) used similar datasets utilized under the current forecasting model of WB to predict the current level and growth of global poverty. These datasets include macroeconomic and social indicators, which were extracted from the World Economic Outlook (WEO) database and World Development Indicators (WDI).[37] Using these as inputs, the authors found that using regularization and tree-based methods to nowcast the said indicator decreased the overall nowcast error by 5.7 percent from 2.8 percentage points (Aguilar et al., 2019). However, Aguilar et al. (2019) 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.

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

Chapter III:
RESEARCH METHODOLOGY

3.1. Primer

The overall methodology of this study is comprehensively discussed in this chapter. In particular, each section presents detailed information about (1) benchmark models, (2) machine learning algorithms, (3) nowcast evaluation methodology, and (4) statistical tool or software used to formulate a nowcasting model that aims to accurately estimate the growth and development of domestic liquidity in the Philippines.

3.2. Models

Time series models and machine learning algorithms are utilized to support the main objective of this research systematically. The former models are used as benchmarks since these are the most commonly used econometric models to predict the current and future growth of a particular macroeconomic indicator or economic phenomenon. Meanwhile, the latter algorithms are used as the alternative quantitative methods to nowcast domestic liquidity growth in the Philippines. This approach is conducted because of two (2) main reasons. The first reason is to establish which quantitative models could accurately estimate the real-time growth of said monetary indicator. Another reason is 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 each time series and machine learning models – which are utilized in this study – are comprehensively discussed in this chapter. The former includes traditional forecasting models such as (1) Autoregressive Model (e.g., Autoregressive Integrated Moving Average and Random Walk) and (2) Vector Autoregression, and (3) Dynamic Factor Model. On the other hand, the latter models are comprised of (1) Regularization Methods such as Ridge Regression, Least Absolute Shrinkage and Selection Operator, and Elastic Net, as well as (2) Tree-Based Methods such as Decision Trees, Random Forest, and Gradient Boosted Trees.

3.2.1. Benchmark Models

3.2.1.1. Autoregressive Models

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

3.2.1.1.1. Autoregressive Integrated Moving Average

There are various AR models that 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 univariate 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. This is 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:

$$y_t = \mu + \phi_0 + \phi_1 y_{t-1} + \ldots + \phi_2 y_{t-p} \ldots + \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q} \qquad (3.1)$$

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).

3.2.1.1.2. 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 the two (2) models similarly use the previous data points as a reference of the future trend of a specific time series. However, compared to ARIMA, the Random Walk model assumes that the next step is only decided by the last data point and takes an independent random step away (Fan, 2019 p. 11-12). This univariate model is also utilized if a particular time series is non-stationary.[38,39] The general forecasting equation using Random Walk is written below:

$$y_t = \epsilon_t + y_{t-1} \tag{3.2}$$

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).

3.2.1.2. Vector Autoregression

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

To address this concern, most studies in the field of economics used multivariate time series models such as Vector Autoregression (VAR). The superiority of this algorithm

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38 Random walk is similar with ARIMA(0,1,0) model.

39 Random walk is a prevalent forecasting model for non-stationary time series data such as foreign exchange rates (FOREX).

against univariate time series models has been proven and established over time. This is 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. Hence, compared to ARIMA or Random Walk, VAR can be considered as a comprehensive forecasting model. 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).

3.2.1.3. Dynamic Factor Model

The Dynamic Factor Model (DFM) is also a prevalent choice for most econometricians that aim to predict the future growth of a particular macroeconomic variable with the use of numerous explanatory variables. This is because it has the 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 can be immediately included in the model, the DFM first reduces the dimension of these datasets by summarizing the information available into a small number of common factors. Each of the variables 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 can be 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).

3.2.2. Machine Learning Models

3.2.2.1. 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 have a strong resemblance with the characteristics of Ordinary Least Squares (OLS) in fitting a linear model (James et al., 2013; Tiffin, 2016). However, in contrast with OLS, regularization methods constrain its coefficient estimates to significantly reduce their variance with the intention to improve the overall model fit (James et al., 2013).

3.2.2.1.1. Ridge Regression

One of the regularization methods used in nowcasting is Ridge Regression. This regularization method is very similar to least squares. Mainly because 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 on 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).

3.2.2.1.2. 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).

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

In contrast with the former regularization method, which only shrinks all of its coefficients towards zero (0) but 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).[40] 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.

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

3.2.2.1.3. Elastic Net

Numerous studies also used Elastic Net (ENET) as their primary approach to perform nowcasting to maximize the strengths of the two (2) aforementioned methods.[41] ENET is a form of regularization method that contains 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 regularization method 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).

3.2.2.2. Tree-Based Methods

Numerous studies also utilized tree-based methods as a primary approach to conduct nowcasting. These studies particularly 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). Tree-based methods involve stratifying or segmenting the predictor space into a number of simple regions. Therefore, in order to make a

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

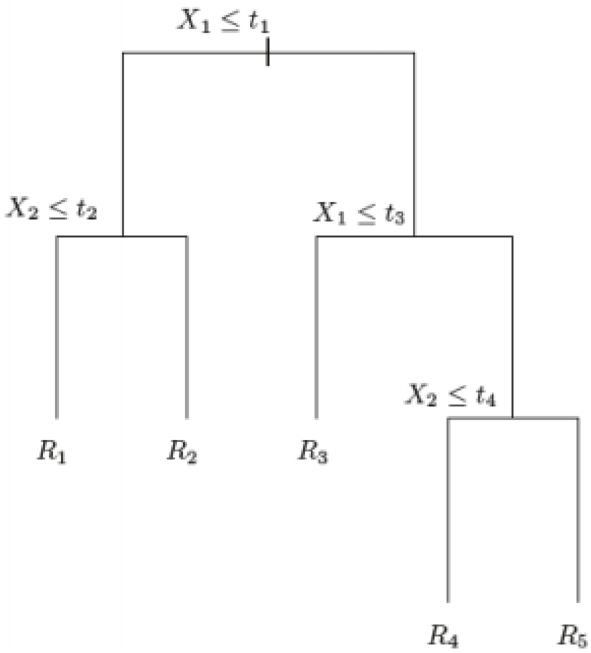
prediction for a given observation, tree-based methods utilize the mean or mode of training observation in the region to which it belongs (James et al., 2013 p. 303).

3.2.2.2.1. Decision Tree

Decision Tree is the fundamental structure of any tree-based machine learning method, which can be used for classification and regression problems (James et al., 2013; Fan, 2019). Basically, 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 prediction by using the mean or mode of training observation in that particular region (James et al., 2013).

Figure 3.1: Decision Tree Growing Process

(Recursive Binary Splitting of Two-Dimensional Feature Space)



Source: James et al. (2013)

3.2.2.2.2. Random Forest

One of the most well-known tree-based machine learning algorithms is the Random Forest (RF). Mainly because this particular model is computationally simple to use, does not require tuning of model parameters, and ideal for forecasting time series data with relatively few observations (James et al., 2013).

RF is a machine learning algorithm that makes use of 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 aggregate prediction that is strong and accurate (Tiffin, 2016; Bolhuis and Rayner, 2020).

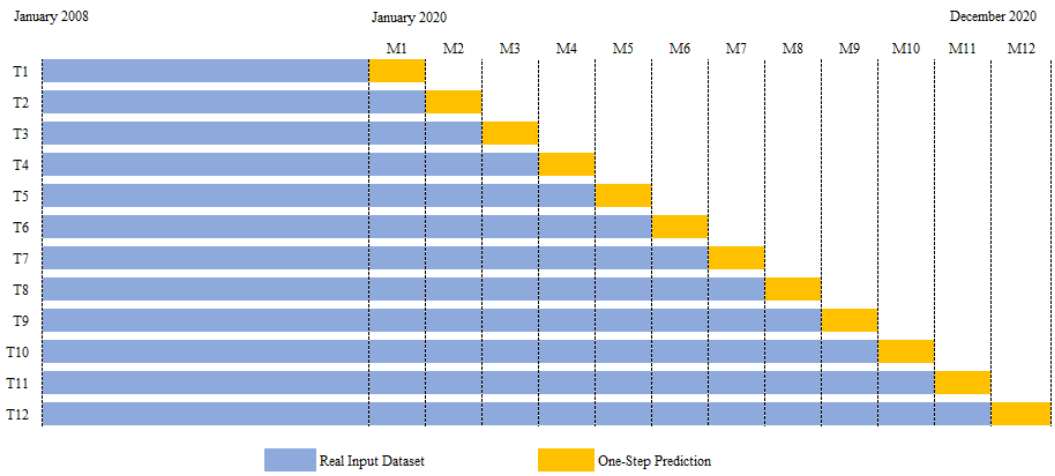
3.2.2.2.3. Gradient Boosted Trees

Gradient Boosted Trees (GBT) is another form of tree-based model that is often used by numerous studies to conduct nowcasting. This is because of its powerful forecasting capability to capture complex non-linear functions (Fan, 2019). However, 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. 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).

3.3. Nowcast Evaluation Methodology

In this study, the performance of time series and machine learning algorithms are evaluated based on their one-step-ahead (out-of-sample) nowcast. The models are trained over an expanding window (also known as recursive) 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. For the second nowcast in February 2020, the dataset used 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.[42]

Figure 3.2: Expanding Window Process



After the individual performance is evaluated, the forecast accuracy of each model is gauged through their respective forecast errors such as Root Mean Square Error (RMSE)

[42] Since there 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: Research Data and Diagnostics.

(Equation 3.8) and Mean Absolute Error (MAE) (Equation 3.9). The RMSE and MAE of each machine learning algorithm are compared against benchmark models (i.e., AR, DFM). This method of comparison is performed to determine whether the nowcast results obtained from the former are significantly superior to the latter methods or vice versa.

$$RMSE = \frac{\sqrt{\sum_{t=1}^{n} y_t - y_t^{\ 2}}}{n} \tag{3.8}$$

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

3.4. Research Tool

The R environment is the primary statistical software used in this study. It is a well-known software environment for statistical computations, mathematical equations, and data visualizations. In particular, this study highly utilized the capacity of R Studio to perform the whole process of this research. This particular includes data integration, data cleaning, model building, and statistical validation.[43]

[43] The R packages used in this study are listed in Annex A.

PART TWO

RESEARCH ANALYSIS:
DATA AND EMPIRICAL RESULTS

Chapter IV:
DATA AND DIAGNOSTICS

4.1. Primer

The activities performed to prepare datasets and enhance the overall performance of benchmark and machine learning models used in this study are presented in this chapter. In particular, each section presents the (1) dataset and variables, (2) averaging and interpolation conducted, and (3) diagnostics and feature engineering efforts performed in this research.

4.2. Data

4.2.1. 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 *Bangko Sentral ng Pilipinas* (BSP) published on its official website from January 2008 to December 2020.[44,45] Figure 3.1 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.

4.2.2. Input Variables

Similar to previous studies that intend to formulate nowcasting models in order to estimate recent developments of various macroeconomic indicators and transmission mechanisms

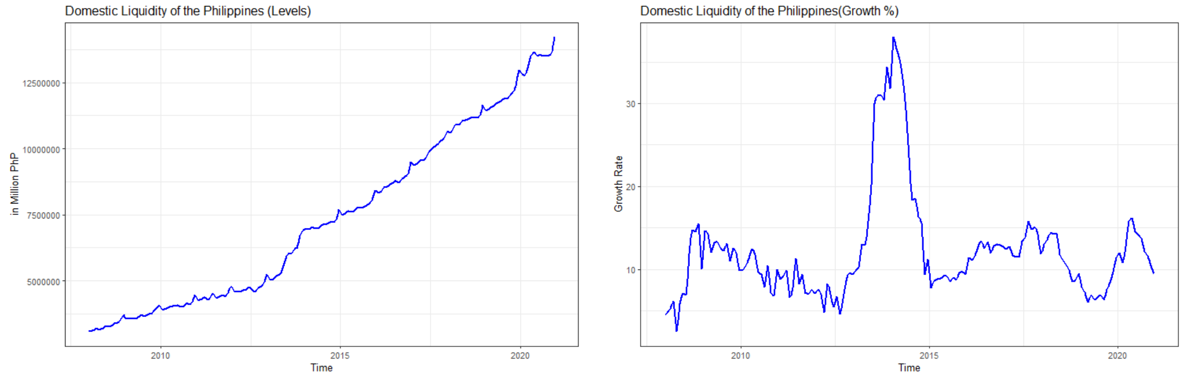
[44] Official BSP Website: https://www.bsp.gov.ph.

[45] 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.

of policies through the use of machine learning algorithms, high-frequency data or information are also used as independent variables in this study. These are comprised of numerous high-frequency monetary, financial, and external sector indicators, which are used as typical components to monitor or observe the growth of domestic liquidity.

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

4.2.2.1. Monetary Indicators

The numerical data of monetary variables used in this study are formally requested from the Department of Economic Statistics (DES) and obtained from the official website of the BSP.[46] A formal request is made because daily figures of these variables are not published nor shared publicly. Monetary indicators that are requested from the DES are the daily (1) available reserves (i.e., required reserves, excess reserves) (2) reserve money (i.e., currency-in-circulation, central bank liabilities). Meanwhile, the central bank (3) claims on National Government (NG) and (4) claims on other sectors are obtained from the monthly

[46] 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).

Central Bank Survey (CBS) posted on the BSP's website. The data of these indicators covers January 2008 to December 2020.

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

4.2.2.2. 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.

4.2.2.3. External Indicators

Statistics for the 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.[47] Similar to the case of available reserves and reserve money, its historical high-frequency 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.

4.2.2.4. Lagged Values of Domestic Liquidity [48]

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 are not included in the dataset could also influence its growth. To address this concern, lagged value of the domestic liquidity is also considered as an input variable. The lagged values used in this study are $t-1$ of the target variable.

4.3. Averaging and Interpolation

Given that the main objective of this study is to provide useful and advance data or information in order to minimize the usual approach in addressing different economic phenomena and formulating policies based on outdated or lagged data, this study aims to nowcast domestic liquidity in the Philippines on a bi-monthly basis, with the second nowcast being the

[47] 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).

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

principal prediction result. This is to maximize the explanatory power of each high-frequency input variable (i.e., variables with daily frequency). 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 level of granularity. Therefore, to align all of the data correctly, averaging and interpolation are conducted in this study.

4.3.1. 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).

4.3.2. 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, which is commonly used for non-linear data estimation.

4.4. Diagnostics and Feature Engineering

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

4.4.1. Seasonal Adjustment

Since most published data in the Philippines are not seasonally adjusted, data of domestic liquidity and most input variables used in this study are deseasonalized accordingly. This includes data that were requested from the DES and IOD as well as the other statistics obtained from the official website of the BSP and Bloomberg (e.g., BSP liabilities to NG, BSP discount rate). 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 not present in each model simulation.

4.4.2. Logarithmic Transformation

The normality of data is also an important factor in economic and statistical modeling. Given that most real-life datasets do not always follow a normal distribution, they are often skewed, which makes 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.[49]

4.4.3. Stationarity

In order to develop an accurate or precise forecasting model, it is crucial to establish that the time series data of each indicator is stationary. This is mainly performed in order to ensure

[49] If the data of a variable is an index or growth rate, it is not transformed to its logarithmic equivalent.

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.

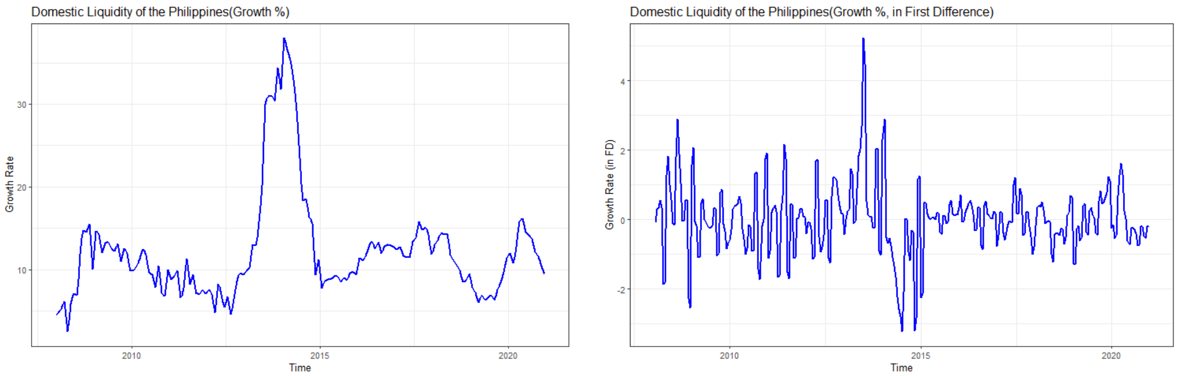
Based on the conducted unit root tests, the level, growth rate, or logarithmic equivalent of domestic liquidity and input variables are non-stationary (Table 4.3).[50] This is because their individual *p-value* is greater than the five (5) percent significance level (except for central bank liabilities to NG). However, when transformed in their respective first difference, ADF and PP tests showed that these variables are stationary. Therefore, to formulate a nowcasting model to estimate domestic liquidity growth in the Philippines, the first difference values of target and input variables (except for BSP Liabilities to NG) are used in this study.[51]

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.)
Domestic Liquidity (M3)	ADF	0.05	0.14	0.01
	PP		0.61	0.01

Figure 4.2: Domestic Liquidity in the Philippines (January 2008 – December 2020)

(a) Growth Rate (in %); (b) Growth Rate (in %, First Difference)

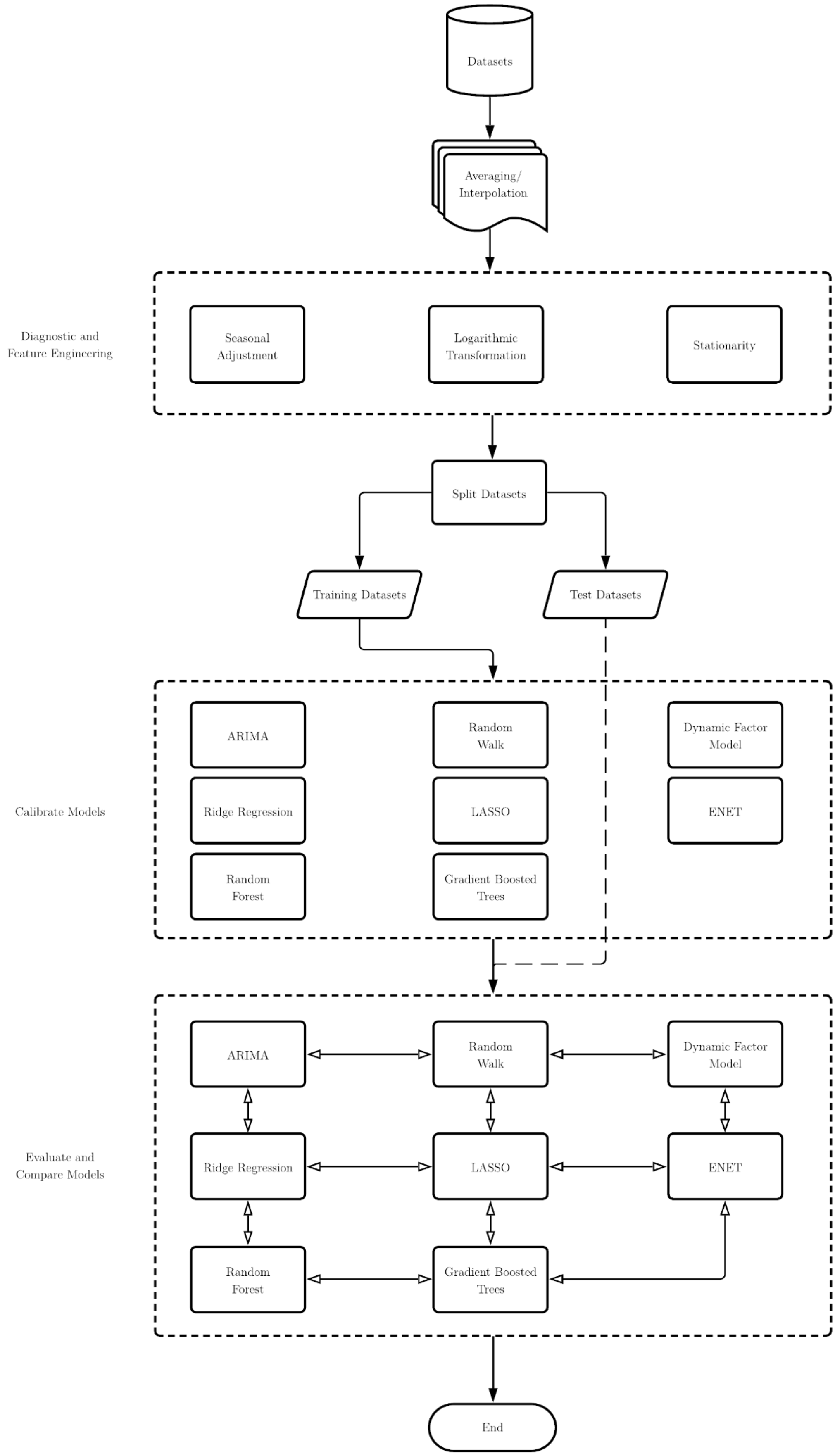


(a) (b)

50 See Annex B for the individual ADF and PP test result of input variables.

51 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.

Figure 4.3: Research Workflow Diagram



Chapter V:

EMPIRICAL RESULTS AND ANALYSIS

5.1. Primer

In this chapter, results of the simulated nowcasts using time series and machine learning algorithms are presented. The sections of this chapter mainly discuss the (1) calibration method performed in each model, (2) individual performance of benchmark and machine learning models through the expanding window validation, and (3) critical high-frequency indicators (i.e., monetary, financial, external sectors) that are considered important to accurately nowcast the real-time growth of domestic liquidity in the Philippines.

5.2. Calibration and Nowcast Results

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

Since the main objective of this study is to accurately determine the growth of domestic liquidity in the short-run, one-step-ahead (out-of-sample) nowcasts are performed. This particular approach is preferred compared with 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 Autoregressive Integrated Moving Average (ARIMA) and Random Walk. Mainly because these univariate models place heavier emphasis on the recent past rather than the distant past in conducting a forecast. Therefore, to appropriately compare 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.

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 is comprised of 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 evaluated individually and collectively based on their Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

5.2.2. Autoregressive Models

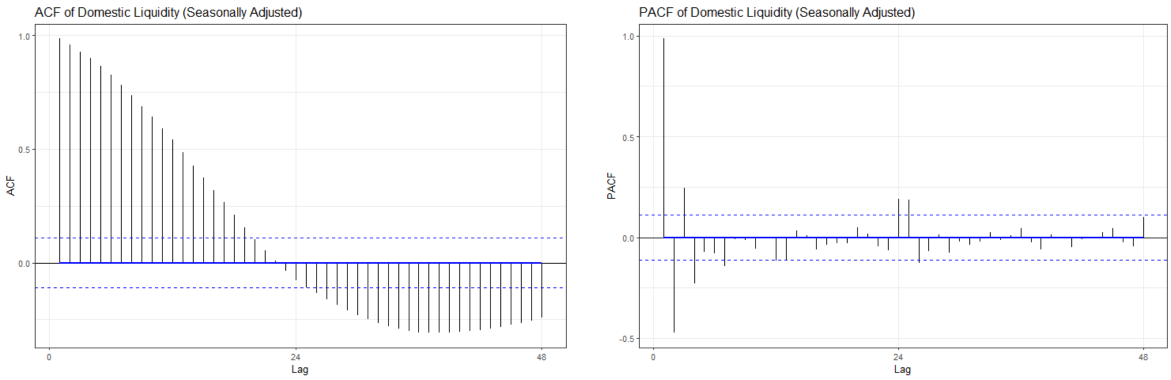
5.2.2.1. Model Calibration

In this study, the trained models under univariate or Autoregressive (AR) methods 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 (RW). This model was formulated because the time series data of domestic liquidity shows an irregular growth as found in the conducted Augmented Dickey-Fuller (ADF) and Philipps-Perron (PP) tests. To address this concern, one of the best strategies is to predict the change that occurs from one period to the next rather than directly predicting the level of the series at each period. 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).

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 forecast domestic liquidity in the Philippines (Figure 5.1). It is also simulated because the time series data of said monetary indicator was found to be non-stationary. Hence, in some cases of non-stationary time series, 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).

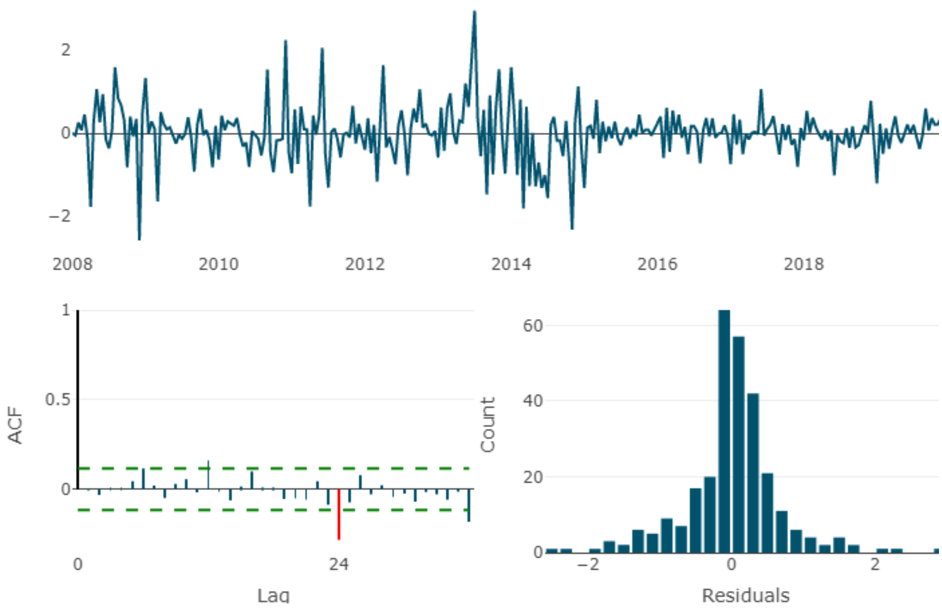
Figure 5.1: ACF and PACF of Domestic Liquidity Growth in the Philippines (Seasonally Adjusted)

(a) ACF of M3 (Seasonally Adjusted); (b) PACF of M3 (Seasonally Adjusted)



(a) (b)

Figure 5.2: Residual Plot for ARIMA (4,1,1)[52]



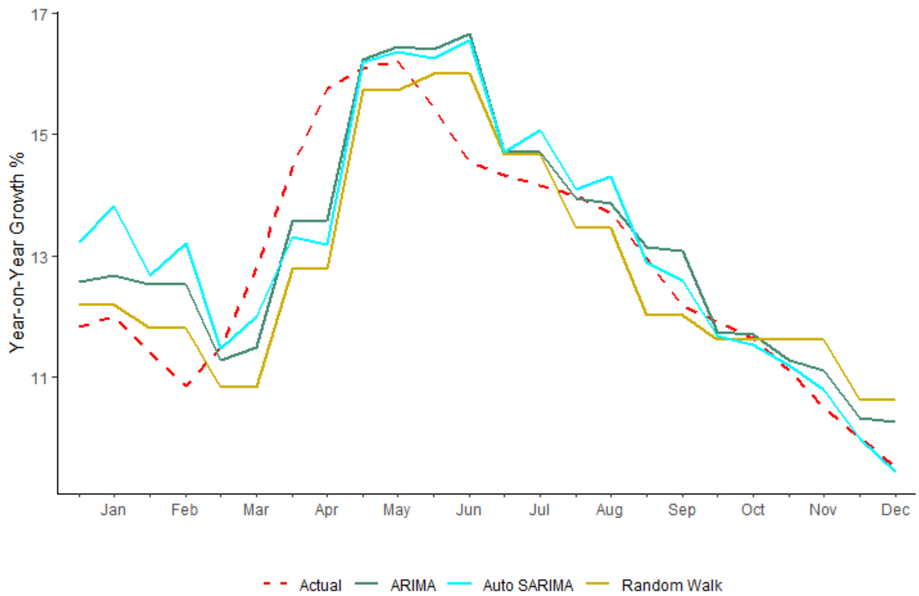
52 The red-colored line under the ACF of ARIMA(4,1,1) indicates that a seasonal lag should be included in overall model.

Lastly, the parameters of the third univariate model 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, the third univariate model utilized in this study is a seasonal ARIMA (SARIMA) with parameters based on the characteristics of the twelve (12) training datasets.[53]

5.2.2.2. *Nowcast Results*

Figure 5.3: Autoregressive Model Nowcasts vs. Actual M3 Growth (January to December 2020)

(In Percent, Year-on-Year Seasonally Adjusted)



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 adhere to the overall trend of domestic liquidity growth in the Philippines (Figure 5.3). The ARIMA, RW, and auto-SARIMA models provided decent estimates in the months where the growth of said monetary indicator (i.e., March, April, May) suddenly expand due to the

[53] 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).

increase in the borrowings of the National Government (NG) to minimize the negative impact of Coronavirus Disease 2019 (COVID-19) pandemic in the economy of said country.[54]

However, by comparing their respective monthly forecast errors, it can be observed that no specific univariate model can accurately estimate the growth of domestic liquidity throughout the expanding window. Tables 5.1 and 5.2 displayed that auto-SARIMA provided the highest number of months with low RMSE and MAE (i.e., March, May, September, November, December). This was followed by Random Walk (i.e., January, February, June, July) and ARIMA (i.e., April, August, October), respectively. The accurate nowcasts from auto-SARIMA are expected since the statistical software R Studio designates its parameters.

Table 5.1: RMSE of Autoregressive Models [55]

	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

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
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

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 time series model to estimate the growth of domestic liquidity. This is because the said model registered the most accurate overall nowcasts with RMSE of 0.917 and MAE of 0.688.

[54] https://www.bsp.gov.ph/SitePages/MediaAndResearch/MediaDisp.aspx?ItemId=5297

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

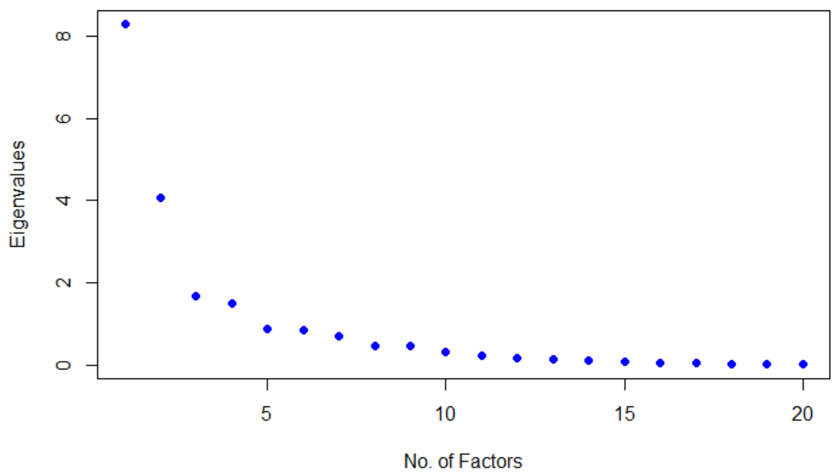
Both of these indicators are lower compared to forecast errors registered by RW (1.016 and 0.766) and auto-SARIMA (1.066 and 0.739), respectively (Tables 5.1 and 5.2).

5.2.3. Dynamic Factor Model

5.2.3.1. Model Calibration

Dynamic Factor Model (DFM) is also utilized in this study 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 the aforementioned are then used to nowcast the target variable.

Figure 5.4: Eigenvalues of Input Variables via Factor Analysis



By performing factor analysis, three (3) determinants were extracted from the initial twenty (20) input variables using the method of maximum likelihood. The decision to use the aforementioned factors was strongly based on each indicator's eigenvalues and cumulative variance.[56] 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.[57]

After the aforementioned process, the three (3) factors identified are then utilized under a VAR framework in order to complete the method of estimating the growth of domestic liquidity 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 should be considered under the twelve (12) training models to determine the estimates from January to December 2020.

5.2.3.2. Nowcast Results

Compared with the three (3) univariate models conducted, DFM, as a nowcasting model, 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 precisely 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).

On the contrary, the DFM 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. This outcome is also 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,

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[56] Eigenvalues refers to the total amount of variance that can be explained by a given principal component/factor.

[57] Sixty (60) to sixty-five (65) percent of variance is the common figure used in economic analysis (Mariano and Ozmucur, 2020).

respectively. These forecast errors are relatively lower than the overall RMSE and MAE displayed by the univariate models (Figure 5.6).

Figure 5.5: DFM Nowcasts vs. Actual M3 Growth (January to December 2020)

(In Percent Difference, Seasonally Adjusted)

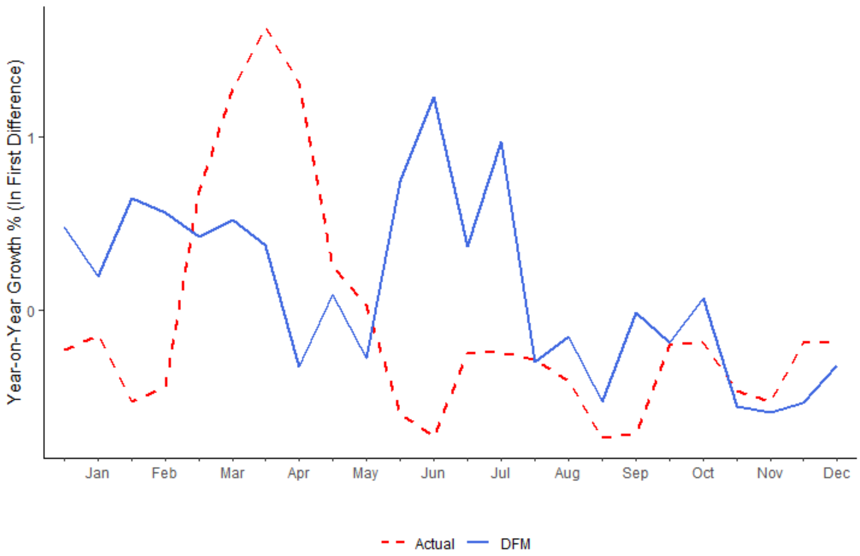


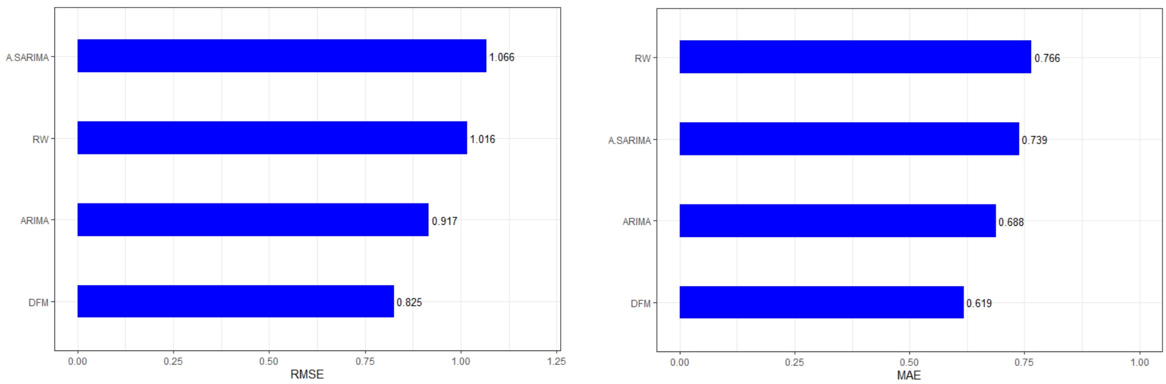
Table 5.3: RMSE of DFM

	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

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



(a) (b)

5.2.4. Machine Learning Models

Before using any machine learning algorithms, it is common to validate their respective stability using the cross-validation method. This is to ensure that the models can strongly regulate the bias-variance tradeoff and accurately provide new estimates based on the training or historical data (James et al., 2013). In this study, therefore, the aforementioned approach is performed before conducting a series of recursive nowcasts on the growth of domestic liquidity in the Philippines via regularization (i.e., Ridge Regression, Least Absolute Shrinkage and Selection Operator, Elastic Net) and tree-based (i.e., Random Forest, Gradient Boosted Trees) methods.

Although there are various methods to cross-validate machine learning methods (e.g., holdout method, stratified K-Fold cross-validation), this study particularly 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, Least Absolute Shrinkage and Selection Operator (LASSO), Elastic Net (ENET), and Gradient Boosted Trees (GBT) are tuned based on a Ten (10)-Fold cross-validation. In contrast, training datasets under Random Forest (RF) are calibrated based on their out-of-bag (OOB) scores.[58,59]

5.2.4.1. Regularization Methods

5.2.4.1.1. 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 values of the said parameter are determined since twelve (12) training datasets are used in each regularization algorithm. In order words, the value of shrinkage penalty is specifically

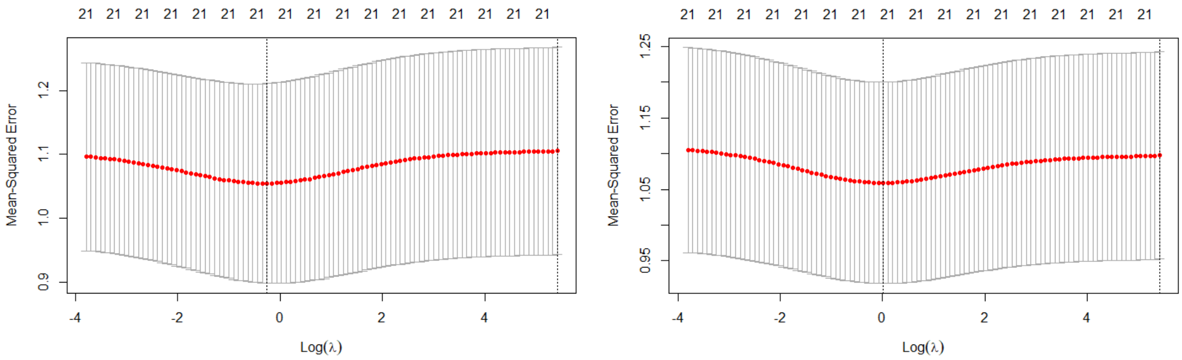
[58] 10-Fold cross-validation is the standard cross-validation technique used in machine learning exercises.

[59] 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 explicitly presents this scenario. It shows that the optimal shrinkage penalty for estimating the domestic liquidity 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.[60]

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)

5.2.4.1.2. *Nowcast Results*

After being calibrated 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 provide more consistent and accurate projections compared to the estimates provided by the benchmark models conducted in this study. Particularly, monthly estimates based on the three (3) machine learning algorithms significantly have lower forecast errors compared to the individual nowcasts stipulated by the benchmark models used in this study, such as ARIMA, RW, auto-SARIMA, and DFM

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

(Tables 5.5 and 5.6), except for September and October 2020 (Figure 5.8). The Ridge Regression, LASSO, and ENET also provided accurate nowcasts on the unexpected increase in the growth of domestic liquidity due to the increase in NG borrowings and deposits to BSP in March and April 2020 (Tables 5.5 and 5.6).

The aforementioned 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), auto-SARIMA (1.066 and 0.739), and DFM (0.825 and 0.619) (Figure 5.9).

Figure 5.8: Regularization Method Nowcasts vs. Actual M3 Growth (January to December 2020)

(In Percent Difference, Seasonally Adjusted)

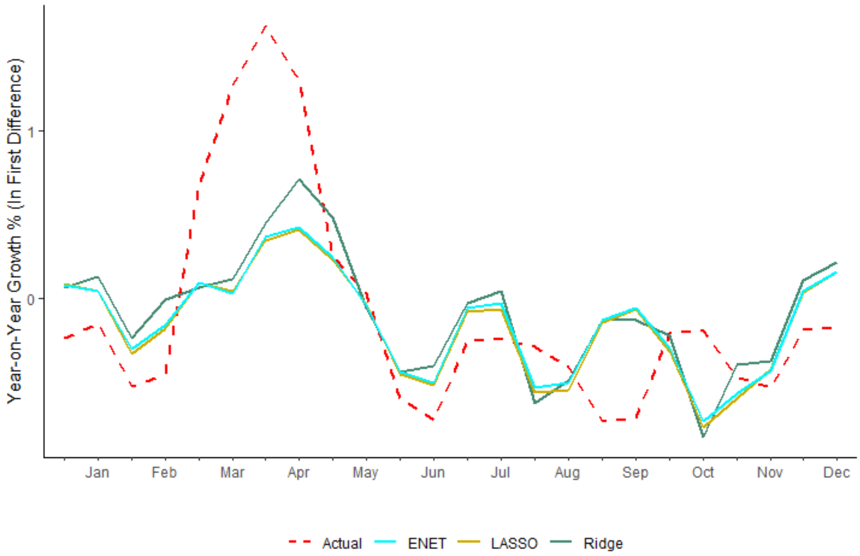


Table 5.5: RMSE of Ridge Regression, LASSO, and ENET

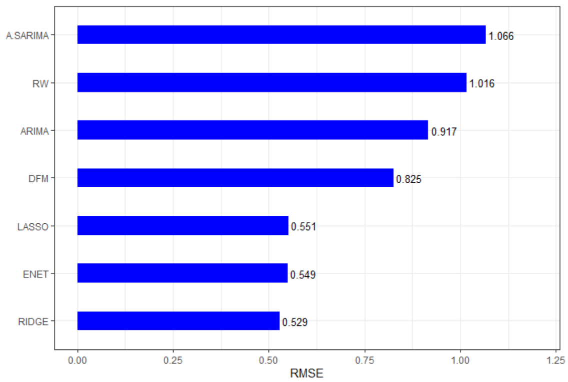
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
Ridge	0.292	0.372	0.928	1.163	0.173	0.258	0.261	0.248	0.596	0.449	0.123	0.349	0.529
LASSO	0.264	0.237	0.964	1.348	0.046	0.185	0.179	0.215	0.621	0.416	0.115	0.286	0.551
ENET	0.262	0.259	0.973	1.328	0.048	0.199	0.206	0.187	0.631	0.390	0.099	0.291	0.549

However, by comparing the three (3) models under the regularization method, it can be observed that LASSO is the most accurate machine learning model to nowcast the growth of domestic liquidity in the Philippines. Mainly because the said machine learning algorithm provided the highest number of months with low forecast error estimates from January to December 2020. Despite the strong monthly accuracy of LASSO, however, Ridge Regression and ENET registered the most accurate overall estimates. This is because the former notably provided an RMSE of 0.529, while the latter registered an MAE of 0.391 – which were both lower compared to the overall forecast error of LASSO (Tables 5.5 and 5.6).

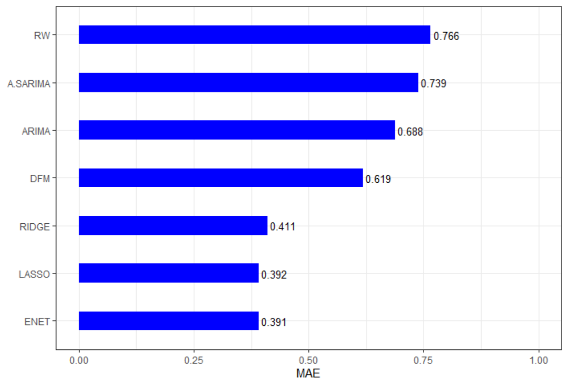
Table 5.6: MAE of Ridge Regression, LASSO, and ENET

	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

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



(a)



(b)

5.2.4.2. Tree-Based Methods

5.2.4.2.1. Model Calibration

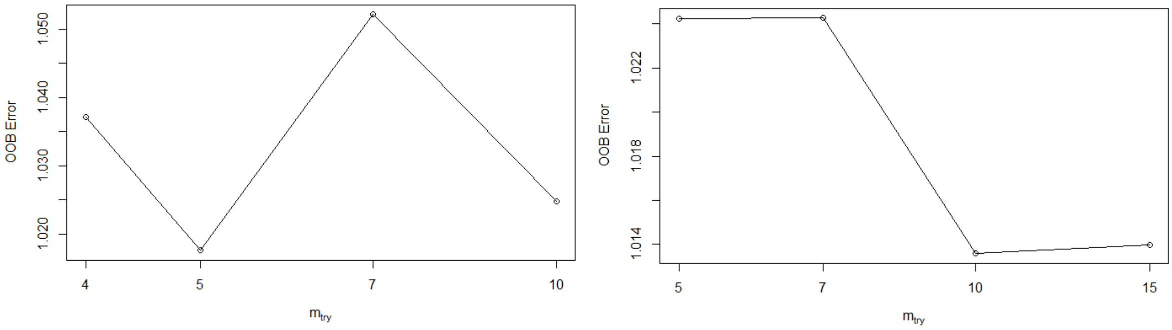
Similar to regularization methods, RF and GBT are tuned under the cross-validation method to provide accurate estimates on domestic liquidity growth from January to December 2020. The methods used to calibrate these two (2) algorithms are OOB scores and 10-Fold cross-validation. By doing this, the twelve (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, respectively.

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 already sufficient to estimate domestic liquidity growth for January 2020 since 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 because it registered the lowest OOB error of 1.014.

Figure 5.10: OOB Error of Training Datasets via Random Forest [61]

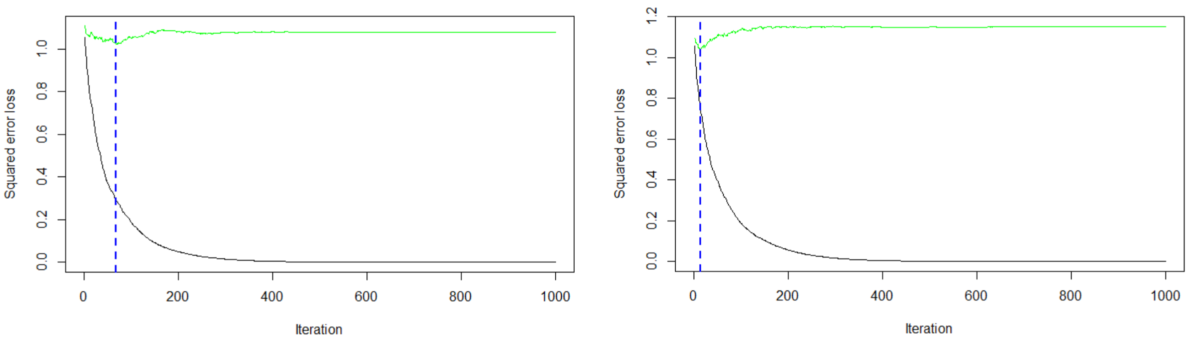
(a) Training Dataset to Estimate M3 Jan. 2020; (b) Training Dataset to Estimate M3 Feb. 2020



(a) (b)

Figure 5.11: Optimal Number of Trees via Gradient Boosted Trees [62]

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



(a) (b)

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

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

Meanwhile, Figure 5.11 illustrates the optimal number of trees that should be considered to accurately nowcast the growth of domestic liquidity under GBT. Panel A presents that sixty-seven (67) iterations are necessary to provide a precise estimate of domestic liquidity growth for January 2020. On the other hand, Panel B depicts that fifteen (15) iterations are already sufficient for the GBT model to accurately nowcast domestic liquidity growth for February 2020.

5.2.4.2.2. Nowcast Results

Similar to the results under regularization methods, utilizing RF and GBT as primary nowcasting models also stipulates more consistent and accurate estimates in contrast with the benchmark models conducted in this study. The monthly forecast errors of the two (2) machine learning models are also significantly lower than those under ARIMA, RW, auto-SARIMA, and DFM, except for the nowcast result of RF in September 2020. Based on the recursive nowcasts, it can also be found that RF and GBT provide decent projections on the months (e.g., March, April, May) where the growth of domestic liquidity unexpectedly expands due to the increased borrowings and deposits of NG to the BSP (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 expanding window also registered a lower set of RMSE and MAE. The result indicates that RF only displayed forecast errors of 0.595 and 0.432 for RMSE and MAE, respectively. Meanwhile, GBT provided marginal RMSE of 0.632 and MAE of 0.469. The figures mentioned are significantly lower than the overall forecast errors provided by the univariate and multivariate models performed in this study (Figure 5.13).

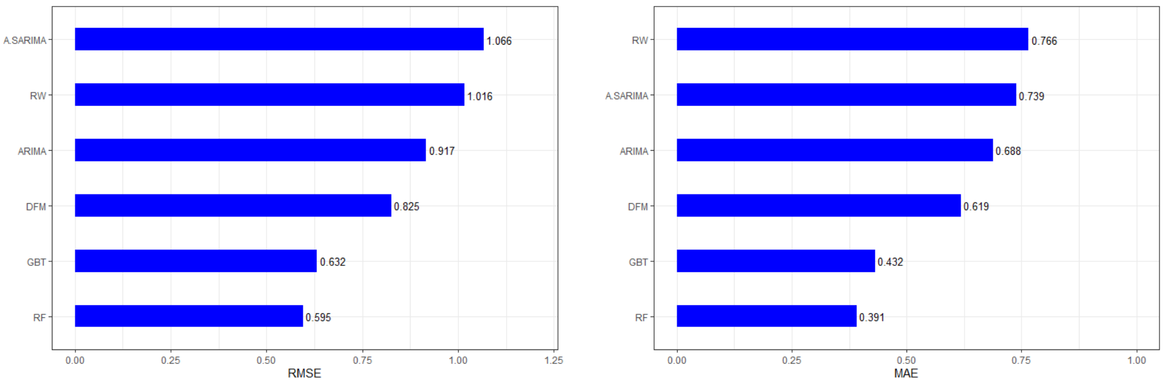
Table 5.7: RMSE of RF and GBT

	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)

Based on the aforementioned discussion, it can also be established that RF is the most accurate tree-based model to nowcast the growth of domestic liquidity despite having an inaccurate estimate in September 2020. Mainly because the said model notably provided the highest number of months with precise estimates 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).

5.3. Further Analysis

5.3.1. 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. Numerous studies have already established that these algorithms can formulate quantitative models with accurate estimates despite using a limited number of indicators.[63] Among the machine learning models that specifically have this ability are regularization and tree-based methods, such as LASSO, ENET, RF, and GBT.[64]

5.3.1.1. LASSO and ENET

Based on the recursive nowcasts conducted by LASSO and ENET from January and February 2020, it was found 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 the growth of domestic liquidity 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 and February 2020 (Table 5.9).[65]

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

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

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

5.3.1.2. 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 provide an accurate estimate of 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) most important variables that should be considered in estimating the growth of domestic liquidity in the Philippines.

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

Figure 5.14: Node Impurity via Random Forest

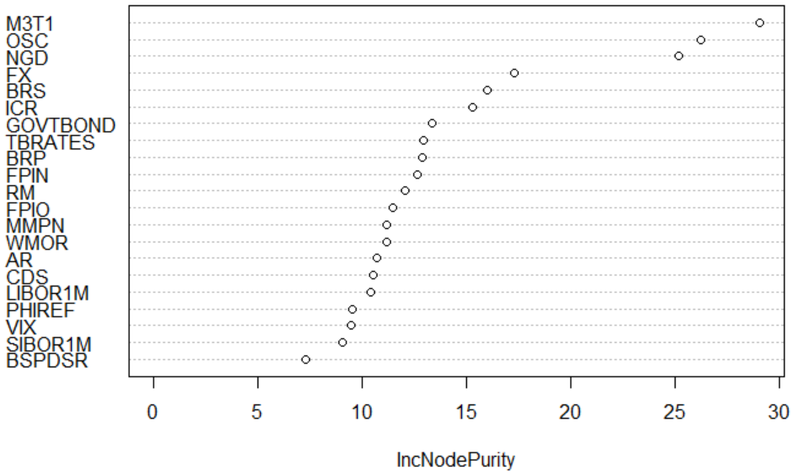
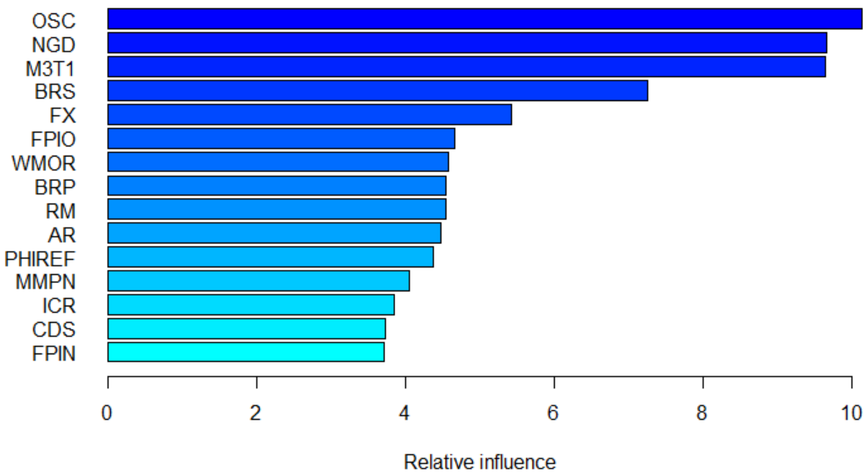


Figure 5.15: Variable Importance Plot via Gradient Boosted Trees



PART THREE

FINAL CHAPTERS

CHAPTER VI: CONCLUSION

CHAPTER VII: RECOMMENDATION

Chapter VI:
CONCLUSION

6.1. Summary and Conclusion

Domestic liquidity (also known as broad money) is defined as the sum of all liquid financial instruments held by money-holding sectors that are 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 important dynamics that numerous central banks are closely monitoring. This is because of its property of being an essential element to the overall transmission mechanism of monetary policy, particularly the impact of money supply expansion or contraction on aggregate demand, interest rates, inflation, and overall economic growth (Mankiw, n.d.).

In the Philippines, data on domestic liquidity is used as a primary component to formulate monetary policy and utilized as a leading indicator to observe price and financial stability. However, similar to the concerns regarding the delayed publication of data or statistical indicators generated by most government offices, data on domestic liquidity in the said country also suffers from series of lags and revisions. Due to this predicament, policymakers in the Central Bank of the Philippines or *Bangko Sentral ng Pilipinas* (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 published 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 in addressing the lag data release on domestic liquidity in the Philippines. This objective intends to formulate an accurate quantitative model that the BSP can sustainably use to estimate the short-run growth of said monetary indicator. Therefore, five (5) popular machine learning algorithms under regularization methods (i.e., Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO), Elastic Net (ENET)) and tree-based method (i.e., Random Forest (RF), Gradient Boosted Trees (GBT)) using different high-frequency monetary, financial, and external sector indicators from January 2008 to December 2020 are performed to support the objective of this study. The performances of these algorithms are then compared against traditional time series models such as Autoregressive (AR) 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 Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

The results demonstrate that machine learning algorithms provide more accurate estimates than the benchmark models used in this study. Mainly because the said approaches registered consistent monthly estimates with low forecast errors. Tables 6.1 and 6.2 depict that the nowcasts of machine learning algorithms are more accurate than the estimates provided by AR models and DFM. It can also be observed that the overall RMSE and MAE of all machine learning models used in this study are more accurate than the benchmark models. These algorithms, in addition, registered precise estimates on the months (i.e., March, April, May) where domestic liquidity growth suddenly expand (e.g., increased borrowings and deposits of the National Government (NG) to BSP) due to the impact of the Coronavirus Disease 2019 (COVID-19) in the Philippines. Based on these outcomes, it can be concluded that both regularization and tree-based machine learning algorithms could be used as alternative models to estimate the growth of domestic liquidity in the Philippines.

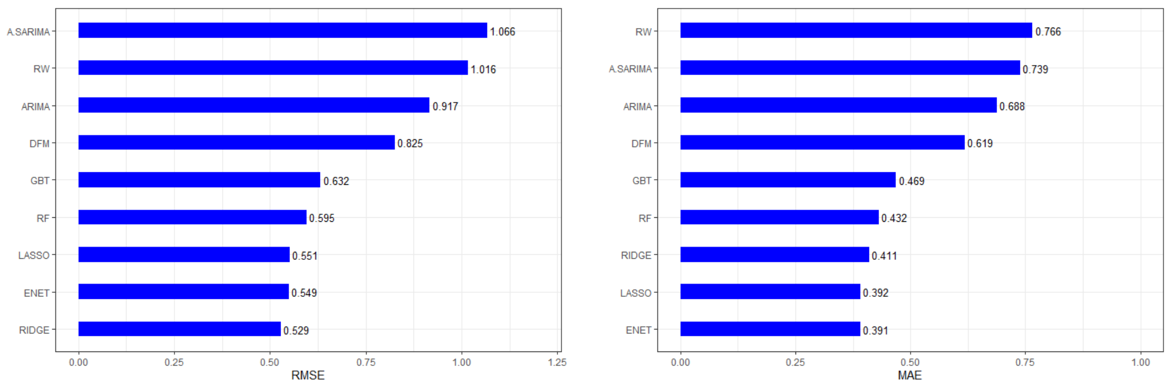
Table 6.1: RMSE of Benchmark and Machine Learning Models (Summary)[66]

	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)

However, among the quantitative models, LASSO and RF provided the highest number of months (i.e., three/four out of twelve) with at least low forecast error 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 using machine learning algorithms.

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

Using machine learning algorithms as a primary nowcasting approach also provides substantial advantages against traditional time series models such as AR and DFM. This is because the regularization and tree-based machine learning models can filter out or identify important indicators that could stipulate parsimonious nowcasting models with precise results. The results of the conducted recursive nowcasts based on LASSO, ENET, Random Forest, and Gradient Boosted Trees indicate that (1) BSP Liabilities on National Government, (2) BSP Claims on Other Sectors, (3) Foreign Exchange Rate, 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.

Chapter VII:
RECOMMENDATION

7.1. Potential Actions

Since the results of the conducted recursive nowcasting established the superiority of different machine learning algorithms in estimating domestic liquidity growth in the Philippines, this study highly recommends that the departments (i.e., statistics, research departments) under the Central Bank of the Philippines or *Bangko Sentral ng Pilipinas* (BSP) should adopt and utilize the concept of big data and machine learning. Implementing these concepts could support the objective of the BSP in conveying data-based monetary policy in the 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 or information than operating with a limited number of indicators.

Among the possible determinants that the BSP could explore and collect over time are high-frequency (e.g., daily, weekly) unconventional data or information regarding the credit condition of the Philippine Banking System (PBS) and the overall demand of the general public to hold or forego money. 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. This could include high-frequency data or information regarding (1) debt securities issued by the National Government (NG) and the BSP, (2) amount of loans granted by the BSP to Other Depository Corporations (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.

7.2. 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 combine the different machine learning algorithms with low monthly and overall forecast errors. This approach (known as the ensemble method) 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 particular methods are mainly used for models with target and input variables with a large number of observations and data with different levels of granularity.
c. Non-parametric machine learning algorithms, such as Neural Networks and Support Vector Machines (SVM), could also be included as models to nowcast domestic liquidity in the Philippines.
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 A

R Studio Packages

NO.	PACKAGE	AUTHOR/S	SOURCE URLs
1	caret	Kuhn et al.	https://cran.r-project.org/web/packages/caret/vignettes/caret.html
2	dplyr	-	https://cran.r-project.org/web/packages/dplyr/dplyr.pdf
3	forecast	Hyndman et al.	https://cran.r-project.org/web/packages/forecast/forecast.pdf
4	gbm	Greenwell et al.	https://cran.r-project.org/web/packages/gbm/gbm.pdf
5	ggplot2	Wickham et al.	https://cran.r-project.org/web/packages/ggplot2/ggplot2.pdf
6	glmnet	Friedman et al.	https://cran.r-project.org/web/packages/glmnet/glmnet.pdf
7	hrbrthemes	Rudis et al.	https://cran.r-project.org/web/packages/hrbrthemes/hrbrthemes.pdf
8	leaps	Lumely, T.	https://cran.r-project.org/web/packages/leaps/leaps.pdf
9	lubridate	Spinu et al.	https://cran.r-project.org/web/packages/lubridate/lubridate.pdf
10	maptree	White and Gramacy	https://cran.r-project.org/web/packages/maptree/maptree.pdf
11	Metrics	Hamner et al.	https://cran.r-project.org/web/packages/Metrics/Metrics.pdf
12	mFilter	Balcilar, M.	https://cran.r-project.org/web/packages/mFilter/mFilter.pdf
13	pls	Mevik et al.	https://cran.r-project.org/web/packages/pls/pls.pdf
14	psych	Revelle, W.	https://cran.r-project.org/web/packages/psych/psych.pdf
15	randomForest	Breiman et al.	https://cran.r-project.org/web/packages/randomForest/randomForest.pdf
16	repr	Angerer P.	https://cran.r-project.org/web/packages/repr/repr.pdf
17	tidyverse	Wickham, H.	https://cran.r-project.org/web/packages/tidyverse/tidyverse.pdf
18	tree	Ripley, B.	https://cran.r-project.org/web/packages/tree/tree.pdf
19	tsDyn	Di Narzo et al.	https://cran.r-project.org/web/packages/tsDyn/tsDyn.pdf
20	tseries	Trapletti et al.	https://cran.r-project.org/web/packages/tseries/tseries.pdf
21	TStudio	Krispin, R.	https://cran.r-project.org/web/packages/TSstudio/TSstudio.pdf
22	urca	Pfaff et al.	https://cran.r-project.org/web/packages/urca/urca.pdf
23	vars	Pfaff and Stigler	https://cran.r-project.org/web/packages/vars/vars.pdf
24	xgboost	Chen et al.	https://cran.r-project.org/web/packages/xgboost/xgboost.pdf

ANNEX B

Unit Root Tests for Input Variables

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

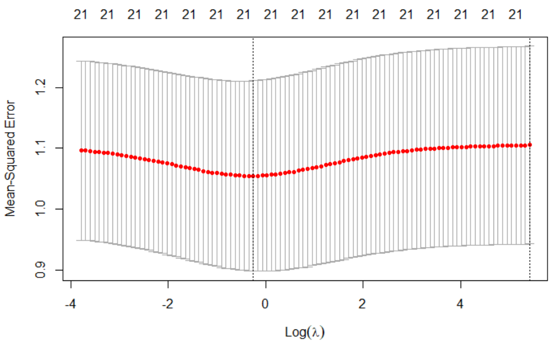
ANNEX B

ADF and PP Tests of Input Variables – Cont.

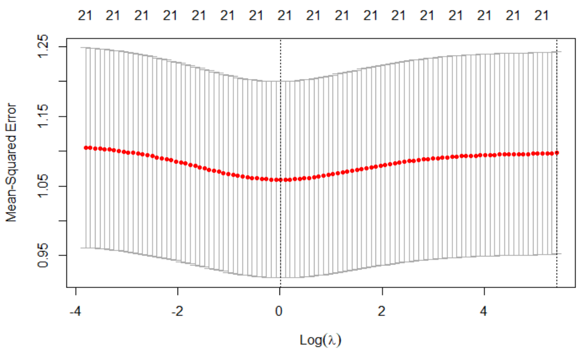
VARIABLE	TEST	LEVEL OF SIGNIF.	P-VALUE (LEVEL/GROWTH /LOG)	P-VALUE (FIRST DIFF.)
Interbank Call Rate	ADF	0.05	0.56	0.01
	PP		0.88	0.01
PHP per USD (FOREX)	ADF	0.05	0.77	0.01
	PP		0.82	0.01
WMOR	ADF	0.05	0.48	0.01
	PP		0.87	0.01

ANNEX C

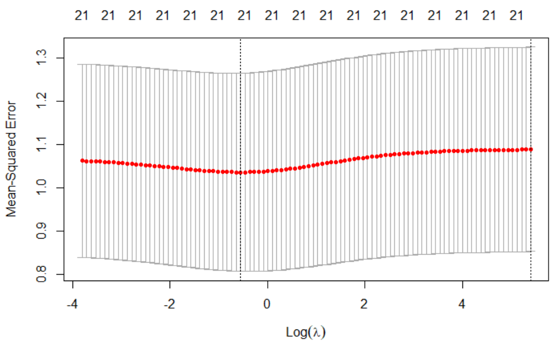
Optimal Shrinkage Penalty via Ridge Regression



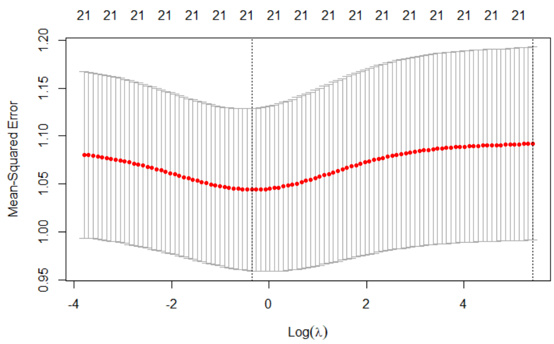
January 2020 – 0.772



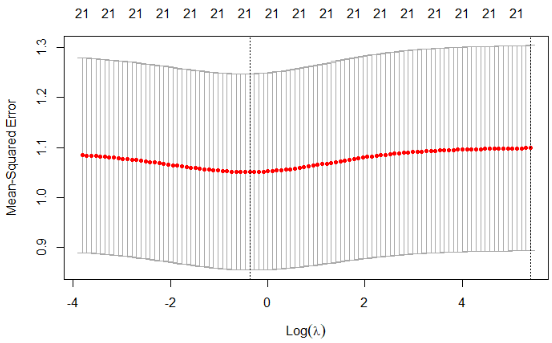
February 2020 – 1.012



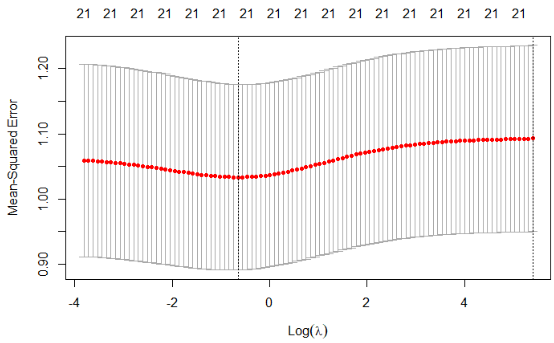
March 2020 – 0.577



April 2020 – 0.700



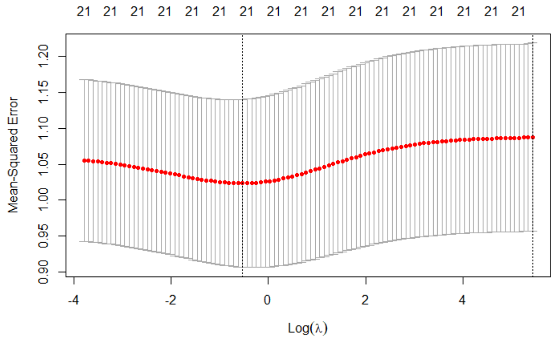
May 2020 – 0.691



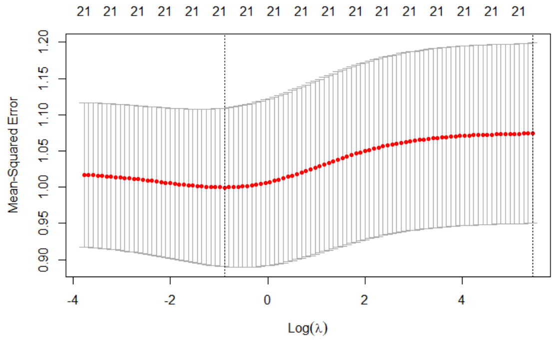
June 2020 – 0.523

ANNEX C

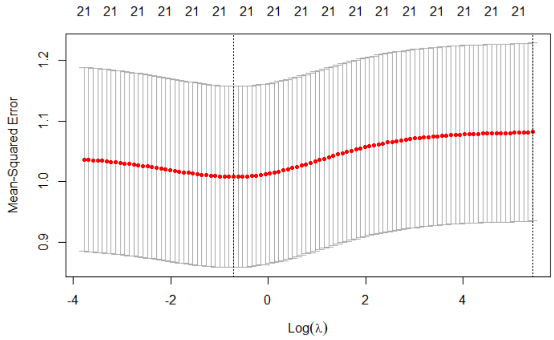
Optimal Shrinkage Penalty via Ridge Regression – Cont.



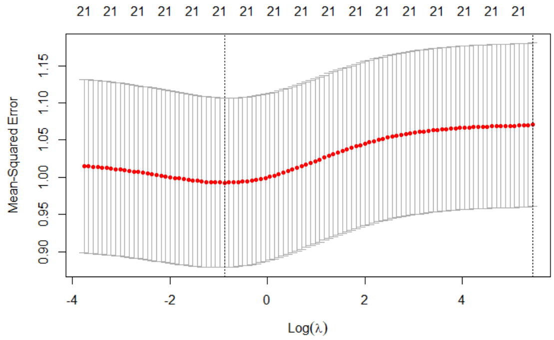
July 2020 – 0.589



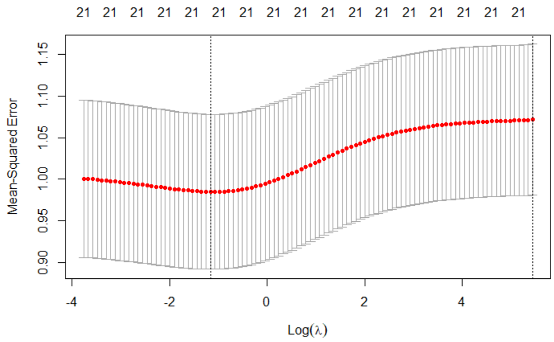
August 2020 – 0.491



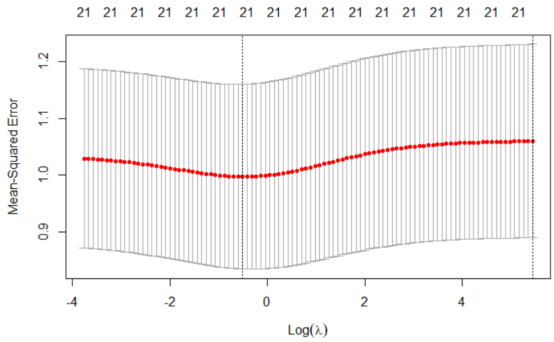
September 2020 – 0.411



October 2020 – 0.415



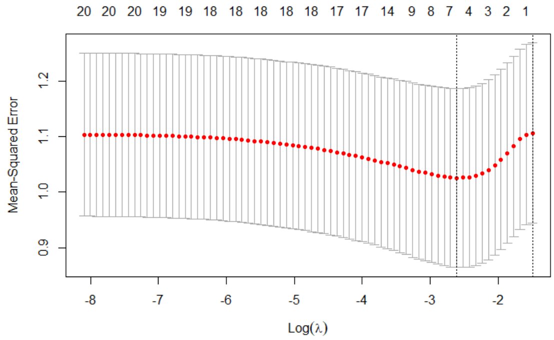
November 2020 – 0.313



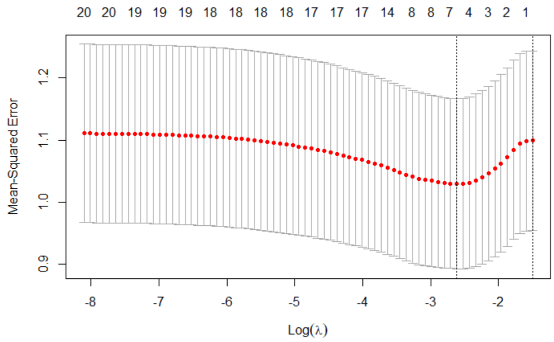
December 2020 – 0.600

ANNEX D

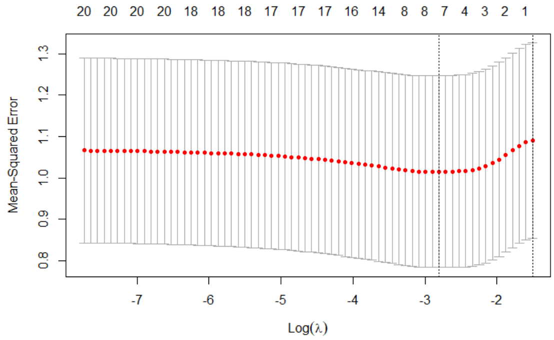
Optimal Shrinkage Penalty via LASSO



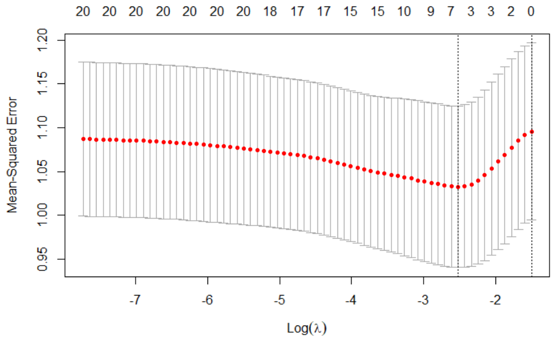
January 2020 – 0.737



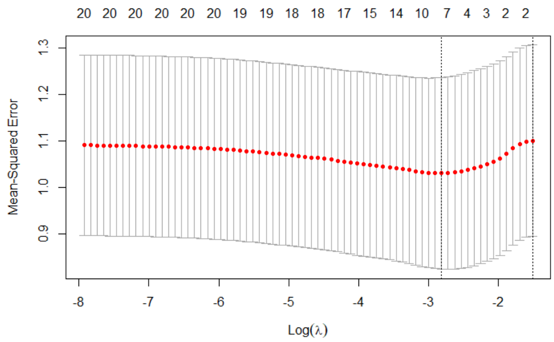
February 2020 – 0.073



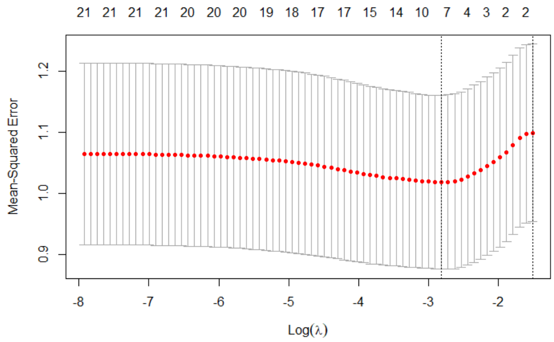
March 2020 – 0.060



April 2020 – 0.080



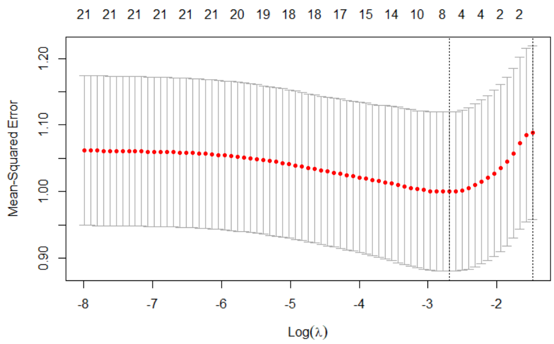
May 2020 – 0.060



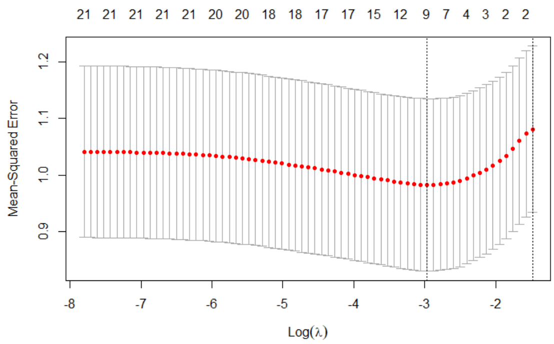
June 2020 – 0.060

ANNEX D

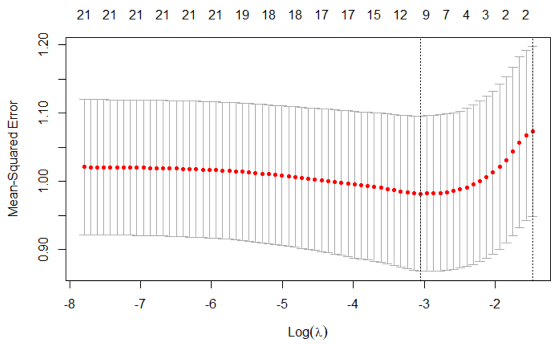
Optimal Shrinkage Penalty via LASSO – Cont.



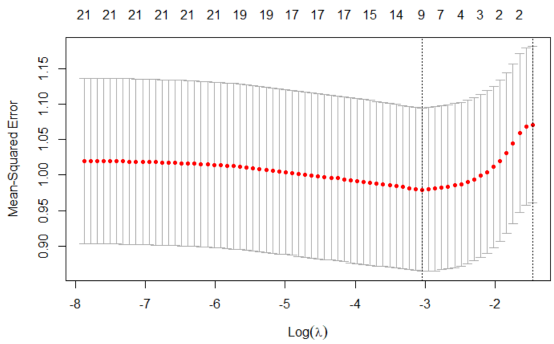
July 2020 – 0.068



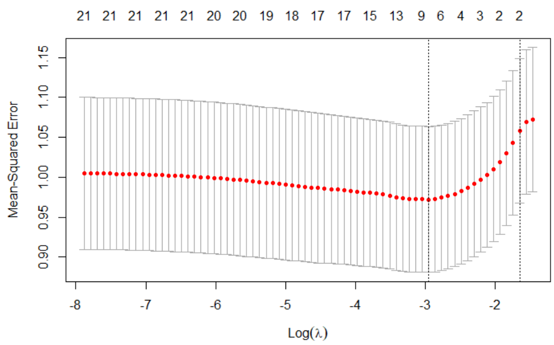
August 2020 – 0.051



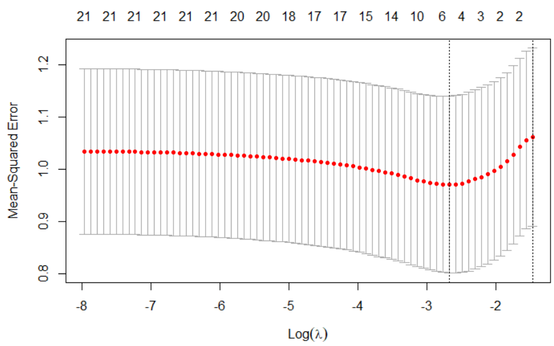
September 2020 – 0.047



October 2020 – 0.048



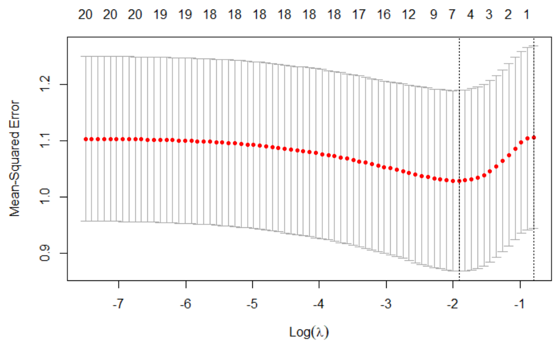
November 2020 – 0.052



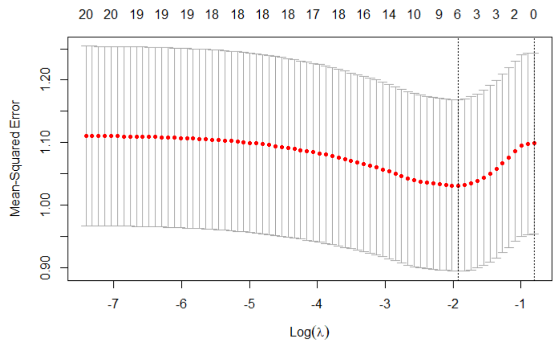
December 2020 – 0.069

ANNEX E

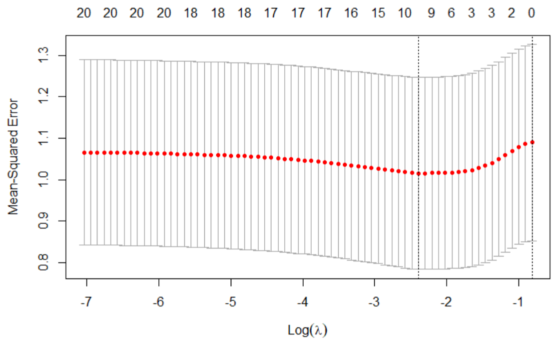
Optimal Shrinkage Penalty via ENET



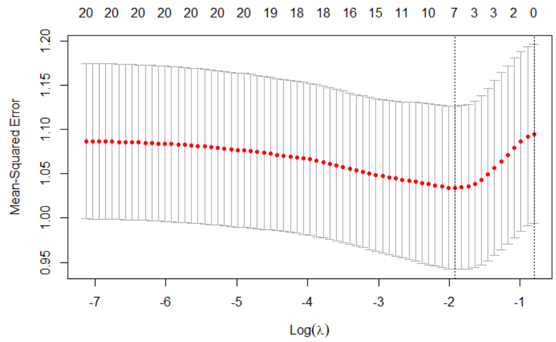
January 2020 – 0.147



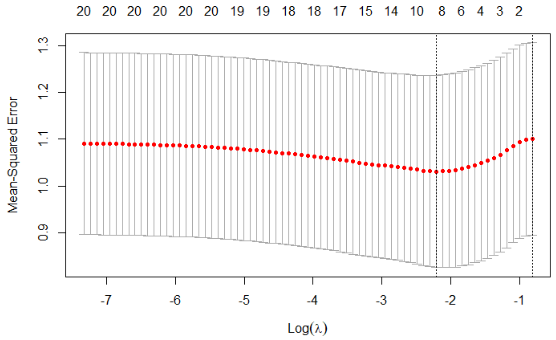
February 2020 – 0.146



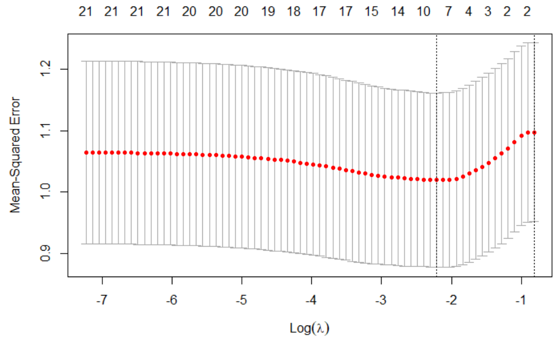
March 2020 – 0.091



April 2020 – 0.147



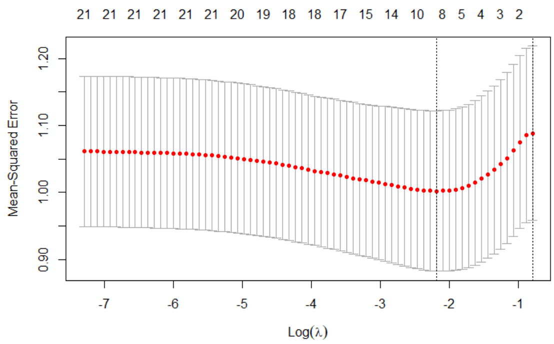
May 2020 – 0.110



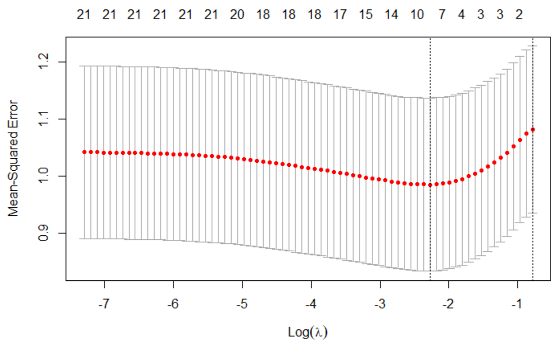
June 2020 – 0.110

ANNEX E

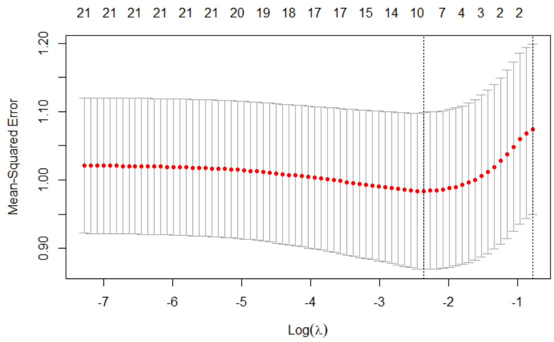
Optimal Shrinkage Penalty via ENET – Cont.



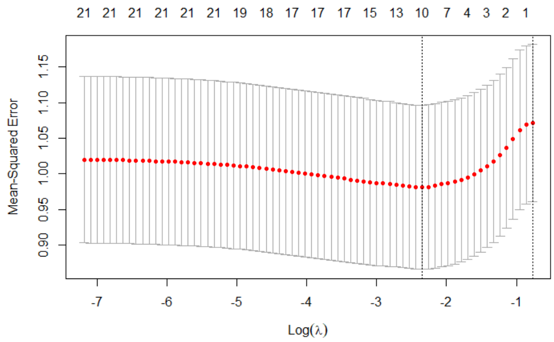
July 2020 – 0.112



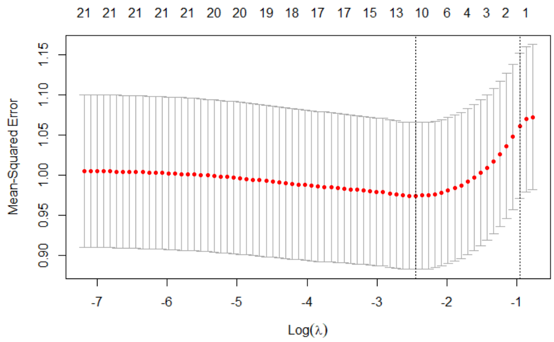
August 2020 – 0.103



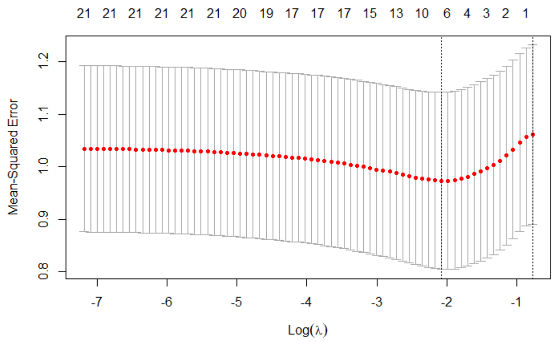
September 2020 – 0.095



October 2020 – 0.095



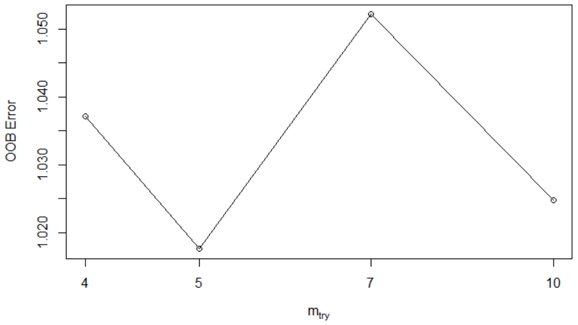
November 2020 – 0.087



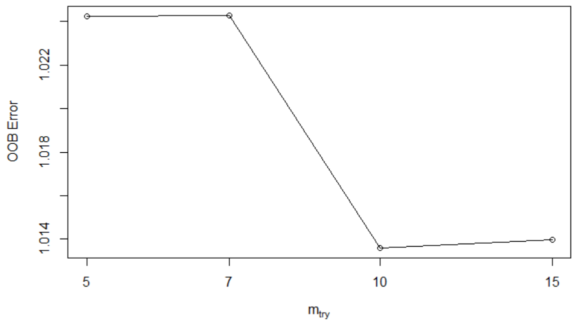
December 2020 – 0.126

ANNEX F

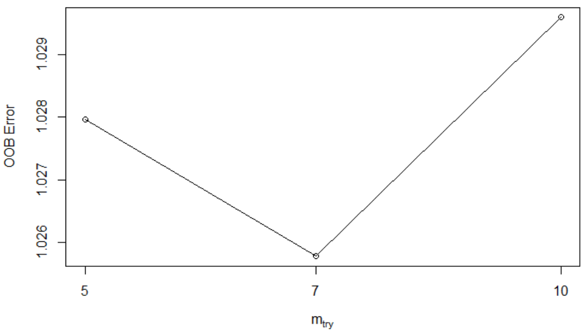
OOB Error of Training Datasets via Random Forest



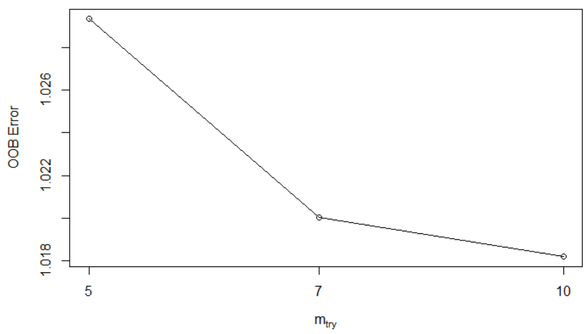
January 2020 – 5 Variables (1.018)



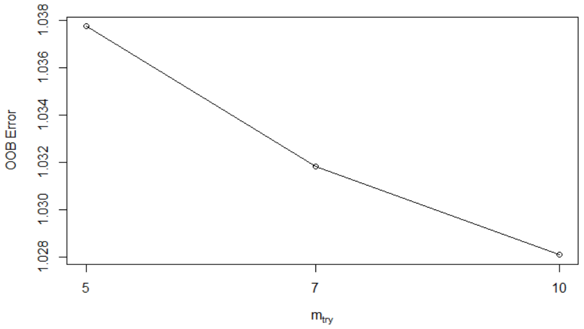
February 2020 – 10 Variables (1.014)



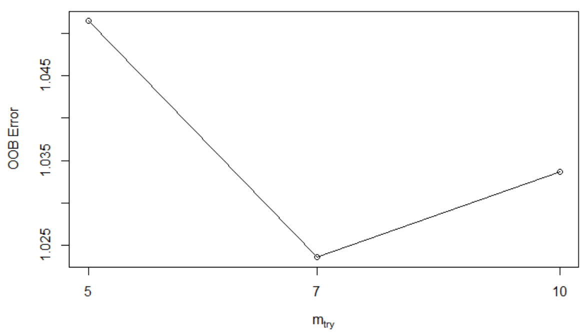
March 2020 – 7 Variables (1.026)



April 2020 – 10 Variables (1.018)



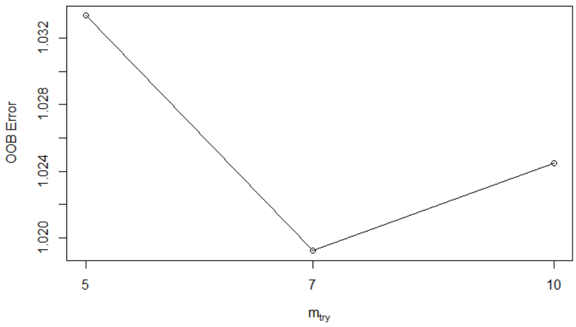
May 2020 – 10 Variables (1.028)



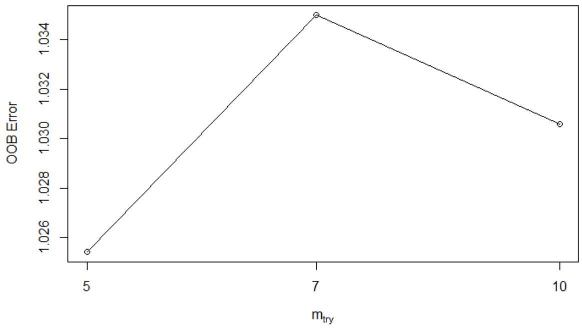
June 2020 – 7 Variables (1.024)

ANNEX F

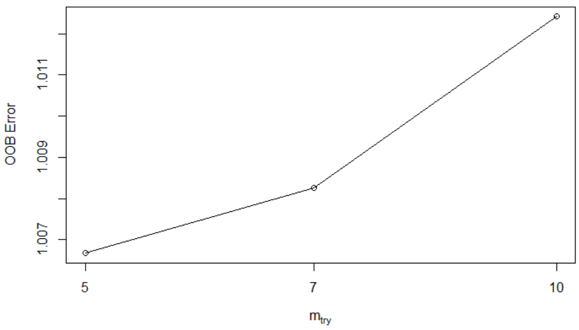
OOB Error of Training Datasets via Random Forest – Cont.



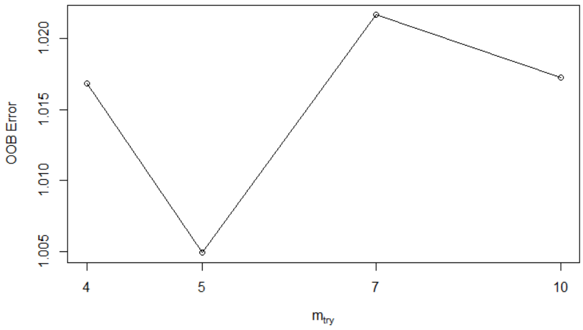
July 2020 – 7 Variables (1.019)



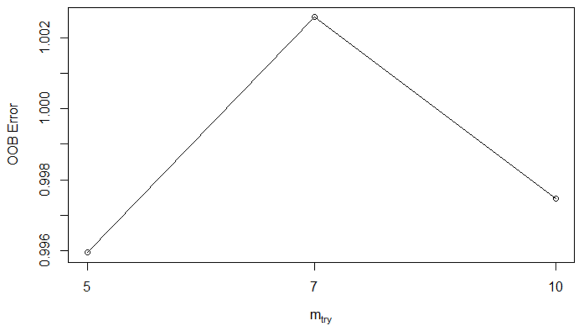
August 2020 – 5 Variables (1.025)



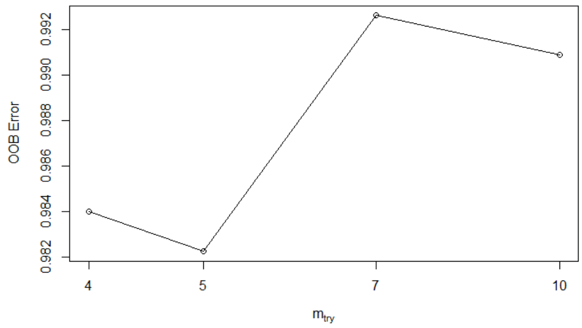
September 2020 – 5 Variables (1.007)



October 2020 – 5 Variables (1.004)



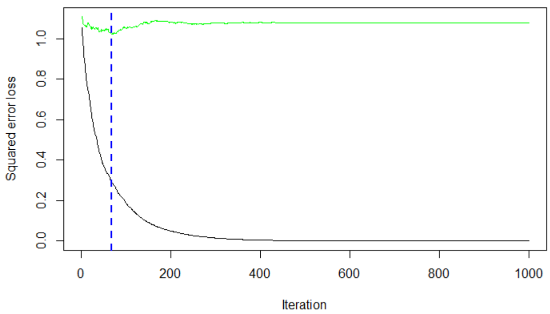
November 2020 – 5 Variables (0.996)



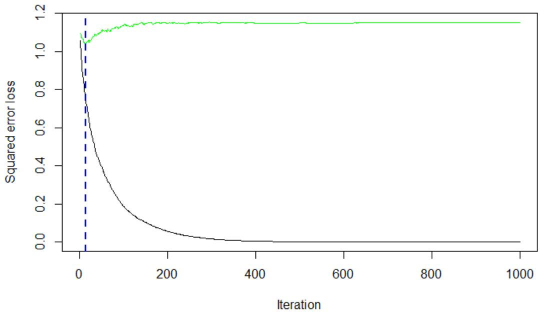
December 2020 – 5 Variables (0.982)

ANNEX G

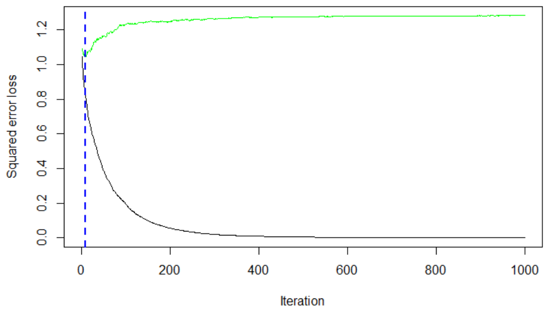
Optimal Number of Trees via Gradient Boosted Trees



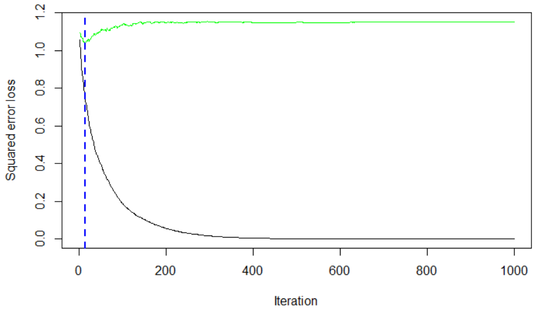
January 2020 – 67 Iterations



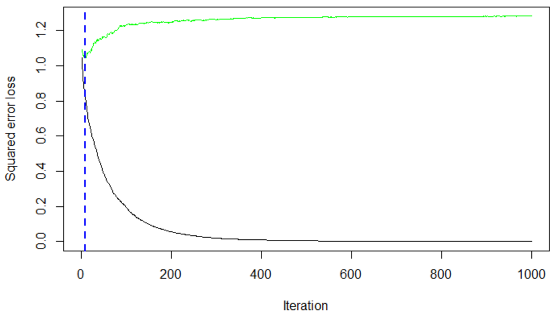
February 2020 – 15 Iterations



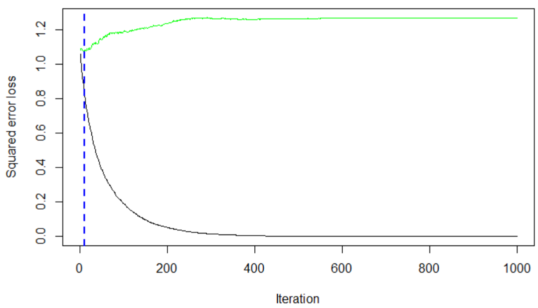
March 2020 – 8 Iterations



April 2020 – 10 Iterations



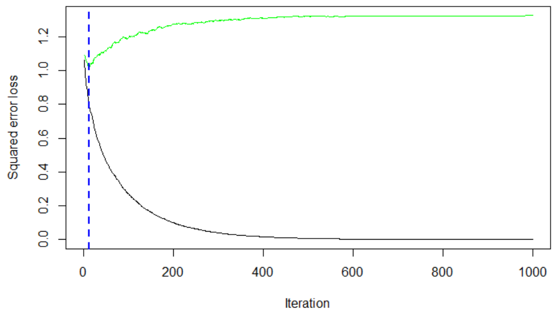
May 2020 – 2 Iterations



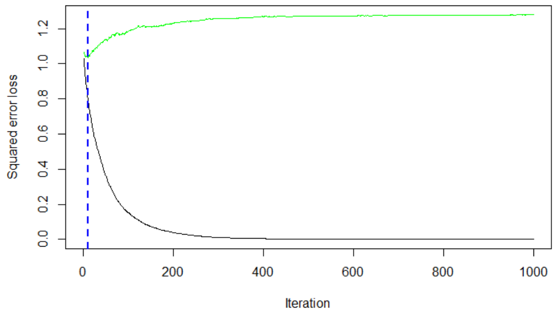
June 2020 – 4 Iterations

ANNEX G

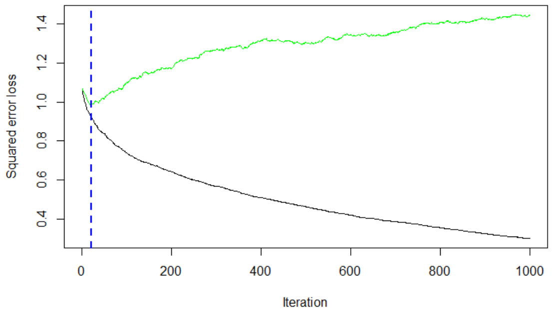
Optimal Number of Trees via Gradient Boosted Trees – Cont.



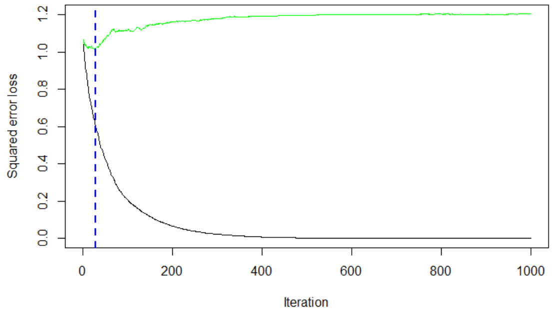
July 2020 – 13 Iterations



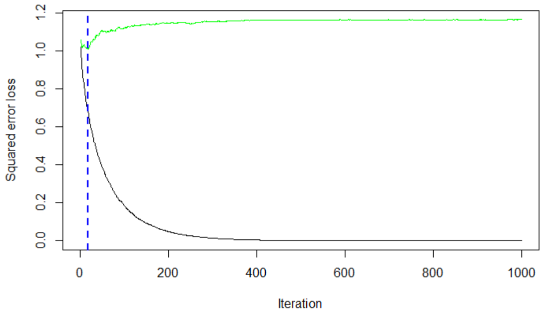
August 2020 – 10 Iterations



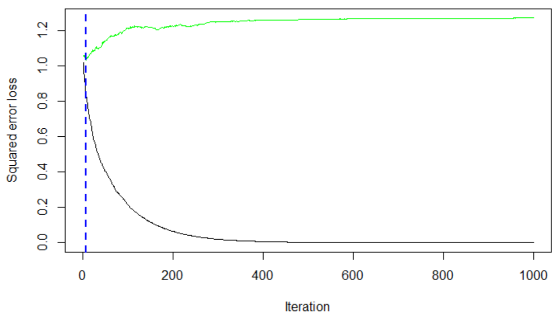
September 2020 – 22 Iterations



October 2020 – 28 Iterations



November 2020 – 17 Iterations



December 2020 – 7 Iterations

ANNEX H

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 National Government	-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	London Interbank Reference Rate	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	Singapore Interbank Reference Rate	-	-	-	-	-	-	-	-	-0.013	-	-	-
12	Philippine Interbank Reference Rate	-	-	-	-	-	-	-	-	-	-	-	-
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 (Promissory 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 H

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	Philippine Peso Per Us Dollar (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	Weighted Monetary Operations Rate	-	-	-	-0.052	-0.844	-0.817	-0.645	-0.935	-1.030	-1.019	-0.920	-0.557

ANNEX I

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 National Government	-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	London Interbank Reference Rate	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	Singapore Interbank Reference Rate	-	-	-	-	-	-	-	-	-0.033	-0.007	-0.053	-
12	Philippine Interbank Reference Rate	-	-	-	-	-	-	-	-	-	-	-	-
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 (Promissory 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 I

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	Philippine Peso Per Us Dollar (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	Weighted Monetary Operations Rate	-	-	-0.285	-0.151	-0.877	-0.851	-0.795	-0.847	-0.936	-0.929	-1.012	-0.590