Economic Forecasting for Thailand using Predictors with Different Frequency

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Abstract

This study examines economic growth of Thailand using predictor variables with different frequencies (yearly, quarterly, and monthly). Mixed Data Sampling (MIDAS) is approached to combine the enormously different frequency data. Ridge, LASSO, and elastic net regression are also used to specify factors affecting to Thailand economic growth. Data have been carefully collected from January 2000 to December 2019, total 20 years. The empirical results show that variables with positive impact on GDP growth consist of industry value added (INDUSVA), tax revenue (TAXREVEN), electricity consumption (ELECC), and investment growth (INVEST), while negative impact of external debt (EXD) on growth also exists.

Keywords: Elastic Net Regression *JEL Classification Codes:* C36, C53, C55, E17, GDP, Growth, MIDAS

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การพยากรณ์ทางเศรษฐกิจของประเทศไทยโดยใช้ตัวแปรทำนายจำนวนมากที่มีความถี่แตกต่างกัน

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บทคัดย่อ

การศึกษานี้ตรวจสอบการเติบโตทางเศรษฐกิจของประเทศไทยโดยใช้ตัวแปรทำนายจำนวนมากที่มีความถี่แตกต่างกัน (รายปีรายไตรมาสและรายเดือน) เราใช้วิธีการสุ่มตัวอย่างข้อมูลแบบผสม (MIDAS) เพื่อรวมข้อมูลความถี่ที่แตกต่างกันอย่างมากและยังใช้การถดถอยแบบริดจ์ LASSO และ Elastic net Regression เพื่อระบุว่าปัจจัยใดที่มีผลต่อการเติบโตทางเศรษฐกิจของประเทศไทย เรารวบรวมข้อมูลอนุกรมเวลาตั้งแต่เดือนมกราคม ปี 2000 ถึงธันวาคม ปี 2019 รวม 20 ปี ผลการวิจัยแสดงให้เห็นว่าอายุขัยและประชากรในเมืองมีผลกระทบเชิงลบต่อการเติบโตทางเศรษฐกิจ ในขณะที่มูลค่าเพิ่มของอุตสาหกรรมทำให้การเติบโตทางเศรษฐกิจเพิ่มขึ้น

คำสำคัญ: แบบจำลองสมการถดถอยแบบ Elastic net แบบจำลองสมการถดถอยแบบ MIDAS ผลิตภัณฑ์มวลรวมภายในประเทศ อัตราการเจริญเติบโตทางเศรษฐกิจ

Introduction

Economic growth is widely accepted as important priority of all countries that they have expanded it as much as possible. Gross domestic product (GDP) can be used as indicator to measure this growth. GDP is market value measurement of all final goods and produced services in country by specific time period. To calculate GDP, it can be determined by three primary methods: expenditure approach, output (or production) approach, and income approach (The Office for National Statistics, 2019). In order to estimate economic growth and make economic policies in the future, economic forecasting is considered necessary to predict future condition of economy using a combination of important and comprehensive indicators.

As GDP is an indicator of economic growth, the forecasting of future GDP from various factors is made. Hicks (1969) and Grabova (2014) stated that economic growth is the increase of real GDP or GDP per capita to increase national product measured with constant prices. Economic growth is influenced by various direct factors for example, human resources (increasing active population, investing in human capital), natural resources (land, underground resources), capital increase employee, or technological advancements. Economic growth is also influenced by indirect factors such as institutions (financial institutions, private administrations), size of aggregate demand, saving rates and investment rates, efficiency of financial system, budgetary and fiscal policies, migration of labor and capital, and efficiency of government. However, it is difficult to assess which factors contribute the most impact on economic growth. Acemoglu (2009) mentioned that public expenditure, capital formation, private or public investment, employment rates, and exchange rates have different impacts on economic growth. It should consider that these factors can be determined different implications. Some socio-political factors and events have a major influence on economic advancement (Acemoglu, 2009).

Furthermore, there are several non-economic determinant factors that impact GDP like government efficiency (Cooray, 2009), institutions (Rodrik, 1999; Acemoglu et al., 2002), political and administrative systems (Svensson, 2003; Grabova, 2014), cultural and social factors, geography, and demography (Acemoglu, 2009).

To forecast GDP, various factors are considered in the study, such as financial, microeconomics, macroeconomics, environment, political, social, health, education, inequality, and poverty. However, there is a different frequency of data available. Information about real economic sector often appears publicly in form of annual, quarterly, or monthly reports such as information about economic growth rate, Consumer Price Index, unemployment rate, and Industrial Production Index. While the most asset pricing is high-frequency data such as stock market index data in 5 minutes, 15 minutes, daily or monthly data. Therefore, it is a challenge for researchers to use these data with different time units to forecast real economy.

To deal with different frequency of data variable, this study uses Mixed Frequency Data Sampling (MIDAS), which is linear regressions allowing weighting functions to match data properties used.

MIDAS approach proposed by Ghysels et al. (2007) enables to use various frequencies in a single univariate model. Moreover, MIDAS regression can be operated to explain a low-frequency variable by using exogenous variables of higher frequency, without any aggregation procedure and within a parsimonious framework. This approach is typically used in macroeconomics to describe quarterly GDP fluctuations using monthly data that are generally available for short-term analysis, such as oil prices, stock prices, and spread between long and short-term interest rates (Ferrara and Marsilli, 2013). Clements and Galvao (2008), Marcellino and Schumacher (2010) employed MIDAS approach to predict macroeconomic fluctuations for the United States and Germany, respectively.

To predict values on different macro variables through forecasts, it is necessary to handle a large data set of multicollinearities. Moreover, one of the major problems in linear regression is it tries to over-fit data. There are some regularization methods which are Ridge Regression, Least Absolute Shrinkage, and Selection Operator Regression (LASSO). Besides, Elastic-Net Regression is used to overcome problem of over-fitting in Linear Regression Models. Li and Chen (2014) used LASSO and elastic net regression to extract important forecasting macroeconomic indicators from 20 different macro variables. Tiffin (2016) applied elastic net regression to select the best predictors from 19 variables for predicting GDP in Lebanon.

This paper aims to forecast economic growth in Thailand using predictors with different frequencies. Mixed Data Sampling (MIDAS) is approached to combine enormously different frequency data (yearly, quarterly, and monthly). Ridge, LASSO, and elastic net regression are also used to specify factors affecting to Thailand economic growth. This study is a fundamental forecast a step ahead. To get the best knowledge, many studies have already forecasted Thai economic growth. However, none of it considered as large determinants, only same frequency is used (Abeysinghe and Rajaguru, 2004; Thianpaen, Liu, and Sriboonchitta, 2016).

The next section provides methodology used in the research. Section 3 is data description. Section 4 discusses empirical results. The final section is conclusion.

Methodology

This study utilizes a mixed data sampling approach (MIDAS) to combine the enormously different frequency data, using ridge, LASSO, and elastic net regression to identify predictors affecting economic growth.

1. The MIDAS Approach

MIDAS regression constitutes methods and tools for mixed frequency time series data analysis that allow estimation, model selection, and forecasting. MIDAS lag structure creates a matrix of selected MIDAS lags. This function can be used to check completion of high-frequency data.

To forecast quarterly GDP using monthly and annual indicators, mixed data sampling (MIDAS) approach is proposed by Ghysels and Valkanov (2006), Ghysels et al. (2007), and Andreou et al. (2010). MIDAS regression is a direct forecasting tool. Dynamic indicators and joint dynamic between GDP and indicators are not explicitly modeled. Instead, MIDAS directly relates future GDP to current and lagged indicators, yielding different forecasting models for each forecast horizon. This approach is typically used in macroeconomics to describe quarterly GDP fluctuations using monthly data that are generally available for short-term analysts.

The standard MIDAS regression for explaining a stationary variable (y_t), augmented with a first-order autoregressive component, is given by

$$y_t = \beta_0 + \beta_1 B(\theta) x_t^{(m)} + \lambda y_{t-1} + \varepsilon_t \ , \tag{1}$$

where $x_t^{(m)}$ is an exogenous stationary variable sampled at a frequency higher than y_t that it observes m times $x_t^{(m)}$ over period [t-1, t]. Term $B(\vartheta)$ controls polynomial weights

that allow frequency mixing. MIDAS specification is consisted in smoothing past values of $x_t^{(m)}$ by using polynomial $B(\vartheta)$ of form,

$$B(\theta) = \sum_{k=1}^{K} b_k(\theta) L^{(k-1)/m} \quad , \tag{2}$$

where K is number of data points on based regression, L is lag operator that $L^{s/m}\, x_t^{(m)} = x^{(m)}_{t-s/m}$ and b_k is weight function to take various shapes. Ghysels et al. (2007) implemented two-parameter exponential Almon lag polynomial such as $\vartheta = (\vartheta_1, \vartheta_2)$,

$$b_k(\theta) \equiv b_k(\theta_1, \theta_2) = \frac{\exp\left(\theta_1 k + \theta_2 k^2\right)}{\sum_{k=1}^{K} \exp\left(\theta_1 k + \theta_2 k^2\right)} \quad , \tag{3}$$

This parameter is a part of estimation problem only influenced by conveyed information from last K values of high-frequency variable, $x_t^{(m)}$ is windows size, K is exogenous specification.

MIDAS model can be estimated using nonlinear least squares (NLS) in a regression of y_t onto $x_{t-k}^{(m)}$, yield coefficients $\hat{\theta}_1, \hat{\theta}_2$, $\hat{\beta}_0$ and $\hat{\beta}_1$. The forecast is given by

$$y_{T_m^y + h_m | T_m^x} = \hat{\beta}_0 + \hat{\beta}_1 b\left(L_m, \hat{\theta}\right) x_{T_m^x} \quad , \tag{4}$$

2. LASSO and Ridge Regression

Ridge regression is very similar to least squares, except coefficients are estimated by minimizing a slightly adjusted quantity. With least squares, ridge regression seeks coefficients that fit data well by making residual sum of squares (RSS) as small as possible. However, regression also seeks to minimize a second term known as a shrinkage penalty, which is small when regression coefficients are close to zero. This term tends to shrink coefficient estimates towards zero. Tuning parameter λ controls relative impact of penalty term. When λ = 0, the penalty does not affect, and ridge regression will produce the least-squares estimates. As λ gets larger, the shrinkage penalty impact grows, and the coefficient estimates will approach zero. Unlike least squares that generate only a set of estimates, ridge regression will produce a different set of coefficients for each value of λ. Therefore, selecting a good value for λ is critical and it will be addressed in cross-validation section below.

$$\hat{\beta} = \arg\min_{\hat{\beta}_j} \left\{ \sum_{i=1}^{n} \left(Y - X\hat{\beta} \right)^2 + \text{Penalty}\left(\hat{\beta} \right) \right\}, \tag{5}$$

Ridge:

$$\text{Penalty}\left(\hat{\beta} \right) = \lambda \sum_{j=1}^{p} \left(\hat{\beta}_j \right)^2, \tag{6}$$

LASSO:

$$\text{Penalty}\left(\hat{\beta} \right) = \lambda \sum_{j=1}^{p} \left| \hat{\beta}_j \right|, \tag{7}$$

where n is number of observations, and p is number of candidate predictors. LASSO regression (Least Absolute Shrinkage and Selection Operator) is similar to ridge regression, but it has a different penalty. With ridge regression, LASSO shrinks coefficient estimates towards zero. However, in LASSO case, penalty has effect forcing some of coefficients to be precisely equal to zero when a tuning parameter λ is large enough. In contrast to ridge regression that may shrink coefficients close to zero, it is never eliminated. Like some of stepwise approaches outlined above, LASSO includes an element of variable selection tended to produce a parsimonious model with fewer predictors (Tiffin, 2016).

3. The Elastic Net Regression

Elastic net regression contains a hybrid of ridge and LASSO penalties. The ridge penalty tends to shrink all coefficients proportionately. For closely correlated variables, it tends to move coefficients toward one another without choosing any of it. On the other hand, LASSO penalty can produce a leaner model by focusing on a small subset of those variables and discarding the rest. Each approach has benefits depending on data, and there is no prior reason to prefer one over another.

$$\sum_{i=1}^{n}\left(Y - X\hat{\beta}\right)^{2} + \lambda\sum_{j=1}^{p}\left[\underbrace{(1-\alpha)\left(\hat{\beta}_j\right)^{2}}_{\text{RIDGE}} + \underbrace{\alpha\left|\hat{\beta}_j\right|}_{\text{LASSO}}\right], \tag{8}$$

Elastic net regression combines strengths of the best selected predictors to provide a parsimonious model while still identifying closely correlated predictors. The relative weights of two penalties are determined by an additional tuning variable (α). Furthermore, with ridge and LASSO regressions, different tuning parameters (α and λ) can produce different sets of coefficients. Therefore, selecting right parameter values is a key (Tiffin, 2016).

Data Description

The purpose of this study is to forecast economic growth of Thailand using predictors with three different frequencies. Mixed Data Sampling (MIDAS) is approached to combine enormously different frequency data as yearly, quarterly, and monthly. Ridge, LASSO, and elastic net regression are also used to specify direct and indirect factors affecting GDP growth of Thailand.

Data have been collected from January 2000 to December 2019 total 20 years. The data used in this study consist of quarterly GDP growth and 32 variables based on empirical study.

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Table 1 Data Description

Variables	Description	Frequency	Source
BB	Budget balance	Monthly	Bank of Thailand
CAB	Current account balance, million currency units	Monthly	World Bank
CONSUM	Consumption growth	Quarterly	World Bank
CPI	Consumer price index	Monthly	Bureau of Trade and Economic Indices of Thailand

Table 1 Data Description (Cont.)

Variables	Description	Frequency	Source
ECONG	Economic growth	Quarterly	World Bank
ELECPRO	Electricity production	Annual	U.S. Energy Information Administration
EXD	External debt	Annual	World Bank
FFCAP	Fossil fuels electricity capacity	Annual	U.S. Energy Information Administration
GDP	Growth rate of real GDP of Thailand	Quarterly	World Bank
GOVEX	Government expenditure	Annual	World Bank
HYCAP	Hydroelectricity capacity	Annual	U.S. Energy Information Administration
INDPRO	Industrial production	Monthly	The Office of Industrial Economics of Thailand
INDUSVA	Industry value added	Annual	World Bank
INFLATION	Inflation rate (% per annual)	Annual	Bureau of Trade and Economic Indices of Thailand
INTERNET	Internet users	Annual	World Bank
INVEST	Investment growth	Quarterly	The Global Economy
LF	Life expectancy	Annual	World Bank
MILITARY	Military spending	Annual	The Stockholm International Peace Research Institute
MS	Money Supply	Monthly	Bank of Thailand
NOEM	Number of labors	Monthly	World Bank
POLICYR	Policy rate	Quarterly	Bank for International Settlements (BIS)
POP	Population size	Annual	United Nations Population Division
RETAIL	Retail sales index	Monthly	Bank of Thailand
RETAILYOY	Retail sales index	Monthly	Bank of Thailand
SERVA	Services value added	Annual	World Bank
SET	SET index	Monthly	Stock Exchange of Thailand
STOCKVOLA	Stock price volatility	Annual	Global Financial Development

Table 1 Data Description (Cont.)

Variables	Description	Frequency	Source
TAXGS	Taxes on goods and services	Annual	World Bank
TAXREVEN	Tax revenue	Annual	World Bank
UNEMP	Unemployment rate (%)	Annual	Bank of Thailand
UNEMP	Unemployment rate (%)	Monthly	Bank of Thailand
URBAN	Percentage urban population	Annual	United Nations Population Division

Table 2 Descriptive Statistics of Monthly and Quarterly Variables

Variables	Monthly variables											Quarterly variables			
	BB	CAB	CPI	INDPRO	MS	NOEM	RETAIL	RETAILYOY	SET	UNEM	CONSUM	POLICYR	ECONG	GDPG	INVEST
Mean	2.43	0.14	0.00	0.18	0.01	0.00	0.01	0.05	0.01	0.03	6.23	0.01	0.96	3.99	7.50
Median	0.75	-0.30	0.00	-0.10	0.00	0.00	0.00	0.00	0.01	-0.01	6.36	0.00	1.00	3.85	5.83
Maximum	416.22	86.96	0.02	107.48	0.03	0.06	0.29	26.00	0.24	1.49	16.52	0.67	9.40	15.50	29.75
Minimum	-136.85	-40.11	-0.03	-72.88	-0.04	-0.07	-0.18	-10.88	-0.30	-0.48	-4.02	-0.45	-6.30	-4.30	-20.50
Std. Dev.	30.00	7.81	0.00	9.00	0.01	0.02	0.08	2.50	0.06	0.30	3.85	0.15	1.66	2.95	9.58
Skewness	10.79	6.86	-0.81	4.98	-0.55	-0.62	0.09	3.97	-0.59	2.09	-0.32	1.04	0.36	0.27	0.02
Kurtosis	154.78	81.17	12.34	103.96	6.72	4.63	3.30	53.49	6.42	9.60	3.13	7.87	14.23	6.39	3.60
Jarque-Bera	235038.2*	62990.3*	899.35*	102914*	150.32*	42.23*	1.24	26127.92*	130.44*	610.65*	1.41	93.40*	422.24*	39.25*	1.21
MBF of unit root test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: "*" indicates strong evidence to support alternative hypothesis

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Table 3 Descriptive Statistics of Quarterly Variables

Variables	ELECC	INTERNET	EXD	FFCAP	GOVEX	HYCAP	INDUSVA	INFLATION	INTERNET	LF	MILITARY	POP	SERVA	STOCKVOLA	TAXGS	TAXREVEN	UNEMP	URBAN
Mean	0.05	0.18	-0.03	0.03	0.08	0.01	0.07	0.07	0.18	0.01	0.07	0.01	0.07	-0.04	0.00	0.01	-0.06	0.02
Median	0.04	0.13	-0.04	0.03	0.09	0.00	0.07	0.00	0.13	0.01	0.05	0.01	0.09	-0.12	0.00	0.01	-0.06	0.03
Maximum	0.13	0.52	0.25	0.13	0.22	0.17	0.25	4.33	0.52	0.03	0.44	0.01	0.18	0.47	0.09	0.10	0.18	0.04
Minimum	0.00	-0.09	-0.18	-0.03	-0.06	-0.01	-0.06	-5.00	-0.09	-0.02	-0.09	0.00	-0.04	-0.30	-0.08	-0.08	-0.40	0.00
Std. Dev.	0.04	0.16	0.12	0.03	0.07	0.04	0.09	1.80	0.16	0.01	0.12	0.00	0.07	0.20	0.05	0.05	0.15	0.01
Skewness	0.48	0.82	1.02	0.89	0.00	4.08	0.22	-0.36	0.82	-0.28	1.59	0.14	-0.05	1.01	0.21	0.18	-0.49	-0.40
Kurtosis	2.23	3.16	3.60	3.99	2.25	17.80	2.08	5.55	3.16	3.07	5.55	3.51	1.85	3.47	2.83	2.09	3.03	2.09
Jarque-Bera	1.27	2.29	3.79	3.45	0.47	237.94	0.87	5.84*	2.29	0.27	13.81*	0.29	1.12	3.60	0.18	0.80	0.81	1.21
MBF of unit root test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: "*" indicates strong evidence to support alternative hypothesis

Empirical Result

Due to nature of elastic net penalty, it seems to possess good properties of both ridge regression and LASSO regression. First of all, ridge regression and its penalty have been estimated. The penalty tends to shrink all coefficients proportionately. For closely correlated variables, it tends to move coefficients toward one another without choosing. Second, LASSO regression and its penalty can produce a leaner model by focusing on a small subset of those variables and discard the rest. To find the best fit model, Akaike information criterion (AIC) is considered to compare model performance. The lowest AIC also indicates the best fit model.

Table 4 Estimation Result of Regression Models

Variables	Ridge regression	LASSO regression	Elastic net regression
(Intercept term)	2.6442	2.4032	2.5020
EXD	-6.7554	-1.8768	-6.8574
INTERNET	-0.3784	-	-
ELECPRO	1.3041	-	-
ELECC	8.3062	1.5859	4.9187
FFCAP	8.5564	-	3.1197
HYCAP	6.2787	-	0.6554
STOCKVOLA	0.1496	-	-
POP	15.7865	-	-
URBAN	-50.0089	-	-31.6077
MILITARY	1.2304	-	-
INFLATION	0.0836	-	-
INDUSVA	8.5955	9.2778	11.9391
SERVA	1.3807	-	-
UNEMP	-3.3477	-	-2.0822
LF	-53.1035	-	-54.9761
GOVEX	-0.2535	-	-
TAXREVEN	11.2811	8.6229	9.2771
TAXGS	-0.6258	-	-

Table 4 Estimation Result of Regression Models (Cont.)

	Ridge regression	LASSO regression	Elastic net regression
MS	14.2333	-	-
CAB	0.0124	-	-
BB	-0.0021	-	-0.0005
INDPRO	-0.0498	-	-
RETAIL	-3.8486	-	-2.2363
RETAILYOY	-0.0322	-	-
UNEM	1.1105	-	0.5381
CPI	33.9741	-	-
NOEM	-0.1843	-	-
SET	1.4612	-	-
ECONG	0.3205	-	-
POLICYR	-1.2937	-	-0.9983
INVEST	0.0964	0.0638	0.1079
AIC	1,694.494	313.675	819.195

Table 4 reports LASSO regression to show the lowest value of AIC, while ridge is the worst method (based on the highest AIC value). Thus, this study can interpret results from using lasso regression. The result shows that 5 variables have an impact on GDP growth. Positive impacts on GDP growth consist of industry value added (INDUSVA), tax revenue (TAXREVEN), electricity consumption (ELECC) and investment growth (INVEST), while a negative impact of external debt (EXD) on growth also exists.

According to the result, primary variable that negatively impacts economic growth is external debt (EXD). The study is consistent with Maestas et al. (2016); the debt variable is likely to result in a decrease in investment reduction. When debt is increased, the country has a budget constraint on national expense, thereby decreasing economic growth. As a result, GDP tends to decrease as well, especially in developing countries like Thailand. While industry value added (INDUSVA) is the main variable that positively impacts GDP. It is considered an important determinant of economic growth in exports. As exports increase, GDP also increases (Ali et al., 2016). Moreover, higher industrial value-added also represents an increase in margins compared with cost (Barua and Chakraborty, 2006).

Besides, this study also observes positive impact of tax revenue on GDP. It indicates that higher government revenue received from tax can generate high economic growth. In the case of electricity consumption, high electrical consumption can contribute a positive impact on economy. It can expect that higher energy consumption may result in higher productivity of people and their well-being. As expected, investment in other countries can boost economic growth, corresponding to growth theory of Solow (Durlauf, Kourtellos, and Minkin, 2001).

Conclusions and Discussions

This study aims to investigate and test variables affecting GDP growth. According to literature reviews, many variables may affect GDP growth with different period (monthly, quarterly, and annual). Therefore, MIDAS approach is applied to each variable. Then, the study also specifies factors affected GDP growth by elastic net regression. Elastic net regression can also solve both multicollinearity and variable selection simultaneously (from ridge and LASSO regression). The result reported that 5 variables have an impact on GDP growth. Notably, the main variables that affect external debt. In contrast, tax revenue is a primary variable that has a positive impact on GDP growth. Therefore, Thai economic policy must closely monitor and control external debt at appropriate level; otherwise, the higher debt would harm economic performance. In addition, the tax revenue can increase economic growth. Thus, the government should impose more tax and use this revenue to develop overall country.

More relevant factors such as financial, environmental, and pollical factors should be considered in further model study. Moreover, nonlinear Midas regression is suggested to investigate nonlinear impact of these factors on economic growth of Thailand.

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