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A MACHINE LEARNING APPROACH TO CONSTRUCTING A WEEKLY GDP TRACKER USING GOOGLE TRENDS

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Introduction

Timely and accurate information are essential inputs for policy formulation, especially in times of crisis, such as the coronavirus disease (COVID-19) pandemic. High frequency and granular data are integral in crafting prompt and appropriate measures toward mitigating the impact of economic headwinds.

However, official statistics are typically published with a significant time lag. At the height of the COVID-19 pandemic, data collection was hampered by the imposition of mobility restrictions. These issues have prompted policymakers, including monetary authorities, to tap alternative data sources to supplement existing traditional indicators.

In macroeconomic surveillance, the gross domestic product (GDP) is one of the widely used and most comprehensive measures of economic activity. In the Philippines, GDP data are released quarterly by the Philippine Statistics Authority (PSA) 40 days after the reference quarter, except for fourth-quarter GDP data that are released 30 days after.[2]

In view of this publication lag, the Bangko Sentral ng Pilipinas (BSP) uses several models to nowcast real GDP, determine the growth outlook, and identify the cyclical position of the economy in the business cycle, all of which are important considerations in monetary policy formulation.

This study attempts to build a near real-time GDP growth tracker that capitalizes on available high frequency alternative data and state-of-the-art machine learning models.[3] Specifically, this study utilizes Google Trends data to track economic activity in the Philippines. It builds on the existing empirical literature, particularly Woloszko (2020) that points to the relative usefulness of internet search data in nowcasting GDP.

Overall, this study shows that ahead of the release of quarterly national accounts, the constructed Google Trends-based weekly GDP tracker may serve as a useful complementary surveillance tool for monitoring economic activity.

Google Trends Data Selection

Google Trends is an analytical tool that allows users to determine relative public interest in a particular search term. Through this tool, users can check how frequent a term is entered into Google's search engine relative to all Google searches for a particular geographical region and time period.

This study utilizes Google search volume indices for the main categories, selected sub-categories, and authors' pre-identified topics that are relevant to the estimation of GDP growth (Table 1).

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[2] PSA, Technical Notes on the National Accounts of the Philippines (https://psa.gov.ph/statistics/technical-notes/node/168102).

[3] Alternative/unconventional data fall under the classification of big data, which among others, include internet search data, mobility data, satellite images, and textual data such as news articles, job postings and blog posts. Big Data is characterized by high volume, velocity, or variety of data that cannot be processed using conventional tools and software that require specific technology and analytical algorithms for its transformation to value for mission-critical processes (Source: BSP Big Data Roadmap).

Table 1. List of Select Google Trends Variables

24 Google Trends categories		
Arts & Entertainment	Health	People & Society
Autos & Vehicles	Hobbies & Leisure	Pets & Animals
Beauty & Fitness	Home & Garden	Real Estate
Books & Literature	Internet & Telecom	Reference
Computers & Electronics	Jobs & Education	Science
Finance	Law & Government	Shopping
Food & Drink	News	Sports
Games	Online Communities	Travel
24 sub-categories of Business & Industrial category		
Advertising & Marketing	Business Services	Manufacturing
Aerospace & Defense	Chemicals Industry	Metals & Mining
Agriculture & Forestry	Business Operations	Pharmaceuticals & Biotech
Automotive Industry	Energy & Utilities	Printing & Publishing
Business Education	Enterprise Technology	Retail Trade
Business Finance	Entertainment Industry	Small Business
Business News	Transportation & Logistics	Textiles & Nonwovens
Hospitality Industry		
Construction & Maintenance		
Industrial Materials & Equipment		
8 Google Trends Topics		
Job	Subsidy	
Unemployment	Tax	
Resignation	Unemployment Benefits	
Investment	Pantawid Pamilyang Pilipino Program	

Source: Google Trends and authors' selection

Data Pre-Processing

Google Trends data series were collected at monthly (January 2004 to August 2022) and weekly (January 2014 to August 2022) frequencies. For the monthly data series, corrections for known breaks in the time series data were implemented.

For the period January 2004 to August 2022, Google reported the following three breaks in time series data: (1) January 2011 due to geographical localization; as well as (2) January 2016 and (3) January 2022, both due to improvements in the data collection system. The breaks in 2011 and 2016 were more evident than the break in 2022 due to limited data sampling from 2022 onwards. Thus, in this study, only the breaks in 2011 and 2016 were corrected to address the potential issue of spikes in growth rates that may be attributed to changes in the data collection methods of Google.

The breaks were addressed by introducing an adjustment that sets the growth rate at the breakpoint to zero. A backward correction approach was used to correct the breaks starting from January 2016 back to January 2011.[4]

This study also uses quarterly real GDP data (with 2018 as the base year) from the PSA. No statistical processing was performed for the quarterly PSA GDP data apart from taking the difference in the natural logarithms of the real GDP to derive the year-on-year GDP growth rates.

Machine Learning Models

This study takes advantage of the empirically documented ability of machine learning algorithms to generate relatively accurate and robust predictions. Machine learning models offer two key capabilities: (a) capture the non-linearities in the data that can better explain the movements in GDP, especially during periods of extreme economic stress and heightened uncertainty; and (b) handle a wide array of variables without leading to issues of overfitting through the multilayer structure of machine learning models.

[4] For each variable, the difference between January 2016 (2011) and January 2015 (2010) is added to observations earlier than January 2016 (2011).

In this study, four machine learning techniques were evaluated, namely 1) Support Vector Regression (SVR); 2) Decision Trees; 3) Random Forest; and 4) Artificial Neural Networks (ANN). For all these models, the data were split into a train dataset (first 65 quarters) and a test dataset (last five quarters). Each model was trained to learn the patterns from the train dataset. Model performances in both the training and test sets were evaluated by computing for the root mean square error (RMSE). The results were also compared with traditional autoregressive models. Table 2 summarizes model performance based on RMSE using train and test datasets. Notably, the ANN outperformed other machine learning models and even the traditional autoregression models such as Autoregression (AR) and Autoregressive Integrated Moving Average (ARIMA). Therefore, the ANN model was chosen to be the main model for this study.

Table 2. Forecast Evaluation of Machine Learning Models vs. Traditional Time Series Models

Models	RMSE using train data	RMSE using test data
SVR	2.55	2.29
Decision Trees	0.50	12.41
Random Forest	1.04	5.62
ANN[5]	0.53	1.49
ARIMA (1,1,1)[6]	2.83	7.26
AR(1)[7]	2.67	6.33

Source: Authors' estimates

Construction of the Weekly GDP Tracker

The Weekly GDP Tracker capitalizes on a more frequent Google Trends data series to extract leading information from this type of unconventional data source. Thus, it infers sensible predictions on economic activity or variations in the business cycle, especially during unprecedented periods.

The Weekly Tracker was constructed using a two-step model approach, broadly following Woloszko's (2020) methodology. First, the machine learner was trained to predict the quarterly GDP growth using topic- and category-based Google Trends searches as outlined in the previous section. Second, by employing the frequency-neutrality assumption of Woloszko (2020), the estimated elasticities from the quarterly model were applied to the weekly Google Trends data series.

This required calibrating the weekly Google Trends series to match the break-corrected monthly Google Trends indices and using the 12-week moving average of the resulting calibrated weekly series as input to the trained model.

Analysis of the Model Results

An important question on the use of the Weekly GDP Tracker is how well it can nowcast economic activity. Overall, the results of the study show that the tracker broadly

[5] The model has 56 input features, 90 neurons in the second layer, and 10 neurons in the third layer.

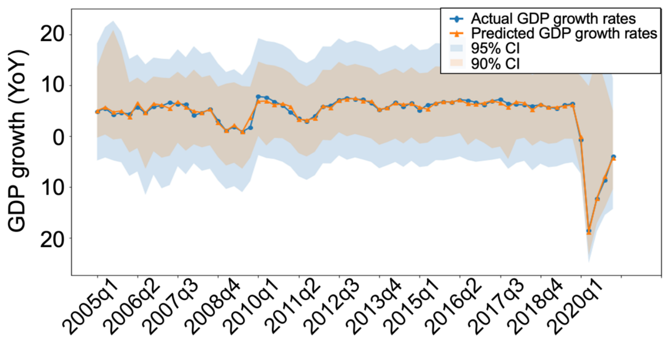
[6] ARIMA (*p*, *d*, *q*) model with an AR term of order one (*p*=1), first difference (*d*=1), and a moving average term of order one (*q*=1).

[7] AR(*p*) model of order one (*p*=1).

mirrored the general trend of the actual output growth. Moreover, the tracker is able to capture important crisis episodes or fluctuations in the business cycle. Thus, the results suggest that the Weekly Tracker may be a useful complementary surveillance tool to official statistics in providing relevant information on the likely trend or path of output growth.

Figures 1 and 2 show the actual quarterly real GDP growth rates and the predicted GDP growth rates based on the trained ANN model along with the usual confidence bands for both the training and test datasets, respectively.[8]

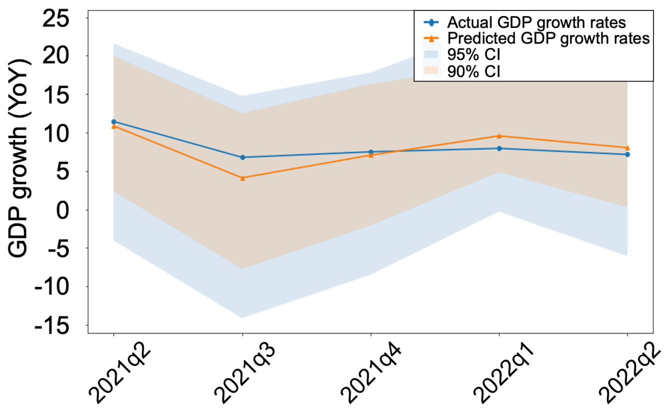
Figure 1. Actual and Predicted Growth Rates (in percent, %); Training Dataset (2005Q1 – 2021Q1)



Source: Authors' estimates

For both the train and test datasets, the results show the relatively reasonable performance of the quarterly machine learning model with the predicted values broadly tracking the movements of actual real GDP growth. However, note that the study used a very limited test dataset. This suggests that the assessment of prediction performance may be revisited in the future as the sample size increases.

Figure 2. Actual and Predicted Growth Rates (in percent, %); Test Dataset (2021Q2 – 2022Q2)

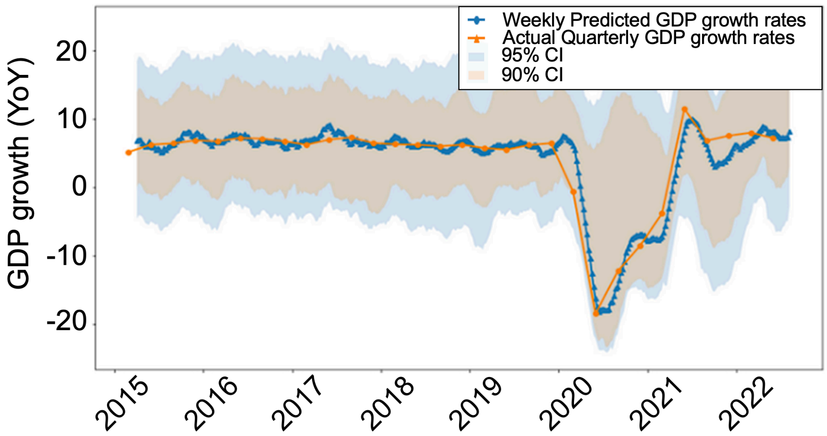


Source: Authors' estimates

Meanwhile, the weekly nowcasts for real GDP growth from January 2015 to August 2022 were plotted against the actual quarterly year-on-year GDP growth in Figure 3. As seen in the said figure, the Weekly Tracker closely followed the general direction of the actual real GDP growth.

[8] Confidence bands are computed for the 95 percent and 90 percent confidence intervals (CI) using the Model Agnostic Prediction Interval Estimator (MAPIE) CVplus method, available through the Scikit-learn package of Python.

Figure 3. Weekly GDP Tracker and Actual Quarterly GDP (in percent, %); (January 2015 – August 2022)



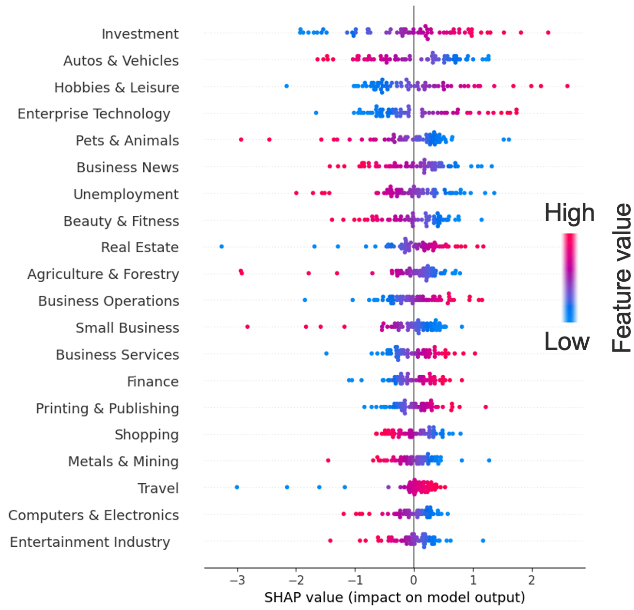
Source: Authors' estimates

Most Important Predictors of GDP Growth Based on SHAP Values

One of the common problems with machine learning algorithms, especially with neural networks, is their black-box nature that makes analytical interpretation of the results difficult. One way to address this is to use an interpretability technique known as the Shapley values, or the average marginal contribution of a variable to the prediction over all possible variable combinations or coalitions. This study used SHapley Additive exPlanations (SHAP), a fast algorithm implementation, to extract SHAP values.

Based on the train dataset, Google searches for investment, unemployment, real estate, business news, and agriculture and forestry along with consumption-related searches such as those for autos and vehicles and hobbies and leisure are found as the top contributors to the predicted GDP growth rate based on their SHAP values (Figure 4).

Figure 4. Most Important Predictors of GDP Based on SHAP Values



Source: Authors' estimates
Note: The color bar in the illustration corresponds to the raw values of the variables for each instance on the graph. That is, variables with high and low values appear as red and blue dots, respectively. Meanwhile, the horizontal axis shows whether the effect of that value is associated with a higher or lower prediction. For example, high searches for investment (denoted by red dots) have positive impact on predicted GDP growth (shown in the horizontal axis).

Intuitively, higher Google searches for investment and real estate may be correlated with higher economic growth while higher searches for unemployment may be associated with weaker GDP growth.

Conclusion

The pandemic highlighted the importance of unconventional data sources, such as internet data, in macroeconomic surveillance. To the authors' knowledge, this is the first empirical research in Philippine literature to leverage data from Google–the world's largest search engine–in near real-time tracking of output growth. To ensure that the use of Google Trends is suitable for statistical and economic analyses, topic- and category-based searches were selected based on the authors' expert and sensible judgment. This study broadly follows the approach of Woloszko (2020) in the construction of the tracker.

The evaluation of model results shows that the Weekly GDP Tracker is a relatively accurate high frequency tool for estimating economic activity. The broad goal is not to replace the existing suite of economic models used by the BSP but to contribute to surveillance and analyses through the use of a high frequency monitoring tool that takes advantage of readily available alternative data and the predictive capacity of advanced algorithms. Thus, pending the availability of quarterly national accounts, the Weekly GDP Tracker may serve as a complementary surveillance tool for economic activity.

Like all models, prediction errors are anticipated, especially when the sample size to train or learn from is limited. Nonetheless, a key advantage of the tracker is its flexibility to re-train and update nowcast predictions for GDP. This improves the model's learning capacity to predict output growth estimates as new actual data become available.

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