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Impact of COVID-19: Nowcasting and Big Data to Track Economic Activity in Sub-Saharan Africa

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Abstract

The COVID-19 pandemic underscores the critical need for detailed, timely information on its evolving economic impacts, particularly for Sub-Saharan Africa (SSA) where data availability and lack of generalizable nowcasting methodologies limit efforts for coordinated policy responses. This paper presents a suite of high frequency and granular country-level indicator tools that can be used to nowcast GDP and track changes in economic activity for countries in SSA. We make two main contributions: (1) demonstration of the predictive power of alternative data variables such as Google search trends and mobile payments, and (2) implementation of two types of modelling methodologies, machine learning and parametric factor models, that have flexibility to incorporate mixed-frequency data variables. We present nowcast results for 2019Q4 and 2020Q1 GDP for Kenya, Nigeria, South Africa, Uganda, and Ghana, and argue that our factor model methodology can be generalized to nowcast and forecast GDP for other SSA countries with limited data availability and shorter timeframes.

JEL Classification Numbers: C53, C55, E37, F17, O11

Keywords: COVID-19; Econometric modeling; Economic activity; GDP; Google Search Trends; Mobile payments; NO2; Nowcasting; Short-term forecasting

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I. Introduction

Detailed, timely information about economic challenges in Sub-Saharan Africa (SSA) countries is imperative for evidence-based policymaking, particularly in the context of the rapidly evolving COVID-19 pandemic. Data limitations pose substantial challenges to evaluating economic activity in real-time for countries in SSA. There is no central repository of high frequency data available for SSA countries and available quarterly or annual macroeconomic data is often further constrained by publishing delays. Moreover, standard macroeconomic forecasting methods have minimal flexibility in incorporating data with different frequencies and/or update intervals, which limits the prediction production cadence and therefore usability of nowcast models.[2]

In this context, how does one assess the impacts of the COVID-19 pandemic on economic activity in Sub-Saharan Africa (SSA)? This paper sets out to answer this question by (1) sourcing novel and relevant high-frequency timeseries data with sufficient historical lookback period for statistical predictions and (2) implementing Machine Learning (ML) and parametric Factor Model (FM) approaches to build a set of enhanced country-level nowcast and forecast models for quarterly GDP that are generalizable for other countries in the SSA region. The nowcasting methodology provide policymakers with a suite of data-driven tools to respond to rapidly evolving situations.

This paper focuses on the top 9 economies in SSA that comprise 73% of the region's GDP in 2019: Angola, Cameroon, Côte d'Ivoire (Ivory Coast), Ethiopia, Ghana, Kenya, Nigeria, South Africa, and Uganda.[3] In addition to assembling a high frequency dataset that includes 350 total data variables including alternative sources such as shipping, mobile payments, and Google Search Trends,[4] this paper presents an expanded nowcasting implementation methodology that a) enables integration of mixed frequency data (i.e., daily, weekly, monthly) and b) has flexibility to accommodate different variable update timeframes (i.e., the nowcast models can continuously update predictions as new information becomes available).

For the Machine Learning (ML) models, we focus on Nigeria, Kenya, and South Africa—among the largest economies in the SSA region with the most data availability. For the parametric factor models (FM), we focus on Uganda, Kenya, and Ghana to test the models on a sample that varies in terms of data availability. The Kenya data is particularly rich in quantity of variables and number of observations, while our data for Ghana is significantly smaller in both regards; Uganda arises as a "middle–of–the–road" country in terms of data availability. Both sets of models present nowcasts and short-term forecasts for 2019Q4 and 2020Q1. The combination of these results offers insights as to the most appropriate methodology to apply in other SSA countries depending on data availability.

There have been few attempts at estimating nowcast models for African countries. Barhoumi et al. 2020 (forthcoming) suggest that a machine learning based nowcast can be successfully implemented for many countries in sub-Saharan Africa. Previous academic research on nowcasting GDP in Sub-Saharan Africa focused on South Africa. Kabundi et al. (2016) create a nowcast for South African real GDP with the dynamic factor model.[5] Kabundi et al. (2016) select 21 time-series covering real variables (real GDP growth, trade, production, and demand), nominal

[2] Nowcasting refers to the forecasting of the present, recent past or near future, as defined by Domenico Giannone, Lucrezia Reichlin, and David Small, "Nowcasting: The Real-Time Informational Content of Macroeconomic Data," Journal of Monetary Economics 55, no. 4 (2008): 665–76.
[3] World Bank, World Development Indicators (2019).
[4] Of the 350 total variables, 110 are shipping trade variables provided by Diego Cerdeiro.
[5] Kabundi, Alain, Elmarie Nel, and Franz Ruch. "Nowcasting Real GDP Growth in South Africa." Working Papers. South African Reserve Bank, February 2016. https://ideas.repec.org/p/rbz/wpaper/7068.html.

variables (producer and consumer price indices), and financial variables (nominal effective exchange rate and the repo rate). We build on Kabundi's study by including additional high-frequency variables with longer lookback periods and by applying multiple modeling methods to other Sub-Saharan African countries. Our application of nonparametric models to nowcasting is informed by the forecast for South African GDP in Martin (2019), which compares traditional VAR forecasting models with machine learning models.[6] Martin (2019) used 15 forecasting variables and found that Elastic-net regression, Random Forests, Support Vector Machines, and Recurrent Neural Networks had promise for South Africa GDP forecasting. The Elastic-net model produced the best performance, lowest Root Mean Squared Error (RMSE), and highest correlation. Our research builds on Martin (2019) by creating machine learning models with more high frequency data with longer lookback periods. Additionally, this paper contributes to the literature by estimating nowcast models of GDP growth for South Africa, Kenya, Nigeria and Uganda with Machine Learning and parametric Factor Model methods.

For the machine learning nowcast models predicting quarterly GDP of South Africa, Kenya, and Nigeria, we find that the linear models (Elastic Net, SVR) in general perform better when predicting recessions, but the tree-based models (Random Forest, XGBoost) outperform in non-recessionary periods. Cross-validation and rolling window tests show a high level of prediction accuracy for Nigeria and South Africa compared to Kenya, while there is no indication of a systematic bias for all three countries. Performance of the models is also evaluated by predicting only on recessionary periods to assess the models' prediction during times of economic distress. Alternative data sources, including mobile payments for Kenya and novel dataset of Google Search Trends, are shown to be relevant and key predictors of GDP.

We find that the three-pass regression parametric factor models for Uganda, Kenya, and Ghana have a high level of prediction accuracy; the results for Kenya are particularly interesting as the parametric factor model prediction performance was higher than for the machine learning methods tested.[7] The factor model results are promising for generalizing methodology to nowcast and forecast GDP for other countries with more limited data availability and/or shorter timeframes.

This paper is organized in the following sections: Section II provides an overview of the wide range of data sources used for our prediction models. Section III outlines the two types of estimation frameworks we explored for nowcasting (machine learning and parametric factor models). We summarize the results of the model predictions and performance evaluation for South Africa, Kenya, Nigeria, Ghana, and Uganda in Section IV. Finally, we conclude in Section V with remarks on the contributions of our work and further areas for model refinement.

II. Summary of Data Sources

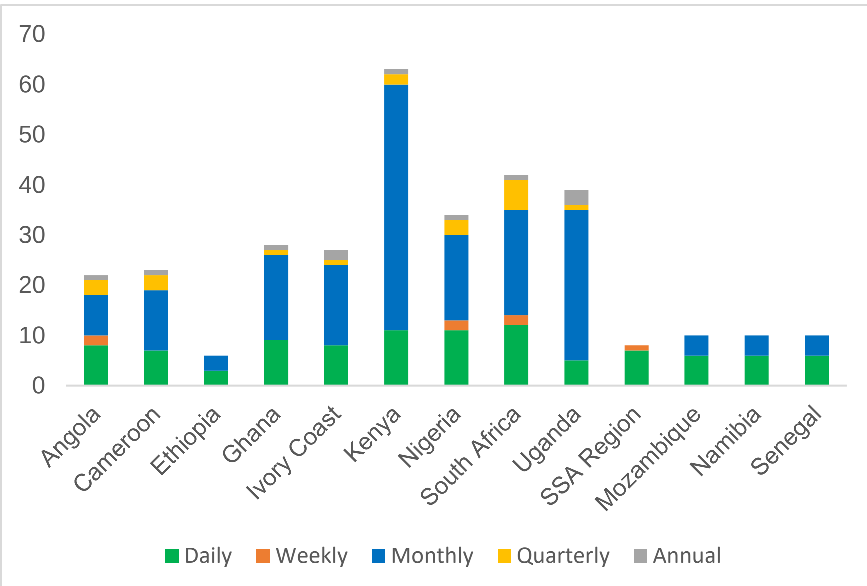
Given that prediction models are only as good as the underlying data, we consolidated a wide variety of data variables for the project. Of the 322 variables we collected for the nine largest economies in SSA, 100 variables are shipping trade data provided by the IMF's Cerdeiro et al.

[6] Martin, Lisa-Cheree. "Machine Learning vs Traditional Forecasting Methods: An Application to South African GDP." Working Papers. Stellenbosch University, Department of Economics, 2019. https://ideas.repec.org/p/sza/wpaper/wpapers326.html.

[7] Further refinement of machine learning methods through feature engineering and iterating on additional models that are suited for time series predictions such as recurrent neural network (RNN) and Long Short-Term Memory (LSTM) may improve the prediction accuracy.

(2020),[8] and the 200+ other variables range from standard macroeconomic variables such as exchange rates and business confidence indexes to alternative sources that were available at higher frequencies such as mobile payments, Google Trend search terms, and air quality. Some variables were sourced from existing databases (e.g., Bloomberg, IMF, Trading Economics, national central bank databases) while others were original datasets created and processed by the research team specifically for this project (Google Trends search terms).

Figure 1. Summary of Variables by Frequency, Country, and Type



Variable Category	Count
Shipping	111
Trade	36
Google Search Trends	34
Financial Market	25
Mobile payments	12
Payment card transactions	12
Manufacturing	11
Debt	10
Interest Rate	9
GDP	8
Inflation Rate	8
Business Confidence	5
Business Tendency Indicator	5
Check EFTs	4
Commodity Prices	4
Interbank	4
Unemployment Rate	4
Air Quality	2
Bank Deposits	2
Consumer Confidence	2
Leading Economic Index	2
Money Supply M3	2
Oil / Gas	2
Private Credit	2
Retail / Sales	2
Bankruptcies	1
Economic Activity Index	1
Purchasing Managers Index	1
Tax Revenue	1
Total	322

Note: SSA Region includes the top 9 largest economies.

Table 1. Breakdown of Variables by Frequency and Country

Country/Region	Daily	Weekly	Monthly	Quarterly	Annual	Total by Country
Angola	8	2	8	3	1	**22**
Cameroon	7	0	12	3	1	**23**
Ethiopia	3	0	3	0	0	**6**
Ghana	9	0	17	1	1	**28**
Ivory Coast	8	0	16	1	2	**27**
Kenya	11	0	49	2	1	**63**
Nigeria	11	2	17	3	1	**34**
South Africa	12	2	21	6	1	**42**
Uganda	5	0	30	1	3	**39**
SSA Region	7	1	0	0	0	**8**
Mozambique	6	0	4	0	0	**10**
Namibia	6	0	4	0	0	**10**
Senegal	6	0	4	0	0	**10**
Total by Frequency	**99**	**7**	**185**	**20**	**11**	**322**

[8] Cerdeiro, Diego, Andras Komaromi, Yang Liu, and Mamoon Saeed. "World Seaborne Trade in Real Time: A Proof of Concept for Building AIS-Based Nowcasts from Scratch." Working Paper No. 20/57. IMF, May 14, 2020. https://www.imf.org/en/Publications/WP/Issues/2020/05/14/World-Seaborne-Trade-in-Real-Time-A-Proof-of-Concept-for-Building-AIS-based-Nowcasts-from-49393.

Macroeconomic and financial data

Macroeconomic variables selected focused on the business cycle, the financial sector, and longer-term structural changes. Giannone, Reichlin, and Small (2008) shows that, if systematically selected variables are chosen, the cross-section does not need to be large for accurate forecasts. Selected business cycle indicators include manufacturing, trade, shipping, business confidence, consumer confidence, unemployment rate, inflation rate, and retail/sales variables. Financial sector variables include interbank rates, capital flows, money supply, and debt to GDP. Longer-term variables include data such as air quality and payment card transactions to represent economic and financial development.

Alternative data

Mobile payments and payment cards are key facilitators of economic activity in Sub-Saharan Africa and therefore we hypothesize monthly transaction volume would be a potential predictor of economic activity. Note that mobile payments and payment card monthly transactional volumes were only publicly available for Kenya, which is a leader in SSA for mobile payment platforms.[9]

Similarly, we hypothesize that search terms related to mobile money, jobs, employment, or mobile airtime may be more likely during times of economic distress. We sourced a list of locally relevant colloquial phrases from native speakers to extract the historical Google Trend search time series for each country, with the exception of Angola where no locally relevant colloquial phrases were readily identified. The list of Google search terms included in the Google Trends data collection are summarized in Table 2. Time series for the Google search terms used in the machine learning Nowcast models for South Africa, Nigeria, and Kenya are shown in Figure 2.[10]

Table 2. Summary of Google Trend Search Terms Collected by Country

#	Country	Search terms for money / job	Local mobile payments vendor(s)
1	**Angola**	*None identified*	*None identified*
2	**Cameroon**	Do, Jockmassi, Front, Pointage	Orange Money, MTN, MoMO, Nexttel
3	**Côte d'Ivoire** (Ivory Coast)	Emploi, L'argent, Salaire, Wari, Sika, Djouman, Bara, Cherchemant	Orange Money, MTN, Moov, Flooz
4	**Ethiopia**	ገንዘብ, ብር, ስራ	m-birr
5	**Ghana**	sika, cesh, dough, dou, cedi, kudi, adwuma	momo, Airtel Tigo cash, Tigo cash, Vodafone cash, MTN
6	**Kenya**	pesa, chapaa, mullah, cheddar, dough, kazi	MPESA, m-pesa, airtime, MTN
7	**Nigeria**	owo, kudi, ego, cash, money, work	737, GTB
8	**South Africa**	money, job, employment, mobile money, airtime	ewallet, money counter
9	**Uganda**	sente, milimu	MTN, airtel mobile money

Note: Only a subset of the search terms were available as some had insufficient searches (i.e., Ethiopia). Full list of search terms tested are included in the table for reference. See Data Dictionary for the final set of search terms.

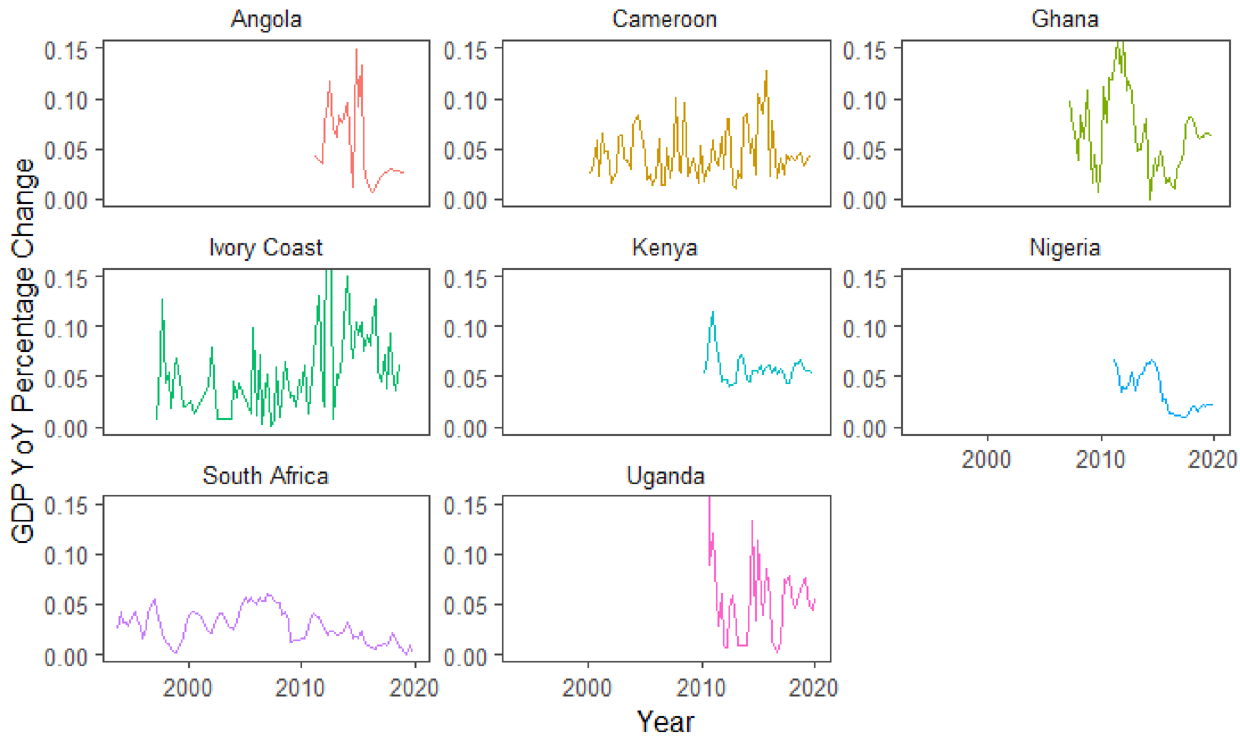
[9] Other countries may only provide data on a quarterly basis. Further research into availability of monthly mobile payments data from other central banks.
[10] See Appendix III Figure 31 for Google Trends Search Term time series for Cameroon, Ivory Coast, Ghana, and Uganda.

Figure 2. Google Trends Search Terms Time Series for South Africa, Nigeria, and Kenya

Source: Google Trends; original novel dataset created by the team based on relevant terms in local languages

Quarterly GDP data availability varies across the 10 SSA countries in our sample, with Ethiopia quarterly GDP data not available. For the remaining 9 countries shown in Figure 3 below, the timeframe of GDP data also varies broadly (i.e., pre-2000 start date for South Africa to 2013 for Uganda). Quarterly GDP is transformed into year-over-year percentage change to adjust for seasonality, though results are presented in quarter-over-quarter percentage change as well.

Figure 3. GDP YoY % Change for Top Economies in SSA Countries



Source: Haver, IMF; Note: GDP data for Ethiopia was not available

Data transformation and aggregation: Variables of different frequencies were combined into four aggregate files by frequency (daily, weekly, monthly, and quarterly) for modelling purposes. All level variables were transformed to year-over-year percentage change in the ML regression models to ensure bounded values between -1 and 1. See Appendix for more details about data sourcing and data aggregation methodology.

III. Estimation Frameworks

This paper presents a set of Machine Learning models for South Africa, Kenya and Nigeria, and a set of parametric Factor Models for Uganda, Kenya, and Ghana, which are summarized in Tables 3 and 4 below.

A. Machine Learning Approach

A.1. Overview of methods

The Machine Learning (ML) approach implemented in this paper addresses common shortfalls of existing nowcasting approaches in the following ways:[11]

1) Implementation of five different ML regression models with cross-frequency skip-sampling method and the inclusion of comprehensive cross-validation checks
2) Integration of mixed and higher frequency data (daily and biweekly, in addition to monthly and quarterly), including alternative data such as Google Trend search terms
3) Ability to handle a wide array of variables (compared to OLS or other parametric modelling approaches), while avoiding overfitting through regularization and parameter tuning
4) Greater flexibility to generate model predictions without the need to wait for all variables to be updated at month or quarter end (e.g., models will update nowcast predictions for quarter-end GDP given any incremental amount of data as it becomes available)

We tested the performance of 5 different ML regression models—Elastic net, SVR, random forest, XGBoost, and Voting Regression—using the implementations as well as the cross-validation method.[12] Descriptions of the five ML regression models are summarized below:

- **Elastic net:** Regularized linear regression that linearly combines L1 and L2 penalties of lasso and ridge methods. The L1 penalty regularizes the number of predictors used to prevent overfitting.
- **Support Vector Regression (SVR):** Transforms data into a higher dimensional space (if using a kernel function), then identifies the hyperplane that maximizes the number of points lying within the associated decision boundaries while staying within the constraints of the specified error tolerance.
- **Random Forest:** Ensemble method that constructs a series of decision trees during training and outputs the mean prediction of the individual trees for prediction.
- **XGBoost:** Implementation of gradient boosted decision trees to optimize speed and performance. Includes a parameter for regularizing the number of predictors used to prevent over-fitting.
- **Voting Regression:** Ensemble meta-estimator that fits above 4 regressors, then averages individual predictions to form final prediction.

[11] For more detailed review of machine learning techniques applied macroeconomic nowcasting, see George Kapetanios and Fotis Papailias, "Big Data & Macroeconomic Nowcasting: Methodological Review," Economic Statistics Centre of Excellence (ESCoE) Discussion Paper (Economic Statistics Centre of Excellence (ESCoE), July 2018), https://econpapers.repec.org/paper/nsrescoed/escoe-dp-2018-12.htm. For an overview of machine learning using big data in econometrics, see Hal R. Varian, "Big Data: New Tricks for Econometrics," Journal of Economic Perspectives 28, no. 2 (May 2014): 3–28, https://doi.org/10.1257/jep.28.2.3.
[12] Cross-validation method used is available in the *scikit* learn package for Python

A.2. Choosing a time horizon

Of the large set of potential predictor variables ensembled, many of the predictors vary in the time horizon covered. For instance, the South African variable corresponding to change in inventories dates back to 1960, but the data on shipping activity in South Africa only dates back to 2015. Since the training data for the ML models chosen above must all cover the same time horizon, there is an inherent trade-off between the number of predictors and the number of observations. In general, increasing the number of predictors increases the model performance, but an insufficient number of observations can lead to overfitting which ultimately decreases out-of-sample model performance. Thus for each country, the chosen start date for the training data is selected to allow utilization of the majority of the predictors while still capturing a time horizon that provides a sufficient number of observations for the number of predictors used.

A.3. Data transformations

All level variables are transformed to a YoY % change. The level variables transformed to YoY % change for each country model are summarized below:

- South Africa: GDP level, vehicle sales, bankruptcies, exports, imports
- Nigeria: GDP level, exports, imports
- Kenya: GDP level, cheques EFTs values, foreign trade summary data, transactions data, non-growth variables in mobile payments data, exports, imports

A.4. Handling mixed-frequency variables

To handle the mixed-frequency variables (i.e., across daily, weekly, monthly, and quarterly frequencies), this paper employs a technique taken from the well-known MIDAS (mixed-data sampling) regression framework known as skip-sampling.[13] To illustrate this method, consider the transformation of a monthly variable. Each monthly variable is skip-sampled into three quarterly time series, each taking values corresponding to the first, second, and third months of each quarter. Daily and weekly variables are first aggregated to a bi-weekly frequency to smooth out noise before the same skip-sampling method is applied.

A.5. Parameter Tuning

Each of the ML models explored included assessment of a number of “tunable” parameters. To determine the specific parameters to use, a grid search is performed over a space of potential parameters and select the set that yields the best cross validation score. A summary of the time horizons, number of predictors and observations for each set of country-level ML models is provided in Table 3 below.[14] Full lists of variables for each set of ML regression country models are in Appendix I Table 22 – Table 24.

[13] Boriss Siliverstovs (2017) Short-term forecasting with mixed- frequency data: a MIDASSO approach, Applied Economics, 49:13, 1326-1343, DOI: 10.1080/00036846.2016.1217310

[14] While there is no strict cutoff governing the number of observations needed to train ML models, we acknowledge that ML model performance would likely improve on larger datasets. Furthermore, linear models generally need less data than non-linear algorithms, and therefore may be better suited for datasets of insufficient size.

Table 3. ML Model Timeframe, Predictors and Observation Count

#	Model	Timeframe	# Predictors[15]	# Observations	Notes
Machine Learning Models					
1	**South Africa**	2007/03/31 – 2019/12/31	74	51	Includes one autoregressive component, lagged variables, and variables for other countries highly correlated with ZAF GDP
2	**Kenya**	2011/03/31 – 2019/12/31	142	35	Includes two autoregressive components
3	**Nigeria**	2011/03/31 – 2019/12/31	51	35	Includes one autoregressive component

Note: Each set of country-level ML models tested the five regression models described above (Elastic net, SVR, Random forest, XGBoost, and Voting Regression)

B. Parametric Factor Model Approach

This paper implements two types of parametric factor models based forecasts: predictive three-pass regression filter factor models for Uganda, Kenya, and Ghana (B.1–B.4) and descriptive high-frequency economic activity indicator generated through a Kalman filter for South Africa (B.5–B.6). A summary of the factor models is provided in Table 4.

Table 4. Parametric Factor Model Timeframe, Predictors and Observation Count

#	Model	Timeframe	# Predictors	# Time Observations
Predictive Factor Models (Monthly)				
1	**Uganda**	2010/10/01 – 2020/03/31	14	81 months
2	**Kenya**	2015/01/01 – 2020/03/31	6	63 months
3	**Ghana**	2010/01/01 – 2020/03/31	6	123 months
Kalman Filtration Factor Model (Daily Economic Activity Indicator) – *Preliminary*				
1	**South Africa**	2006/06/05 – 2020/04/15	3	3,618 days

Note: Predictor count does not include the country GDP variable. See Appendix II for full variable list.

B.1. Three-Pass Regression Filter Method

The predictive parametric factor model closely follows the methodology outlined in Hepenstrick and Marcellino (2016),[16] which assumes a partial least-squares approach to estimating linear coefficients. This method is designed to be particularly beneficial when the number of predictor variables is similar to the number of total observations–i.e., when the look-back horizon of the available data is short or the data is sparse, as it is the case for many SSA countries—and has advantageous applications to economic forecasting for African countries. The models for Uganda, Kenya, and Ghana make use of a univariate latent factor to predict GDP year–over–year growth, but the code generalizes for factors of multiple dimensions. In each of these models, the highest

[15] Count includes all instances of skip-sampled variables (i.e. each monthly variable is counted three times in the total number of predictors)

[16] Hepenstrick, C. and M. Marcellino. (2016). Forecasting with Large Unbalanced Datasets: The Mixed-Frequency Three-Pass Regression Filter, Swiss National Bank Working Papers.

frequency data is provided at monthly intervals, such that all daily variables utilized are aggregated to the monthly frequency.

The logic of the mixed-frequency three-pass regression filter is as follows. Suppose there are *n* predictor variables and one response series for a country (i.e., GDP), where each is τ months long, but may be missing observations and some variables are published more or less frequently than monthly. GDP is published at quarterly intervals, and so every three months corresponds to one measurement of GDP. Let this data be organized into three matrices: An X_M matrix of aggregated monthly predictor data (where lower frequency variables are sparse and missing observations, except in the months where new data is published), an X_Q matrix of aggregated quarterly predictor data, and a *Y* [column] vector of quarterly GDP that is *not sparse* (and thus τ / 3 quarters long).

In the first pass, we run *n* simple linear time series regressions for each predictor variable on GDP using the X_Q quarterly matrix, and then collect the *n* resulting slope coefficients. In this instance, GDP serves as the initialization of the univariate latent factor; Hepenstrick and Marcellino (2016) provide a methodology by which one may obtain a set of initial values if one prefers to instead utilize a multivariate latent factor.[17]

In the second pass, we run τ linear regressions in the cross-section for each row of the X_M monthly matrix on the coefficients extracted from Pass 1 and suppress estimation of the intercept coefficient. There are two motivations for suppressing the intercept. First, it was not uncommon during the development of this model for the countries of Uganda, Kenya, and Ghana to encounter time periods in which there was only one observation among any of the predictor variables. If the predictor variable decidedly should be included in the model, then the times where it is the only observation present must either be excluded or more variables with similar look-back horizons must be included since two OLS coefficients cannot be estimated on zero degrees of freedom. This may seem restrictive, but because Pass 2 takes year-over-year changes as a response and the Pass 1 slope coefficient estimates as regressors, the intercept is usually estimated to be near-zero with *p*-values near 1. The resulting slope coefficients from Pass 2 are extracted as the monthly latent factor series, *F*; this unobserved factor is uninterruptable, but proximates real economic activity.

In the third pass, we apply the unrestricted mixed data sampling approach (U-MIDAS) to predict quarterly GDP as a linear combination of the monthly latent factors associated with each respective quarter. We also add an original feature: Because the GDP growth of these countries tend to have short look-back horizons and be highly volatile, an AR(1) error term is introduced to better train the model. Thus, in the second phase of Pass 3, the U-MIDAS regression is re-run with the lagged-by-1 residual series from the first U--MIDAS regression.

The three pass procedure described mathematically as follows:

$$
\begin{array}{ll}
\text{Pass 1: } n \text{ Time Series Regressions} & \boldsymbol{x}^{(i)} = \phi_0^{(i)} + \phi^{(i)}\boldsymbol{z} + \boldsymbol{\eta}^{(i)} \\
\text{Pass 2: } \tau \text{ Cross–Sectional Regressions} & \boldsymbol{x}_t = F_t\boldsymbol{\phi} + \boldsymbol{\zeta}_t \\
\text{Pass 3(a): U–MIDAS} & y_t = \beta_0 + \beta_1 F_t^{(M1)} + \beta_2 F_t^{(M2)} + \beta_3 F_t^{(M3)} + \varepsilon_t \\
\text{Pass 3(b): U–MIDAS with AR(1) Errors} & y_t = \beta_0 + \beta_1 F_t^{(M1)} + \beta_2 F_t^{(M2)} + \beta_3 F_t^{(M3)} + \beta_4\varepsilon_{t-1} + \psi_t
\end{array}
$$

[17] Our implementation in R generalizes for higher dimensional factors and represents the initialization of the latent factor series as Z.

where i indexes the predictor variable and t indexes time – which is on a quarterly basis in Passes 1 and 3, and on a monthly basis in Pass 2. Bolded characters designate vectors, such that $\boldsymbol{x}^{(i)}$ represents the i^{th} column of the X_Q matrix and $\boldsymbol{x}_t$ represents the t^{th} row of the X_M matrix. The noise terms (eta, zeta, epsilon, and psi) are Gaussian series that are uncorrelated amongst each other.

Since the lookback horizons of the predictor data may be short, introducing lagged GDP in Pass 3, rather than the residual series, may cause the model to favor it as the only significant term—and thus greatly diminish the model's predictive power. We evaluate the success of our implementation by comparing the pseudo–out–of–sample root mean squared errors (RMSEs) and true out-of-sample forecasts between an AR(1) or ARMA(1,0) GDP model and our three-pass regression model for each of Uganda, Kenya, and Ghana (see Table 13 through Table 15). The parameters of the ARMA models are determined by the autocorrelation and partial autocorrelation plots of the GDP series used in the three-pass regression and are found in Appendix II.

B.2. Choosing a Time Horizon

Our implementation of the three-pass regression model requires user input of the start dates of the training, testing, and true forecasting periods; the selection of a specific start date greatly affects the accuracy of the forecast estimates, and may even be relevant to whether or not the Pass 2 cross-sectional regressions can be solved.

Recall that our model formulation ultimately relies on OLS methods, which requires observation sets to have at least one observation of the predictor data. In other words, for Pass 2 to produce (weak) estimates of the latent factor, F, there must be at least zero degrees of freedom and the X_M matrix cannot have rows of only missing values. As such, it is advised to initialize the predictor data with all variables in the sample for which time periods match the availability of the GDP time series. If in the first pass the only predictor variables that appear significant are ones which all have look-back horizons less than that of the GDP series, then the GDP series must be truncated or a predictor variable must be added with a longer horizon to ensure no missing rows in X_M.

Due to high historical volatility in GDP for some SSA countries, the exclusion of earlier periods of high volatility may be useful and justified. For instance, the Uganda GDP time series used begins in 2008, but data from 2008–10 is excluded from our model estimation because the variance observed then is significantly different from that of the rest of the data set. Since OLS further assumes homoscedasticity in the response variable, this omission is justified.[18]

B.3. Data Transformations

All data utilized are transformed to a year–over–year (YoY) percent change with a log-ratio approximation. Since data is provided monthly and quarterly, a YoY change helps to both satisfy the Gaussian distribution assumption of the regression responses and mitigate a seasonality effect in the regression residuals. Note that a YoY transformation in the quarterly GDP response variable may lead to less efficiency if the true model is quarter-on-quarter (QoQ) and autocorrelation issues may arise in the residuals. We checked for autocorrelation and partial autocorrelation in the Factor Models and do not find evidence of autocorrelation for Uganda and Kenya models (see Figure 25 and Figure 26). For Ghana, we identified a potential concern with autocorrelation in the model residuals in the Pass 3(a) step and mitigate this issue using the Pass 3(b) adjustment to the U-MIDAS framework to remove the partial autocorrelation (Figure 27). Future work can incorporate QoQ transformation in quarterly GDP with seasonality adjustment to

[18] One can explore using methods to correct for heteroskedasticity to address the omission of data.

compare whether the QoQ transformation significantly improves the nowcast prediction, however, it is imperative to consider the tradeoff to model implementation that estimating seasonality adds in terms of operational complexity. [19]

B.4. Three-Pass Regression Parameter Tuning

In contrast to the Machine Learning models, our three-pass regression models are designed to work on a relatively small data sample and to use a simpler variable selection rule. Besides removing predictor variables that are too sparse or too short in time duration, our implementation also removes variables without observations in the forecast period and removes variables whose adjusted R-squared in their Pass 1 linear regressions are less than 0. This threshold for acceptable adjusted R-squared values may be changed in the code, or, instead of using adjusted R-squared, users may set a threshold for the Pass 1 regression *p*-values.

B.5. Kalman Filtration

We also refined the monthly latent factor generated by the three-pass regression by utilizing the Kalman filter on our data for South Africa where the highest frequency of occurrence is daily. This approach was designed following the approach outlined in Aruoba et al. (2009) as a real-time indicator of economic activity rather than a predictive model of GDP.[20] A preliminary version of this model was implemented for South Africa and makes use of three variables with mixed observation frequencies (Table 4):

1. Daily share price of the Johannesburg Stock Exchange (JSE: JSE) in local currency (ZAR), beginning on June 5, 2006
2. Monthly number of total vehicle sales, beginning in January 1994
3. Quarterly real GDP (in ZAR millions), beginning in Q1 1990

As a first iteration, the daily share price and monthly vehicle sales series were selected based on high linear correlations with GDP. Following Aruoba et al. (2009), we began by only using one variable per frequency, and excluded any weekly variables because those assembled for South Africa had too few observations. Low-frequency variables are denoted as being observed at the end of their respective periods (i.e., vehicle sales are observed on the last business day of each month and quarterly GDP is observed on the last business day of each fiscal quarter). Note that these variables entered the model as level quantities, and not as growth changes.

At each date beginning on June 5, 2006, the model estimates the value of a latent variable (unobserved) factor that is linearly related to each of the three observed economic variables through a Kalman filtration. This daily factor is meant to proxy real economic activity in South Africa. The linear coefficients are assumed static across time, the residuals of the observed series' linear fit are assumed to follow AR(1) processes, and the latent variable is assumed to follow an AR(1) process with standard Normal errors. These assumptions lead to the following model formulation:

[19] Given the authors' goal is developing nowcasting tools that can be implemented effectively in SSA countries, model efficiency is a secondary objective relative to the model prediction performance and operational ease.
[20] Aruoba, S. B., F. X. Diebold, and C. Scotti (2009). "Real-Time Measurement of Business Conditions," *Journal of Business and Economic Statistics*, 27(4): 417-427.

$$
\begin{aligned}
y_t^{\$\text{JSE}} &= \beta_1 x_t + u_t^{(1)} \\
y_t^{\text{Vehicle Sales}} &= \beta_2 \sum_{j=0}^{29} x_{t-j} + \gamma_2 y_{t-M_t}^{\text{Vehicle Sales}} + u_t^{(2)} \\
y_t^{\text{GDP}} &= \beta_3 \sum_{j=0}^{91} x_{t-j} + \gamma_3 y_{t-Q_t}^{\text{GDP}} + u_t^{(3)} \\
x_t &= \rho x_{t-1} + \varepsilon_t \\
u_t^{(1)} &= \gamma_1 u_{t-1}^{(1)} + \zeta_t \\
(\varepsilon_t, \zeta_t, u_t^{(2)}, u_t^{(3)})' &\overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(\vec{0},\ \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \sigma_1^2 & 0 & 0 \\ 0 & 0 & \sigma_2^2 & 0 \\ 0 & 0 & 0 & \sigma_3^2 \end{pmatrix}\right)
\end{aligned}
$$

where the *y*-variables represent the three observed series and the *x*-variable represents the unobserved daily factor. We further let *t* index time in days and assume that there are 30 days in each month and 92 days in each fiscal quarter for the purpose of calculating sums of the daily factor. The autoregressive component for the lower-frequency variables (monthly vehicle sales and quarterly real GDP) refers to the observation from the last respective period (i.e., at any time a low-frequency variable is observed, last month's vehicle sales or last quarter's GDP). For days where there is no observation (such as weekends and holidays for the daily stock price series, and most daily observations for the lower-frequency variables), the variable is coded as *NA* ("missing"). Note that encoding gaps in observation frequencies as *NA* allows the Kalman filter to automatically handle the mixed frequencies in the data and update the daily factor in corresponding periods when new low-frequency data becomes available.

B.6. Kalman Parameter Tuning

There are ten parameters associated with the aforementioned Kalman filter factor model for South Africa: Three linear coefficients relating the factor to each of the observed series, three AR(1) parameters for the resulting residuals, three AR(1) variance parameters for the residuals, and one AR(1) parameter for the factor variable process with standard Normal white noise. These parameters are optimized by maximizing the sum of log-likelihoods outputted as a by-product of each iteration of the Kalman filter. The point estimates of each parameter are summarized in Figure 4 below, and a detailed discussion of the optimization procedure follows.

Figure 4. Maximum-Likelihood Estimates of Factor Model Parameters

β_1	22,261	ρ	0.9982
β_2	−243.1	γ_1	0.017
β_3	7,455	σ_1^2	3.146
γ_2	0.780	σ_2^2	0.014
γ_3	0.999	σ_3^2	0.014

There are 3,618 days in the sample period between June 5, 2006 and April 15, 2020 where there is at least one observed data point among the three variables. Since a single iteration of the Kalman filter has *O(n)* runtime, optimizing the parameters can become a very time-intensive process as the number of observed series increases in both number of variables and number of observations. As such, this paper adopts the procedure outlined in Aruoba et al. (2009), which provides a more sophisticated means of initializing prior estimates of the full-model parameters.

Aruoba et al. (2009) suggests first running the factor model on series that are observed daily or are "stock" (as opposed to "flow") variables; in our implementation, only the JSE share price satisfy either of the criteria as a daily variable. After finding the maximum-likelihood estimates of the parameters of the JSE-only factor model,[21] the filtered means are extracted from the optimized model, and then smoothed out the means using the Kalman smoother. At this point, quality prior estimates of β_1, ρ, γ_1, and σ_1^2 are obtained from the JSE-only factor model. Prior estimates of β_2 and β_3 are then obtained from simple linear regressions of the vehicle sales and GDP series onto the smoothed factor means, respectively, and the remaining γ- and σ^2-estimates came from fitting the residuals of these linear regressions to separate AR(1) processes without a mean. The final maximum-likelihood estimates of the full factor model parameters came from re-running the Kalman filter with all three variables and re-optimizing across all ten parameters using 25 iterations of the BFGS algorithm.[22]

IV. Model Results

This section summarizes the Machine Learning model performance for South Africa, Kenya, and Nigeria, and the parametric factor model performances for Uganda, Ghana, and Kenya, as well as the quarterly GDP nowcasts for each country and the three types of model validation approaches applied.

A. Machine Learning Model Predictions

This section presents the quarterly GDP YoY % change Machine Learning model nowcast estimations for the train and test sets for South Africa, Kenya, and Nigeria. Each nowcast estimate is based on all the data available for that quarter (end-quarter nowcast), and the periods included in each train and test set are summarized in Table 5. The discrepancies in train and test periods across the three sets of country models are driven by differences in availability of data and different numbers of autoregressive components used.

Table 5. ML Model Train and Test periods for South Africa, Kenya, and Nigeria

Country	Train Period	Test Period
South Africa	2007Q2 – 2017Q2	2017Q3 – 2019Q4
Kenya	2011Q3 – 2017Q4	2018Q1 – 2019Q3
Nigeria	2011Q2 – 2018Q1	2018Q2 – 2019Q4

[21] Implemented through the BFGS algorithm built into the *optim()* function in R.
[22] Using RStudio, this optimization process took approximately four hours, but could likely be greatly reduced if a language more adept at matrix calculations (such as MATLAB or C) was utilized instead.

Figure 5. ML Model Time Series Comparison for South Africa

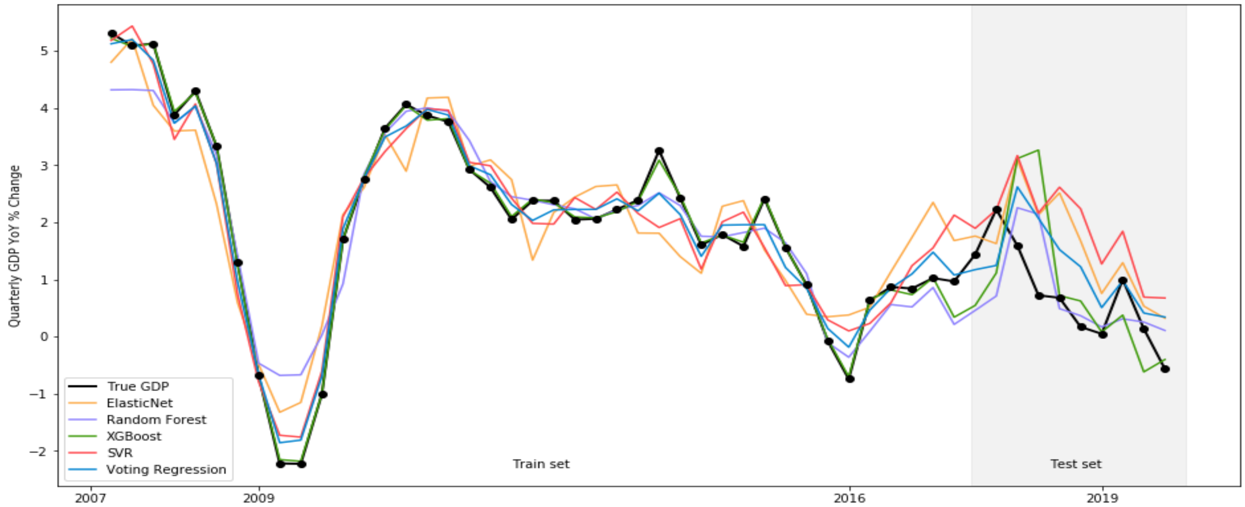


Figure 6. ML Model Time Series Comparison for Kenya

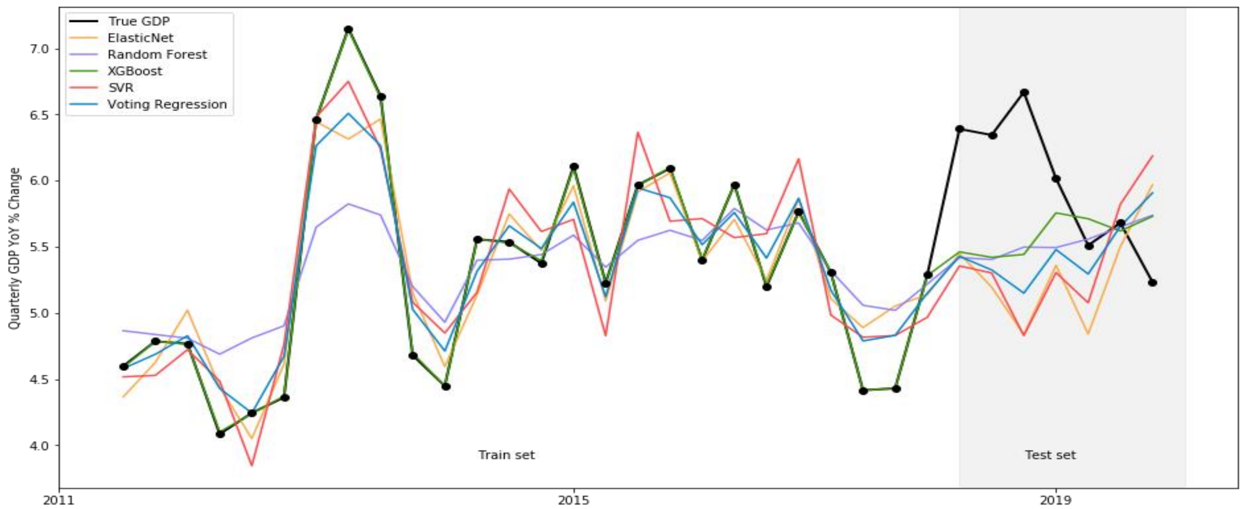
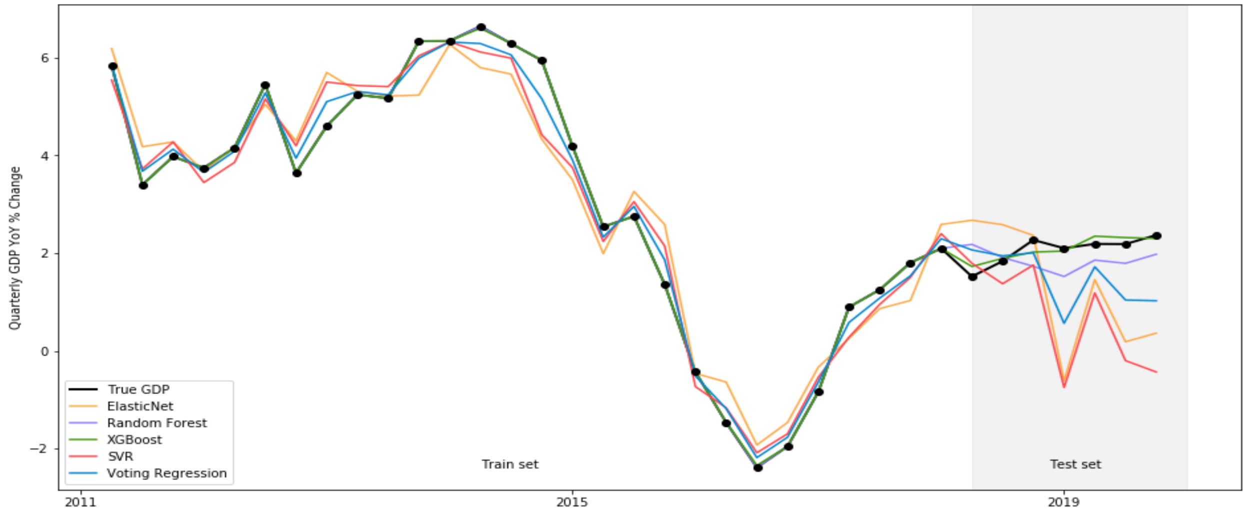


Figure 7. ML Model Time Series Comparison for Nigeria



The next set of ML model results summarize the nowcasts for both 2019Q4 and 2020Q1 quarterly GDP YoY and QoQ % change estimates across the five regression models. To nowcast 2019Q4, the models are trained using data up to 2019Q3, then make a prediction based on all available data within 2019Q3 and 2019Q4. Similarly, to nowcast 2020Q1, the models are trained using data up to 2019Q4, then make a prediction based on all available data within 2019Q4 and 2020Q1. For Kenya, 2019Q4 GDP was not available and therefore the Kenya nowcasts do not include actual GDP. For South Africa and Nigeria, given that the actual GDP values for 2019Q4 are available, we can compare the percentage point difference in each model's prediction against the actuals. We find that the tree-based algorithms, Random Forest and XGBoost, provide the most accurate nowcasts for 2019Q4.

Figure 8. ML Model Predictions for YoY GDP Percent Change

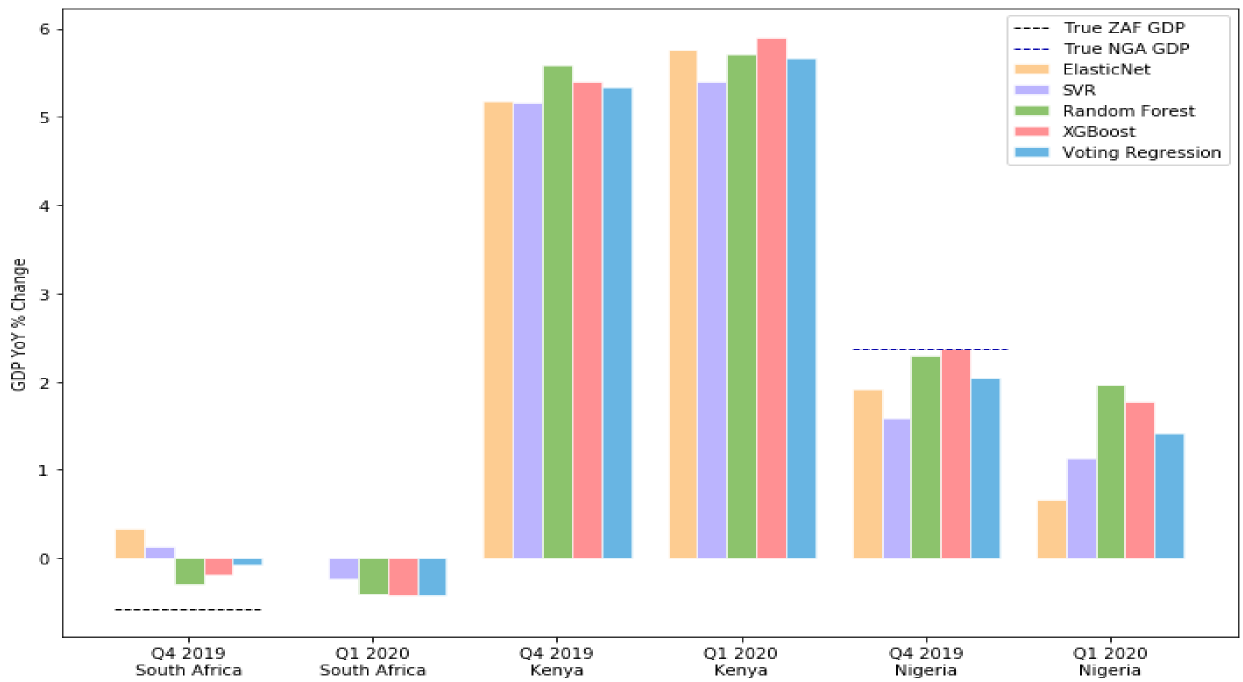


Table 6. ML Model Predictions for YoY GDP Percent Change - Comparison with Actuals

Country	Date	Actual GDP	Machine Learning (ML) Model Predictions YoY GDP Percent Change (% PP error) Elastic net	SVR	Random Forest	XGBoost	Voting
South Africa	Q4 2019	-0.57%	0.33% (+90bp)	0.13% (+70bp)	-0.3% (+27bp)	-0.18% (+39bp)	-0.07% (+50bp)
	Q1 2020	*N/A*	0.00%	-0.23%	-0.40%	-0.42%	-0.42%
Kenya	Q4 2019	*N/A*	5.15%	5.30%	5.55%	5.36%	5.35%
	Q1 2020	*N/A*	5.70%	5.45%	5.73%	5.95%	5.70%
Nigeria	Q4 2019	2.37%	1.92% (-45bp)	1.60% (-77bp)	2.29% (-8bp)	2.37% (-)	2.04% (-33bp)
	Q1 2020	*N/A*	0.68%	1.15%	2.04%	1.81%	1.41%

Table 7. ML Model Predictions for QoQ GDP Percent Change - Comparison with Actuals

Machine Learning (ML) Model Predictions

YoY GDP Percent Change (% PP error)

Country	Date	Actual GDP	Elastic net	SVR	Random Forest	XGBoost	Voting
South Africa	Q4 2019	-0.36	-0.05% (+31bp)	0.24% (+60bp)	-0.09% (+27bp)	-0.36% (+0bp)	-0.03% (+33bp)
	Q1 2020	*N/A*	-0.06%	-0.06%	0.28%	0.04%	0.04%
Kenya	Q4 2019	*N/A*	1.48%	1.48%	1.36%	1.99%	1.58%
	Q1 2020	*N/A*	1.43%	1.47%	1.41%	1.80%	1.53%
Nigeria	Q4 2019	1.02	0.50% (-52bp)	0.50% (-52bp)	92% (-10bp)	1.01% (-1bp)	0.73% (-29bp)
	Q1 2020	*N/A*	0.34%	0.46%	0.78%	0.68%	0.56%

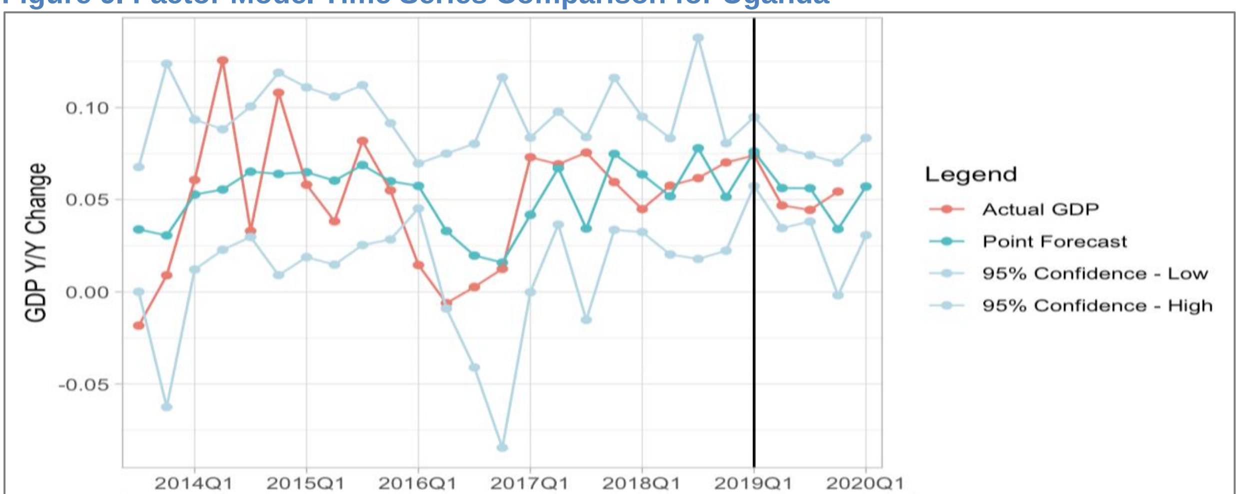
B. Parametric Factor Model Predictions

This section presents the quarterly GDP YoY % change factor model nowcast estimations for the train and test sets for Uganda, Kenya, and Ghana. See Section D.2 for discussion of parametric factor model prediction and model performance.

Table 8. Factor Model Estimation and Test periods for Uganda, Kenya, and Ghana

Country	Estimation Period	Test Period
Uganda	2013Q3 – 2018Q4	2019Q1 – 2019Q4
Kenya	2015Q1 – 2018Q2	2018Q3 – 2019Q3
Ghana	2010Q1 – 2017Q4	2018Q1 – 2019Q3

Figure 9. Factor Model Time Series Comparison for Uganda



In-Sample RMSE = 2.98% ; Pseudo-Out-of-Sample RMSE = 1.27%

Figure 10. Factor Model Time Series Comparison for Kenya

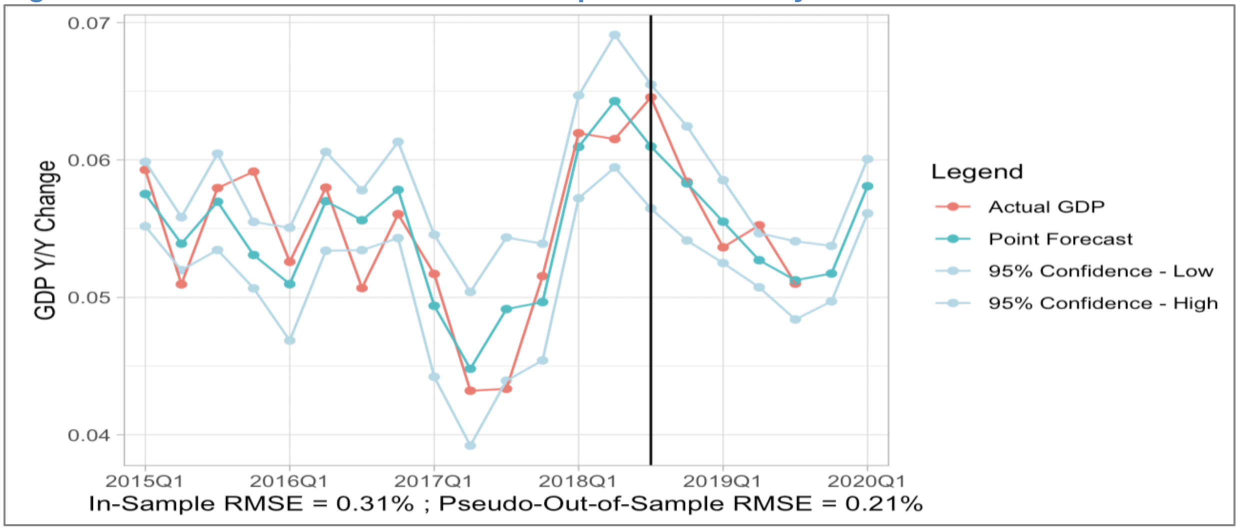


Figure 11. Factor Model Time Series Comparison for Ghana

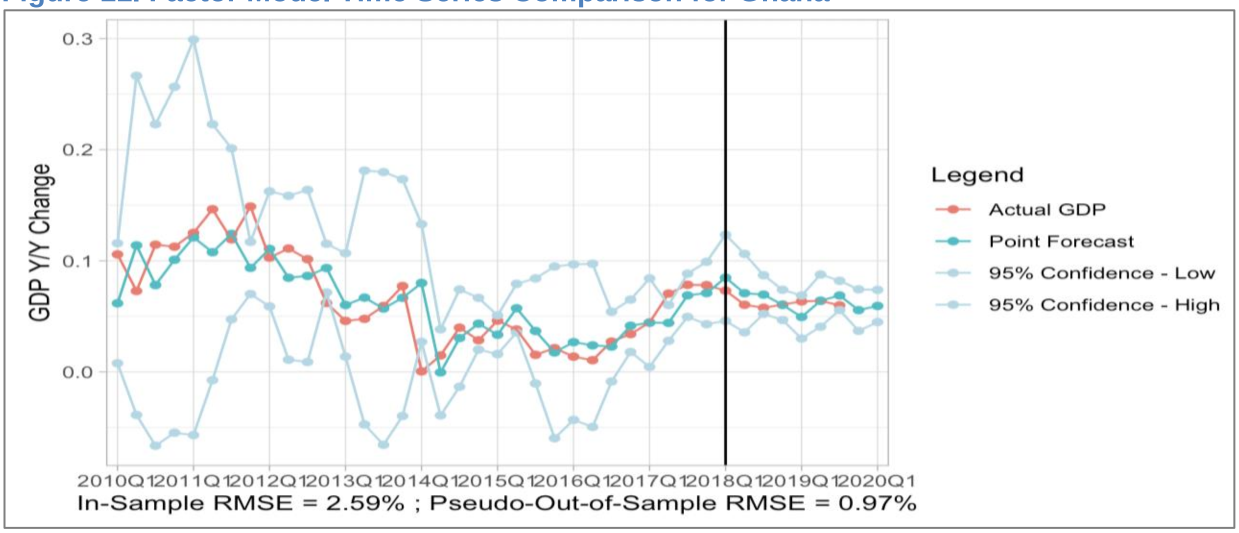


Table 9. Factor Model Predictions for YoY GDP Percent Change – Comparison with Actuals

Country	Date	Actual GDP	ARMA *Predicted GDP*	Three-Pass Model *Predicted GDP*
Uganda	Q4 2019	5.43%	4.72% (–71bps)	3.41% (–202bps)
	Q1 2020	*N/A*	4.96%	5.71%
Kenya	Q4 2019	*N/A*	5.46%	5.17%
	Q1 2020	*N/A*	5.48%	5.81%
Ghana	Q4 2019	*N/A*	6.40%	5.57%
	Q1 2020	*N/A*	6.49%	5.95%

C. Parametric Factor Model Economic Activity Latent Factors

C.1. Three-Pass Regression Monthly Factor

We also examined the movement in the monthly latent factor for each three-pass regression model to understand the direction of economic activity between ends of quarters. While these latent factors are unobserved and cannot be directly interpreted, the trend is expected to generally correspond to improving or diminishing economic conditions. Therefore, given the latent variable can be generated on a monthly basis, it can serve as a higher frequency directional indicator for economic activity in advance of quarterly GDP releases. For instance, we observe that while the latent factor indicates the economic activity is tempered in 2020M1-2020M3 for all three countries, the situation is not worse than recent historical lows (e.g., 2016M11 for Uganda, 2017M9 for Kenya, and 2012M3 for Ghana).

Figure 12. Monthly Latent Factor – Uganda

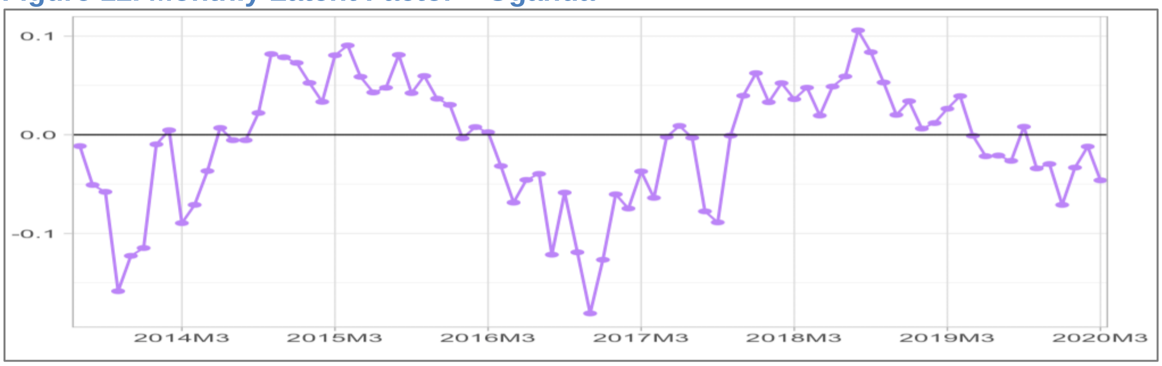


Figure 13. Monthly Latent Factor – Kenya

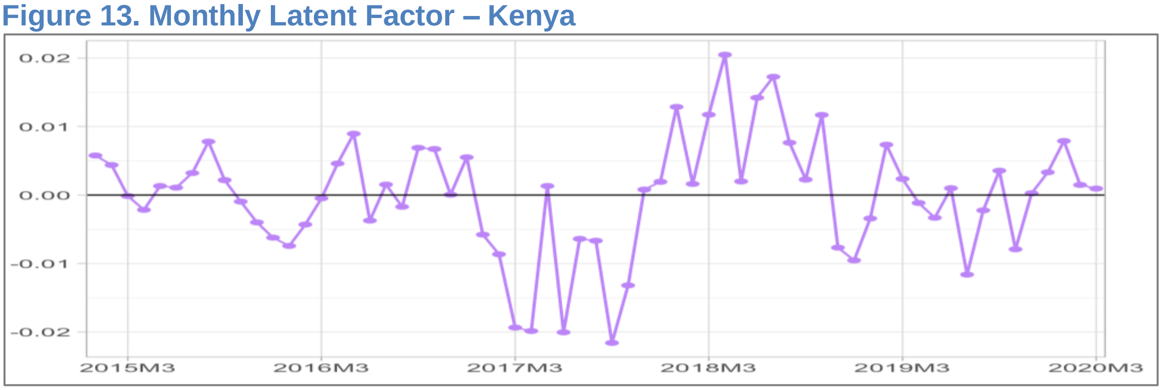
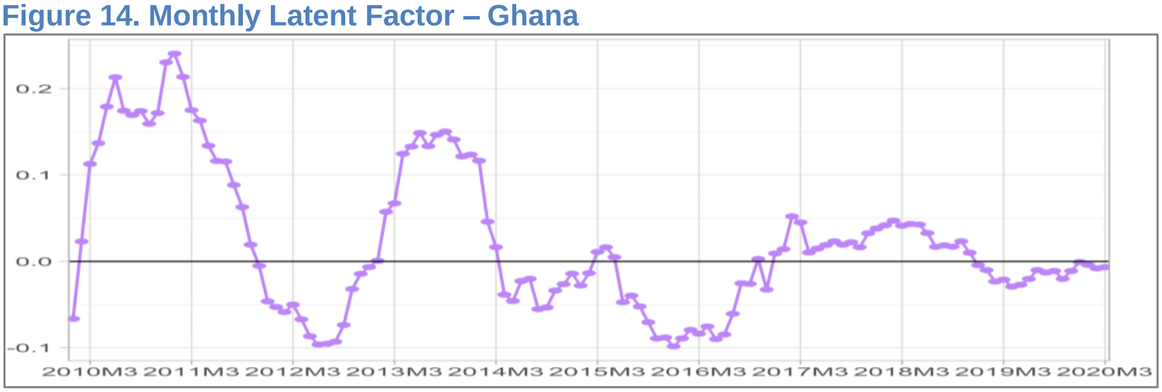


Figure 14. Monthly Latent Factor – Ghana

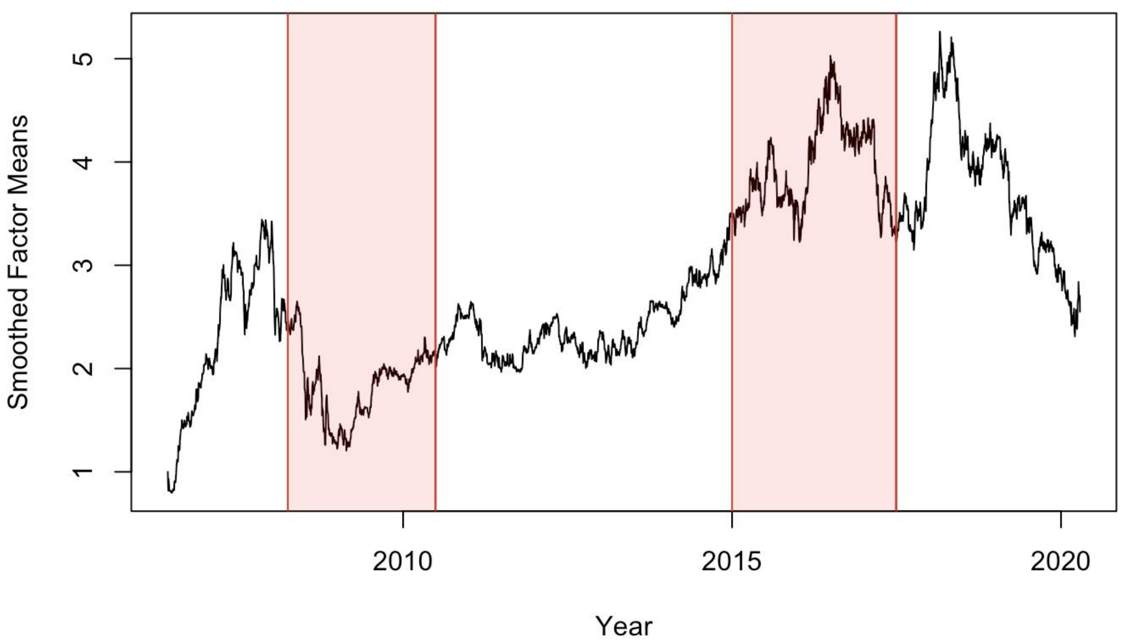


C.2. Kalman Filter Daily Factor

Figure 15 plots the daily latent factor extracted from the preliminary Kalman filtration of the South Africa model. The latent factor is not directly interpretable but is designed to proxy real economic activity by being a linear function of daily stock market performance, monthly vehicle sales, and quarterly real GDP. Thus, decreases in the latent variable is expected to trend with or be an indicator of economic downturns, while increases in the latent variable is expected to correlate with expansionary periods. The figure below shows the strength of this relationship by denoting in red recessionary periods: Q2 2008 through Q2 2010 and Q1 2015 through Q2 2017, as declared by the South African Reserve Bank.

Note that the South Africa Kalman filter daily latent factor is a preliminary result due to limited variables that were able to be incorporated into the daily model and further refinements are needed to assess whether there is robust relationship between movements in the latent factor and changes in real GDP growth. We found that the daily stock market data for South Africa was too volatile for the model to be initialized on.[23] Including additional variables—and particularly high-frequency variables—would have reduced this issue, but greatly increased the runtime of the Kalman filter and maximum-likelihood estimation of the parameters.

Figure 15. Smoothed Means of the Latent Factor for South African Economic Activity



Note: Red bars denote recessionary periods as declared by the South African Reserve Bank: Q2 2008 through Q2 2010 and Q1 2015 through Q2 2017.

Note that the results presented for the Kalman Filter are preliminary results. We recommend three changes for the next iteration of a Kalman model to improve fit and runtime:

[23] The daily stock market data for South Africa begins in 2006, yet the daily series of U.S. Treasury term premia utilized by Aruoba et al. (2009) spans the past several decades. Since optimizing the factor model parameters first required initializing on the daily series, a short daily series makes for exponentially shorter low-frequency series; with fewer observations of all the variables, it becomes more difficult for the latent factor to detect relationships between them. This is further complicated by a potential design error in which we used a highly volatile daily series; Aruoba et al. (2009)'s configuration may have benefitted from the term premium being much slower-moving than stock market valuations.

- First, the variables should be transformed to growth rates so that each time series is relatively stationary
- Second, high–frequency data should be aggregated into weekly or monthly intervals to reduce the runtime of a single filtration.[24]
- Third, we recommend the inclusion of additional variables to improve the factor's explanatory power.

D. Evaluation of Model Performance by Country

D.1. Machine Learning Model Evaluation

To evaluate and compare model performances, this paper uses three different evaluation metrics: a *rolling score,* a *recession score*, and a *cross validation score.*

- **Rolling Score:** This metric measures the model's out of sample performance taking into consideration the time series nature of the data by using a sliding window of fixed size to iteratively determine the training and test sets. To determine the size of the window, S_W, the total number of observations is divided by 4 for a total of 3 iterations. In the first iteration, the model is fit on the first S_W observations and tested on the next S_W observations. In the second iteration, we slide the window over to train the model on the second set of S_W observations and test on the third set of S_W observations. This process is repeated for the third iteration and take the average of the RMSEs over each iteration to calculate the final rolling score.[25]

- **Recession Score:** This metric measures a model's performance during recessions by fitting the model on all data from all non-recessionary periods and calculating the RMSE when testing on recessions. The following periods were designated as "recessions" for the purposes of determining this score for each of the countries modeled:
  - **South Africa:** Q2 2008 through Q2 2010 and Q1 2015 through Q2 2017
  - **Kenya:** Q4 2016 through Q4 2017
  - **Nigeria:** Q3 2015 through Q1 2017

- **Cross Validation Score:** This is a common metric used to evaluate out-of-sample performance by shuffling the data, splitting the dataset into *k* groups, and iteratively holding out one of the *k* groups as the test set while training on the remaining groups. On each iteration, the model is fit on all but one of the *k* groups and tested on the withheld group. The RMSEs from each iteration are averaged to obtain the final cross validation score. We use a standard 5 k-fold iteration, meaning that the data is split into 5 distinct groups.

We find that different ML models perform best across the three metrics for each country. For the three countries assessed, the linear models (Elastic Net, SVR) perform better when predicting recessions, but the tree-based models (Random Forest, XGBoost) perform better when predicting

[24] If it is imperative that the factor be on a daily basis, we recommend using a language that is better than R at matrix calculations (e.g., MATLAB or C).

[25] RMSE is the is the square root of the average prediction error and is calculated as $RMSE = \sqrt{\frac{\sum_{t=1}^{T}(\hat{y}_t - y_t)^2}{T}}$, where $\hat{y}_t$ is the predicted value at time *t.*

non-recessionary periods. This result is in line with the well-known bias variance tradeoff between the expressiveness of a model and over-fitting (see Athey 2018).[26] The tree-based ML models are more flexible than their linear model counterparts and can capture more complex relationships. Since most periods in the training data are non-recessionary, tree-based models in general have better performance in predicting non-recessionary periods. However, tree-based models display overfitting due to higher variance and therefore underperform in predicting the less frequent recession events. Linear ML models, on the other hand, exhibit lower variance and lower bias because of their simpler functional form, and thus out-perform in predicting recessions.[27] The best performing ML models for each country are:

- **South Africa:** SVR, Voting Regression
- **Kenya:** Elastic Net, Random Forest
- **Nigeria:** Random Forest, XGBoost

In the model performance comparison tables below for South Africa, Kenya, and Nigeria (Table 10 to Table 12), we present the quarterly GDP predictions for two quarters and the evaluation metrics for the respective test periods (Table 5).[28] For comparison, we also present the results of an ordinary least squares (OLS) regression fit on the variables used by the IMF's preliminary nowcast model for the weighted average SSA regional GDP.[29] We find that the other five machine learning models significantly outperform the OLS regression on almost all of the evaluation metrics across the three countries. This result is in line with other studies that have found non-parametric machine learning models can outperform traditional parametric methods such as OLS, AR, and ARMA by capturing nonlinearities in macroeconomic variables, though note that non-linearities are more useful for predictions over a longer horizon in data-rich environments.[30]

Table 10. ML Model Performance Comparison – South Africa

SOUTH AFRICA		**Predictions** (Quarterly GDP, YoY%)		**Pseudo Out of Sample RMSE**		
#	**Model**	***Q4 2019*** ***Actual: -0.57%***	***Q12020***	***Rolling***	***Recessions***	***Cross Validation***
Baseline						
0	OLS	*1.17%*	*-*	*1.03*	*N/A*[31]	*2.79*
Machine Learning						

[26] Susan Athey, 2018. "The Impact of Machine Learning on Economics," NBER Chapters, in: The Economics of Artificial Intelligence: An Agenda, pages 507-547, National Bureau of Economic Research, Inc. https://ideas.repec.org/h/nbr/nberch/14009.html.
[27] The relative performance of linear vs. tree-based ML models is not intended to suggest one type of ML model is necessarily superior. Predicting "outlier" or "rare" events such as recessions is difficult and model selection depends on the intended purpose. For instance, if the goal is to maximize the accuracy of nowcasting during "normal" times, we find that tree-based models are in general better suited; however, if the goal is to be able to accurately predict GDP change during times of economic crisis, linear ML models are valuable.
[28] Predictions are presented for two quarters given the focus is on nowcasting rather than forecasting; "Pseudo out of sample" references the fact that the evaluation metrics are assessing the ML model predictions against actual values.
[29] These variables are REER, Oil price, ZAF PMI, ZAF BCI, ZAF stock, NGA PMIN, NGA PMIM, GHA stock, KEN stock, and UGA stock. All variables are at a monthly frequency and have no missing values.
[30] Philippe Goulet Coulombe et al., "How Is Machine Learning Useful for Macroeconomic Forecasting?," ArXiv:2008.12477, 2020, http://arxiv.org/abs/2008.12477.
[31] As the South Africa OLS model only covers years from 2011 onward but the other models cover years from 2007 onward and spans the 2008-2009 recession, we are not able to conduct a comparable recession test.

1	ElasticNet	0.10%	-0.34%	1.57	1.65	1.11
2	SVR	0.24%	0.22%	1.39	1.54	1.19
3	Random Forest	-0.21%	0.18%	0.96	1.98	1.10
4	XGBoost	-0.56%	0.60%	1.24	1.63	1.03
5	Voting Regression	-0.09%	0.15%	1.06	1.63	0.97

Note: Highlighting denotes models with the lowest RMSE for each of the three evaluation metrics and the model with most accurate GDP prediction for 2019Q4 (compared to actual).

Table 11. ML Model Performance Comparison – Kenya

KENYA		Predictions (Quarterly GDP, YoY%)		Pseudo Out of Sample RMSE		
#	**Model**	***Q4 2019***	***Q12020***	***Rolling***	***Recessions***	***Cross Validation***
Baseline						
0	OLS	*-0.94%*	*-*	*2.66*	*4.37*	*2.97*
Machine Learning						
1	ElasticNet	5.13%	5.70%	1.13	1.04	1.44
2	SVR	5.30%	5.45%	1.01	0.85	1.08
3	Random Forest	5.55%	5.73%	0.67	0.89	0.82
4	XGBoost	5.36%	5.95%	0.84	0.75	0.80
5	Voting Regression	5.34%	5.70%	0.75	0.86	0.97

Note: Highlighting denotes models with the lowest RMSE for each of the three evaluation metrics.

Table 12. ML Model Performance Comparison – Nigeria

NIGERIA		Predictions (Quarterly GDP, YoY%)		Pseudo Out of Sample RMSE		
#	**Model**	***Q4 2019 Actual: 2.37%***	***Q12020***	***Rolling***	***Recessions***	***Cross Validation***
Baseline						
0	OLS	*1.02%*	*-*	*2.00*	*1.97*	*2.71*
Machine Learning						
1	ElasticNet	1.92%	0.67%	1.10	1.37	0.83
2	SVR	1.59%	1.15%	0.92	1.13	1.02
3	Random Forest	2.29%	2.05%	0.77	1.24	0.79
4	XGBoost	2.37%	1.81%	0.87	1.06	0.96
5	Voting Regression	2.04%	1.41%	0.84	1.18	0.79

Note: Highlighting denotes models with the lowest RMSE for each of the three evaluation metrics and the model with most accurate GDP prediction for 2019Q4 (compared to actual).

D.2. Parametric Factor Model Evaluation

In the evaluation of the three-pass regression models, we use the pseudo out–of–sample RMSE produced in the specified test periods. To understand how well the factor models fit the actual GDP data, the RMSEs are then compared against those obtained from fitting an AR(1) or ARMA(1,1) model of GDP over the same estimation and test periods. Table 13 through Table 15 summarize the parametric model performance for Uganda, Kenya, and Ghana.

We find that the three-pass regression factor models have a high degree of prediction accuracy for all three countries, given the data limitation challenges, with the predictions improving in accuracy for more recent periods when data availability is higher. The narrowing of the 95% confidence interval over time (e.g., Uganda and Ghana predictions) is encouraging evidence of the predictive potential of the factor model method. While each country model's pseudo out of sample RMSEs are similar to or higher than the baseline comparison, the low RMSE for the baseline ARMA model is expected given GDP growth has decreased in volatility over time for all three countries and the persistence of GDP growth over time; however, the ARMA model is less useful for the purposes of nowcasting economic activity during times of crisis when historical persistence is not an appropriate guide.

The factor model prediction result for Kenya is particularly notable given that the Kenya ML models had relatively lower performance, despite having the greatest number of country-specific variables. Our results indicate that the three-pass regression filter parametric method has potential for nowcasting (and forecasting) countries with either higher volatility in GDP and/or countries with more limited data availability and shorter time horizons.

Table 13. Parametric Factor Model Performance Comparison – Uganda

UGANDA		**Predictions (Quarterly GDP, YoY%)**		**Pseudo Out of Sample RMSE**
#	**Model**	***Q4 2019 Actual: 5.43%***	***Q12020***	
Baseline				
0	ARMA(1,1) (95% Confidence Interval)	4.72% (–1.48%, 10.93%)	4.96% (–1.48%, 11.41%)	1.14pp
Parametric Factor Model				
1	Three-Pass Regression (95% Confidence Interval)	3.41% (–0.02%, 7.00%)	5.71% (3.07%, 8.35%)	1.27pp

Table 14. Parametric Factor Model Performance Comparison – Kenya

KENYA		**Predictions (Quarterly GDP, YoY%)**		**Pseudo Out of Sample RMSE**
#	**Model**	***Q4 2019***	***Q12020***	
Baseline				
0	ARMA(1,1) (95% Confidence Interval)	5.46% (4.36%, 6.56%)	5.48% (4.37%, 6.58%)	0.47pp

Parametric Factor Model				
1	Three-Pass Regression (95% Confidence Interval)	5.17% (4.97%, 5.37%)	5.81% (5.61%, 6.01%)	0.21pp

Table 15. Parametric Model Performance Comparison – Ghana

GHANA		**Predictions (Quarterly GDP, YoY%)**		**Pseudo Out of Sample RMSE**
#	**Model**	***Q4 2019***	***Q12020***	
Baseline				
0	ARMA(1,1) (95% Confidence Interval)	6.40% (0.36%, 12.44%)	6.49% (0.03%, 12.94%)	0.55pp
Parametric Factor Model				
1	Three-Pass Regression (95% Confidence Interval)	5.57% (3.70%, 7.44%)	5.95% (4.50%, 7.40%)	0.97pp

E. Discussion of Model Variable Importance

E.1. Machine Learning Model Variable Importance

To aid in the interpretation of the models presented in this report, as well as in the prioritization of data collection by the fund, rankings of variable importance (i.e., feature importance) for the top two ML models for each country (determined by the cross validation RMSE score) are included. **All variables in Table 16 through**

Table 18 refer to the variable corresponding to the country under which it is listed. The letter in the parentheses refers to the frequency of the variable ("q" for quarterly, "m" for monthly, and "d" for daily), and the number in the parentheses refer to which skip-sampled time series the variable corresponds to (i.e. m1 refers to the time series with the data from the first month of each quarter). For the ElasticNet and Support Vector Regressions, rankings are determined using the absolute value of the coefficients assigned by the model. For the Random Forest and XGBoost regressions, the rankings are determined using the *Gini Importance* or Mean Decrease in Impurity (MDI) assigned by the model. For the graphical presentation of variable importance for the top two ML models for each country, see Appendix II.

We find that many of the Google Search Trends variables that form a novel dataset created specifically for this nowcast project and mobile payment data (Kenya only) were ranked as high importance in the top two ML models across all three countries (highlighted in blue in the tables below). Because of the skip-sampling method used for the ML models, the variable importance tables also highlight potential leading or lagging indicator relationships.

Table 16. Most important variables in top performing South Africa ML models

Ranking	Random Forest Regression	XGBoost Regression
1	Autoregression 1 (q1)	Autoregression 1 (q1)
2	USDZAR Spot Exchange Rate – Price of 1 USD in ZAR (d3)	South Africa export to world (m1)
3	USDZAR Spot Exchange Rate – Price of 1 USD in ZAR (d4)	USDZAR Spot Exchange Rate – Price of 1 USD in ZAR (d1)
4	South Africa import from world (m3)	USDZAR Spot Exchange Rate – Price of 1 USD in ZAR (d6)
5	USDZAR Spot Exchange Rate – Price of 1 USD in ZAR (d2)	Industrial Production (m2)
6	South Africa import from world (m1)	South Africa import from world (m3)
7	USDZAR Spot Exchange Rate – Price of 1 USD in ZAR (d6)	Google Search Trends – “money” (m3)
8	USDZAR Spot Exchange Rate – Price of 1 USD in ZAR (d1)	Google Search Trends – “mobile money” (m1)
9	South Africa export to world (m1)	Google Search Trends – “ewallet” (m2)
10	Lagged SA Business Confidence (q)	USDZAR Spot Exchange Rate – Price of 1 USD in ZAR (d2)
11	South Africa export to world (m2)	SA Business Confidence (q)
12	Industrial Production (m1)	Google Search Trends – “mobile money” (m2)
13	SA Business Confidence (q)	South Africa import from world (m2)
14	Google Search Trends – “money” (m3)	Industrial Production (m1)
15	Industrial Production (m2)	Google Search Trends – “airtime” (m2)
16	South Africa import from world (m2)	USDZAR Spot Exchange Rate – Price of 1 USD in ZAR (d4)
17	Lagged Vehicle Sales (m2)	South Africa export to world (m2)
18	Lagged Vehicle Sales (m1)	South Africa import from world (m1)
19	Industrial Production (m3)	Bankruptcies (m1)
20	Private Sector Credit (m1)	Retail Sales, MoM (m3)

Table 17. Most important variables in top performing Nigeria ML models

Ranking	Random Forest Regression	XGBoost Regression
1	USDNGN Spot Exchange Rate – Price of 1 USD in NGN (d1)	USDNGN Spot Exchange Rate – Price of 1 USD in NGN (d1)
2	USDNGN Spot Exchange Rate – Price of 1 USD in NGN (d2)	Autoregression 1 (q1)
3	USDNGN Spot Exchange Rate – Price of 1 USD in NGN (d3)	Nigeria Business Confidence (m3)
4	USDNGN Spot Exchange Rate – Price of 1 USD in NGN (d6)	NigeriaUE (q)
5	Nigeria Business Confidence (m3)	ACCESS BANK PLC (d1)
6	Nigeria Inflation (m3)	Nigeria export to world (m1)
7	Autoregression 1 (q1)	ACCESS BANK PLC (d3)
8	USDNGN Spot Exchange Rate – Price of 1 USD in NGN (d4)	Nigeria Inflation (m3)
9	USDNGN Spot Exchange Rate – Price of 1 USD in NGN (d5)	Google Search Trends – “cash” (m2)
10	Nigeria Inflation (m3)	Nigeria export to world (m3)
11	NigeriaUE (q)	Nigeria import from world (m3)

12	NigeriaConsConfidence (q)	Google Search Trends – “737” (m1)
13	Nigeria Inflation (m1)	NigeriaConsConfidence (q)
14	ZENITH BANK PLC (d3)	Google Search Trends – “ego” (m1)
15	ZENITH BANK PLC (d2)	Nigeria Inflation (m1)
16	Nigeria Interest Rate (m2)	Google Search Trends – “money” (m3)
17	ACCESS BANK PLC (d2)	Nigeria Interest Rate (m1)
18	ACCESS BANK PLC (d1)	Google Search Trends – “cash” (m1)
19	Nigeria export to world (m2)	Nigeria import from world (m1)
20	ACCESS BANK PLC (d3)	USDNGN Spot Exchange Rate – Price of 1 USD in NGN (d4)

Table 18. Most important variables in top performing Kenya ML models

Ranking	Random Forest Regression	XGBoost Regression
1	Inflation (m1)	(Number of Transactions) Pos Machines (m2)
2	Computed variable – Payments Volume growth MoM (m2)	Inflation (m1)
3	Interbank Rate (m1)	Agents (m1)
4	(Value of Transactions) Change Cards (m2)	(Number of Transactions) Debit Cards (m2)
5	Computed variable – Transactions per account (m2)	(Foreign Trade Summary) Trade Balance (m3)
6	Computed variable – Accounts (original in millions) (m3)	Kenya Interest Rate (m3)
7	(Number of Transactions) Change Cards (m2)	Kenya import from world (m3)
8	Autoregression 1 (q)	(Cheques EFTS) Debit Values (m1)
9	Kenya import from world (m3)	(Number of Transactions) Change Cards (m3)
10	(Value of Transactions) Pos Machines (m3)	Computed variable – Accounts (original in millions) (m3)
11	Computed variable – Transactions per account (m3)	(Cheques EFTS) Credit Values (m2)
12	(Cheques EFTS) Debit Values (m2)	(Foreign Trade Summary) Domestic FOB (m2)
13	(Number of Transactions) CreditCards (m3)	(Value of Transactions) Credit Cards (m3)
14	(Number of Transactions) Change Cards (m1)	Computed variable – Average transaction size (m3)
15	Computed variable – Payments volume per account growth MoM (m3)	Computed variable – Payments Volume growth MoM (m2)
16	(Foreign Trade Summary) Trade Balance (m1)	(Cheques EFTS) Debit Volumes (m1)
17	(Number of Transactions) Credit Cards (m2)	(Cheques EFTS) Credit Volumes (m1)
18	Computed variable – Transaction growth MoM (m2)	(Number of Transactions) Change Cards (m1)
19	(Number of Transactions) Debit Cards (m3)	(Value of Transactions) Debit Cards (m2)
20	Computed variable – Accounts (original in millions) (m2)	(Value of Transactions) Prepaid Cards (m1)

E.2. Factor Model Variable Importance

The tables below summarize the three-pass regression factor model variable coefficients and statistical significance for Uganda, Kenya, and Ghana, ordered by magnitude of coefficient estimate. All three country models selected trade variables such as imports and exports, with many of the commodity-specific indicators for Uganda being significant. Inflation or money supply indicators were statistically significant at the 99% level for both Uganda and Kenya and financial equity prices for Equity Bank (one of the largest private banks in the region) was selected through the three-pass method for both Uganda and Ghana. Additional supplemental figures for Factor Model results can be found in Appendix II.

Table 19. Factor Model Variable Importance – Uganda

No.	Variable Name	Variable Descriptions	Frequency	Coefficient (Std. Error)	P-value
1	uga_ushloans_m	Private Sector Credit – USh	Monthly	13.348 (7.037)	0.074
2	uga_ushdeposits_m	Private Sector Deposits – USh	Monthly	-9.42 (5.529)	0.101
3	uga_cementexports_m	Trade – Exports – Cement	Monthly	-4.955 (3.463)	0.165
4	uga_maizeexports_m	Trade – Exports – Maize	Monthly	4.577 (3.84)	0.245
5	uga_oilimports_m	Trade – Imports – Oil (Private)	Monthly	2.801 (1.364)	0.051
6	uga_nonoilimports_m	Trade – Imports – Non-Oil (Private)	Monthly	1.97 (0.83)	0.026
7	uga_equitysb_d	Financial – Equity Price	Daily	1.489 (0.93)	0.122
8	uga_wholesaleindex_m	Business Indicator – Wholesale Trade	Monthly	-1.26 (0.362)	0.002
9	uga_agindex_m	Business Indicator – Agriculture	Monthly	-0.753 (0.554)	0.186
10	uga_buscon_m	Business Confidence	Monthly	-0.624 (0.297)	0.047
11	uga_bizindex_m	Business Indicator – Overall	Monthly	-0.618 (0.297)	0.048
12	uga_m3_m	Money Supply M3	Monthly	0.594 (0.133)	<0.001
13	uga_contrindex_m	Business Indicator – Construction	Monthly	-0.484 (0.42)	0.26
14	uga_taxrev_m	Tax Revenue	Monthly	0.377 (0.314)	0.241
15	uga_gdp_q	Real GDP	Quarterly		

Table 20. Factor Model Variable Importance – Kenya

No.	Variable Name	Variable Descriptions	Frequency	Coefficient (Std. Error)	P-value
1	ken_inflat_m	Inflation Rate	Monthly	-45.996 (11.502)	0.001
2	ken_expnum_d	Exports – Number of Ships Daily	Daily	-31.292 (7.365)	0.001
3	ken_expmtc_d	Exports – Ship Load Daily	Daily	-31.038 (12.82)	0.032
4	ken_impmtc_d	Imports – Ship Load Daily	Daily	-10.218 (4.162)	0.03
5	ken_impdwt_d	Imports – Ship Design Capacity Daily	Daily	-9.059 (3.387)	0.02
6	ken_10yrbd_d	10 Year Bond Yield	Daily	2.584 (1.01)	0.038
7	ken_gdp_q	Real GDP	Quarterly		

Table 21. Factor Model Variable Importance – Ghana

No.	Variable Name	Variable Descriptions	Frequency	Coefficient (Std. Error)	P-value
1	gha_smi_d	Financial - Stock Market	Daily	14.029 (13.393)	0.325
2	gha_equitygcb_d	Financial - Equity Price	Daily	4.11 (1.847)	0.032
3	gha_intrst_m	Interest Rate	Monthly	-2.676 (0.622)	<0.001
4	gha_expdwt_d	Exports - Ship Design Capacity Daily	Daily	2.337 (1.869)	0.235
5	gha_impdwt_d	Imports - Ship Design Capacity Daily	Daily	-2.078 (1.726)	0.252
6	gha_spotrate_d	Spot Exchange Rate	Daily	-1.013 (0.494)	0.048
7	gha_gdp_q	Real GDP	Quarterly		

V. Conclusion

Summary of contributions and key results

During a time of distress, access to accurate, timely information of on-the-ground economic conditions is vital to enable data-driven policy responses. This paper presents a set of statistical modellingand other economic indicator tracker tools that improve nowcasting and short-term forecasting of economic activity in Sub-Saharan Africa. We develop and implement two types of predictive models, machine learning and parametric factor models, to nowcast quarterly GDP for countries in SSA. Our implementation of the two sets of nowcasting techniques is uniquely tailored for policy usability, with the ability to incorporate mixed-frequency data variables together and to accommodate differing source data update timeframes; our modelling approach enables maximum flexibility to generate nowcast predictions using a variety of high-frequency data (from daily up to monthly) and continuous improve the nowcast of quarterly GDP throughout the quarter, as updated source data becomes readily available.

The two modelling approaches can be used in complement as part of an expanded set of prediction tools to nowcast GDP in other countries in SSA or other emerging market / developing countries that face similar data availability constraints. We argue that the three-pass regression factor model is particularly well suited to be generalizable to other SSA countries with limited data over shorter time horizons as it is parsimonious and built on a foundation of OLS regressions.

We show that alternative data such as shipping data, mobile payments, and Google Search Trends can be useful high-frequency predictors of GDP in nowcast models, outweighing traditional macroeconomic variables in terms of variable importance (i.e., feature importance) in the machine learning models. The Google Search Trends data is a novel dataset generated based on economy-related vernacular phrases in local languages, which demonstrates the importance of incorporating local context in nowcasting models.

Areas for future work

Future research can expand the set of nowcast prediction models presented in this paper to other countries in SSA and beyond through two complimentary modelling approaches—Machine Learning and parametric Factor Models—that are flexible enough to accommodate for varying data frequency and data availability contexts. There are several areas for future exploration outlined below.

For machine learning models, further feature engineering can include cross-country variables (e.g., Nigeria PMI for other SSA countries) or interaction terms using the expanded dataset we have assembled. Iterating on additional machine learning methods such as recurrent neural network (RNN) and Long Short-Term Memory (LSTM), which are suitable for time series predictions, may further improve prediction accuracy. The variable importance (i.e., feature importance) findings from the Machine Learning models can also guide variable selection to develop more parsimonious country-level Factor Models. The parametric Factor Models may be useful for many countries in SSA with more limited data availability, given that it is more suitable to handling fewer variables and shorter time horizons than Machine Learning regression methods that are reliant on large quantities of data.

Another avenue of future work is to run both sets of modelling approaches together across all countries to compare the nowcasting performance under different scenarios (similar to what we have performed with South Africa). Given vector autoregressions (VARs) are common tools used among central banks in the SSA, the nowcast methods presented in this paper can be compared to a benchmark Bayesian vector autoregression (B-VAR) with shrinkage; doing so will further demonstrate how a combination of different methods can improve the prediction performance for different countries.

Further investigation into appropriate estimation of values for missing variables (e.g., simple mean or mode, k nearest neighbor) may improve prediction performance for the three-pass regression method. Additional refinements to the Kalman filtration to develop a daily or weekly high frequency latent factor that is correlated with GDP change would improve the latent factor's usability and help build a leading economic indicator for quarterly GDP.

Adding relevant, monthly (or higher) frequency variables will likely yield more accurate nowcast models. For instance, incorporating monthly mobile payments data from other central banks in the region in addition to Kenya may improve the GDP nowcasts and forecasts in SSA countries, particularly using the factor model method. Given the promising results we showed with Google Trends search terms, future refinements to identify additional relevant search words may improve model predictions as well.

Finally, future work can include additional visualizations of nowcasts to aid policymaking, such as computation of density nowcasts, generation of predictive distributions (e.g., alternative future sample paths) for GDP growth point estimates, and further decomposition of how different data categories contribute to the nowcast outcome.

Appendix I. Machine Learning Model Supplemental Materials

Table 22. Machine Learning Model Variable List for South Africa

Country	No.	Variable Name	Variable Descriptions	Unit	Frequency
Nigeria	1	nga_concon_q	Consumer Confidence	Points (net percentage share of respondents answering positively vs. negatively)	Quarterly
South Africa	2	zaf_bnkrp_m	Bankruptcies	# of Companies	Monthly
	3	zaf_buscon_q	Business Confidence	Points	Quarterly
	4	zaf_chainv_q	Inventory	ZAR Million	Quarterly
	5	zaf_concon_q	Consumer Confidence	Points	Quarterly
	6	zaf_equitysbk_d	Financial - Equity price	zaf	Daily
	7	zaf_gglai_m	Google Search Trends - airtime	Relative to highest level	Monthly
	8	zaf_gglem_m	Google Search Trends - employment	Relative to highest level	Monthly
	9	zaf_gglew_m	Google Search Trends - ewallet	Relative to highest level	Monthly
	10	zaf_ggljo_m	Google Search Trends - job	Relative to highest level	Monthly
	11	zaf_gglmob_m	Google Search Trends - mobile money	Relative to highest level	Monthly
	12	zaf_gglmon_m	Google Search Trends - money	Relative to highest level	Monthly
	13	zaf_indpro_m	Industrial Production	% (YoY)	Monthly
	14	zaf_inflat_m	Inflation Rate	% (YoY)	Monthly
	15	zaf_lei_m	Leading Economic Index	% (month over month)	Monthly
	16	zaf_nexport_m	Trade - Exports	Nominal exports (USD)	Monthly
	17	zaf_nimport_m	Trade - Imports	Nominal imports (USD)	Monthly
	18	zaf_psc_m	Private Sector Credit	ZAR Million	Monthly
	19	zaf_retail_m	Retail	% (month over month)	Monthly
	20	zaf_spotrate_d	Exchange Rate (Spot)	1 USD/ZAR	Daily
	21	zaf_unemp_q	Unemployment Rate	% (People looking for a job/ tot labor force)	Quarterly
	22	zaf_vehic_m	Vehicle Sales	Total number of vehicles sold	Monthly

Table 23. Machine Learning Model Variable List for Nigeria

Country	No.	Variable Name	Variable Descriptions	Unit	Frequency
Nigeria	1	nga_buscon_m	Business Confidence	Points	Monthly
Nigeria	2	nga_concon_q	Consumer Confidence	Points (net percentage share of respondents answering positively vs. negatively)	Quarterly
Nigeria	3	nga_equityaccess_d	Financial - Equity price	ngn	Daily
Nigeria	4	nga_equityzen_d	Financial - Equity price	ngn	Daily
Nigeria	5	nga_spotrate_d	Exchange Rate (Spot)	1 USD/NGN	Daily
Nigeria	6	nga_gdp_q	GDP	Local currency unit	Quarterly
Nigeria	7	nga_ggleg_m	Google Search Trends - ego	Relative to highest level	Monthly
Nigeria	8	nga_gglca_m	Google Search Trends - cash	Relative to highest level	Monthly
Nigeria	9	nga_gglmo_m	Google Search Trends - money	Relative to highest level	Monthly

Nigeria	10	nga_gglwo_m	Google Search Trends - work	Relative to highest level	Monthly
Nigeria	11	nga_ggl73_m	Google Search Trends - 737	Relative to highest level	Monthly
Nigeria	12	nga_inflat_m	Inflation Rate	% (YoY)	Monthly
Nigeria	13	nga_unemp_q	Unemployment Rate	% (People looking for a job/ tot labor force, QoQ)	Quarterly
Nigeria	14	nga_nexport_m	Trade - Exports	Nominal exports (USD)	Monthly
Nigeria	15	nga_nimport_m	Trade - Imports	Nominal imports (USD)	Monthly

Table 24. Machine Learning Model Variable List for Kenya

Country	No.	Variable Name	Variable Descriptions	Unit	Frequency
Kenya	1	ken_eftscredval_m	Check EFTs	Kshs Billions	Monthly
Kenya	2	ken_eftscredvol_m	Check EFTs	Number of Credit Volumes	Monthly
Kenya	3	ken_eftsdebval_m	Check EFTs	Kshs Billions	Monthly
Kenya	4	ken_eftsdebvol_m	Check EFTs	Number of Debit Volumes	Monthly
Kenya	5	ken_spotrate_d	Exchange Rate (Spot)	1 USD/KES	Daily
Kenya	6	ken_gdp_q	GDP	Local currency unit	Quarterly
Kenya	7	ken_gglch_m	Google Search Trends - cheddar	Relative to highest level	Monthly
Kenya	8	ken_ggldo_m	Google Search Trends - dough	Relative to highest level	Monthly
Kenya	9	ken_gglmt_m	Google Search Trends - MTN	Relative to highest level	Monthly
Kenya	10	ken_inflat_m	Inflation Rate	% (YoY)	Monthly
Kenya	11	ken_intrbk_m	Interbank - Rate	% (Month over previous Month)	Monthly
Kenya	12	ken_intrst_m	Interest Rate	% (percentage of interest rate)	Monthly
Kenya	13	ken_mpagents_m	Mobile payments	Level - Number of agents	Monthly
Kenya	14	ken_mpaccounts_m	Mobile payments	Level - Number of accounts	Monthly
Kenya	15	ken_mptxns_m	Mobile payments	Level - Number of transactions	Monthly
Kenya	16	ken_mpvalue_m	Mobile payments	Level - Ksh	Monthly
Kenya	17	ken_mpavgtxnsz_m	Mobile payments	Ratio - Ksh per transaction	Monthly
Kenya	18	ken_mpvolacct_m	Mobile payments	Ratio - Ksh per account	Monthly
Kenya	19	ken_mpvolagent_m	Mobile payments	Ratio - Ksh per agent	Monthly
Kenya	20	ken_mptxnperacct_m	Mobile payments	Ratio - Transactions per account	Monthly
Kenya	21	ken_mptxnMOM_m	Mobile payments	Percent Change - MoM % Change in Transactions	Monthly
Kenya	22	ken_mpvolMOM_m	Mobile payments	Percent Change - MoM % Change in Payments Volume	Monthly
Kenya	23	ken_mpagentsMOM_m	Mobile payments	Percent Change - MoM % Change in Agents	Monthly
Kenya	24	ken_mpvolacctMOM_m	Mobile payments	Percent Change - MoM % Change in Payments Volume per Agent	Monthly
Kenya	25	ken_gaspr_m	Oil / Gas	USD/Liter	Monthly

Kenya	26	ken_numtranschange_m	Payment card transactions - Change Card Txn	# of transactions by change cards	Monthly
Kenya	27	ken_valtranschange_m	Payment card transactions - Change Card Value	Kshs Millions	Monthly
Kenya	28	ken_numtranscredit_m	Payment card transactions - Credit Card Txn	# of transactions by credit cards	Monthly
Kenya	29	ken_valtranscredit_m	Payment card transactions - Credit Card Value	Kshs Millions	Monthly
Kenya	30	ken_numtransdebit_m	Payment card transactions - Debit Card Txn	# of transactions by debit cards	Monthly
Kenya	31	ken_valtransdebit_m	Payment card transactions - Debit Card Value	Kshs Millions	Monthly
Kenya	32	ken_numtranspos_m	Payment card transactions - POS Machine Txn	# of transactions by pos machines	Monthly
Kenya	33	ken_valtranspos_m	Payment card transactions - POS Machine Value	Kshs Millions	Monthly
Kenya	34	ken_numtransprepaid_m	Payment card transactions - Prepaid Card Txn	# of transactions by prepaid cards	Monthly
Kenya	35	ken_valtransprepaid_m	Payment card transactions - Prepaid Card Value	Kshs Millions	Monthly
Kenya	36	ken_numtranstot_m	Payment card transactions - Total Txn	# of transactions total	Monthly
Kenya	37	ken_valtranstot_m	Payment card transactions - Total Value	Kshs Millions	Monthly
Kenya	38	ken_pmi_m	PMI	Index	Monthly
Kenya	39	ken_ftscomimp_m	Trade - Commercial Imports	Ksh Million	Monthly
Kenya	40	ken_ftsdomfob_m	Trade - Domestic FOB	Ksh Million	Monthly
Kenya	41	ken_nexport_m	Trade - Exports	Nominal exports (USD)	Monthly
Kenya	42	ken_ftstot_m	Trade - Foreign Trade Total	Ksh Million	Monthly
Kenya	43	ken_ftsgvtimp_m	Trade - Government Imports	Ksh Million	Monthly
Kenya	44	ken_nimport_m	Trade - Imports	Nominal imports (USD)	Monthly
Kenya	45	ken_ftsexp_m	Trade - Re-exports	Ksh Million	Monthly
Kenya	46	ken_ftstotfob_m	Trade - Total FOB	Ksh Million	Monthly
Kenya	47	ken_ftstb_m	Trade - Trade Balance	Ksh Million	Monthly

South Africa

Figure 16. Top 20 most important variables for South Africa random forest regression

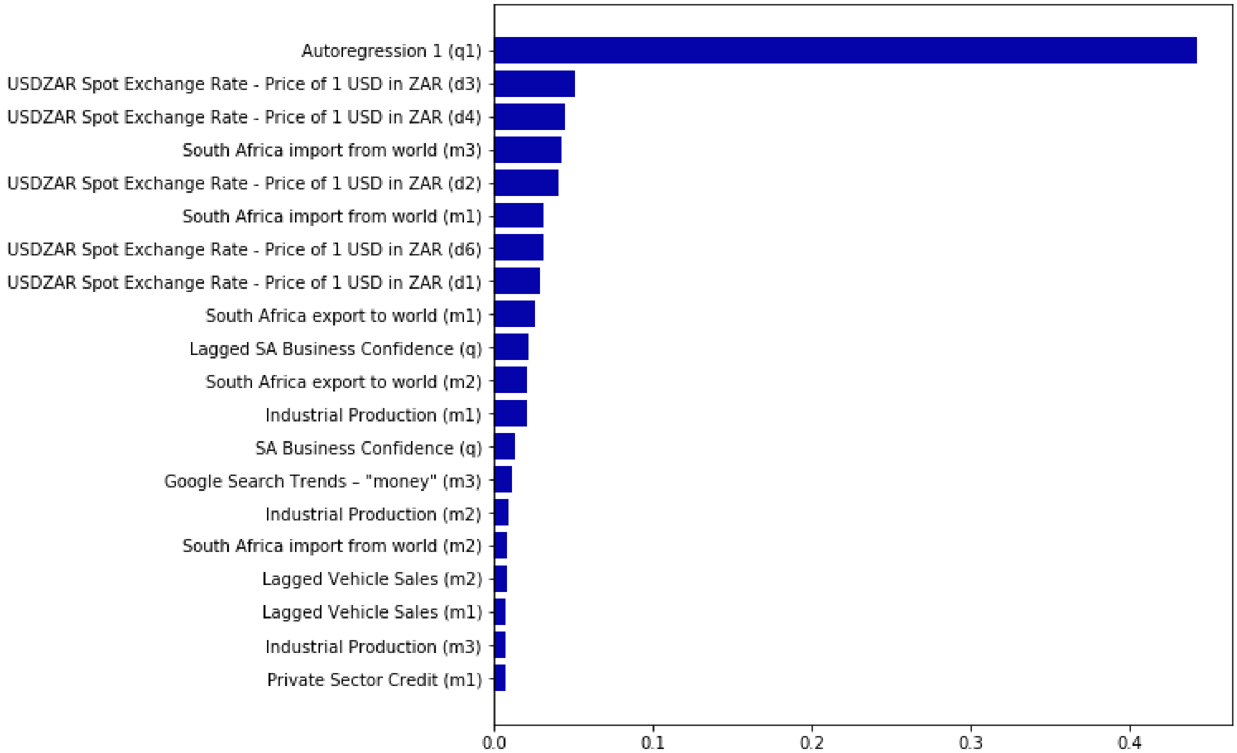
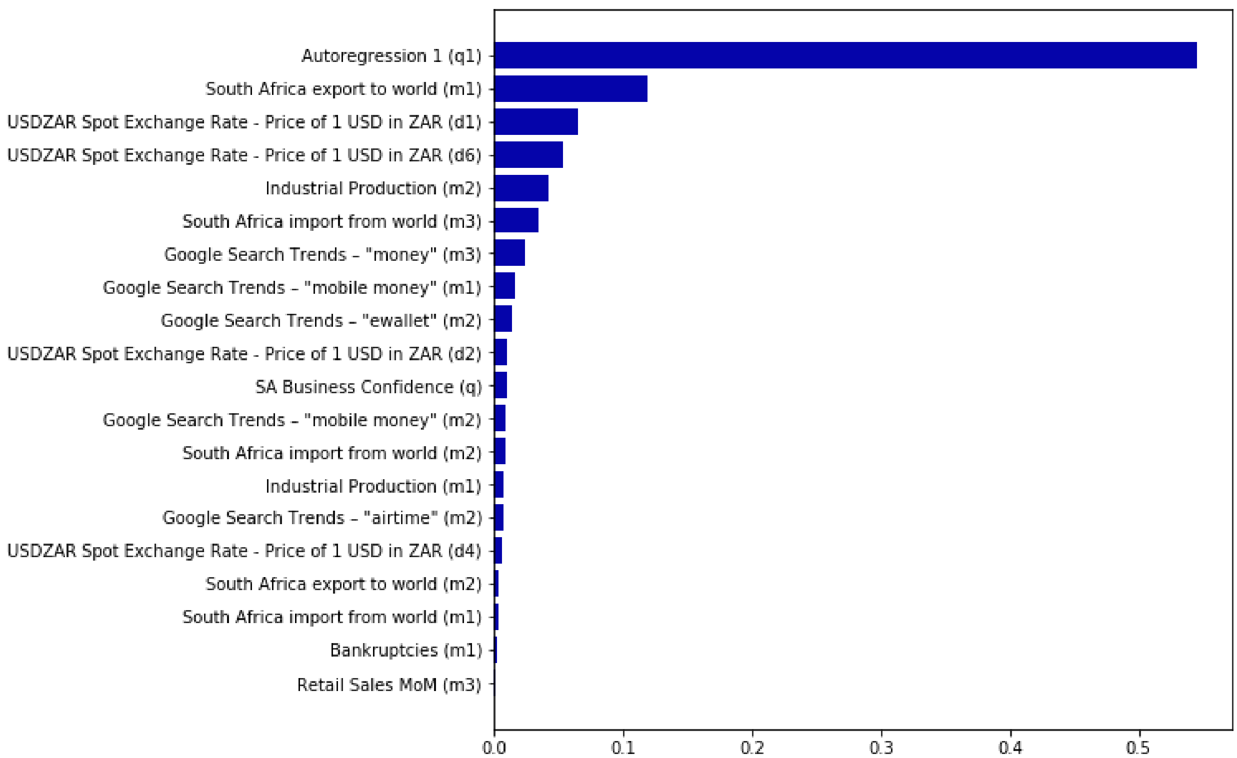


Figure 17. Top 20 coefficients with highest absolute value for South Africa XGBoost regression



Nigeria

Figure 18. Top 20 most important variables for Nigeria random forest regression

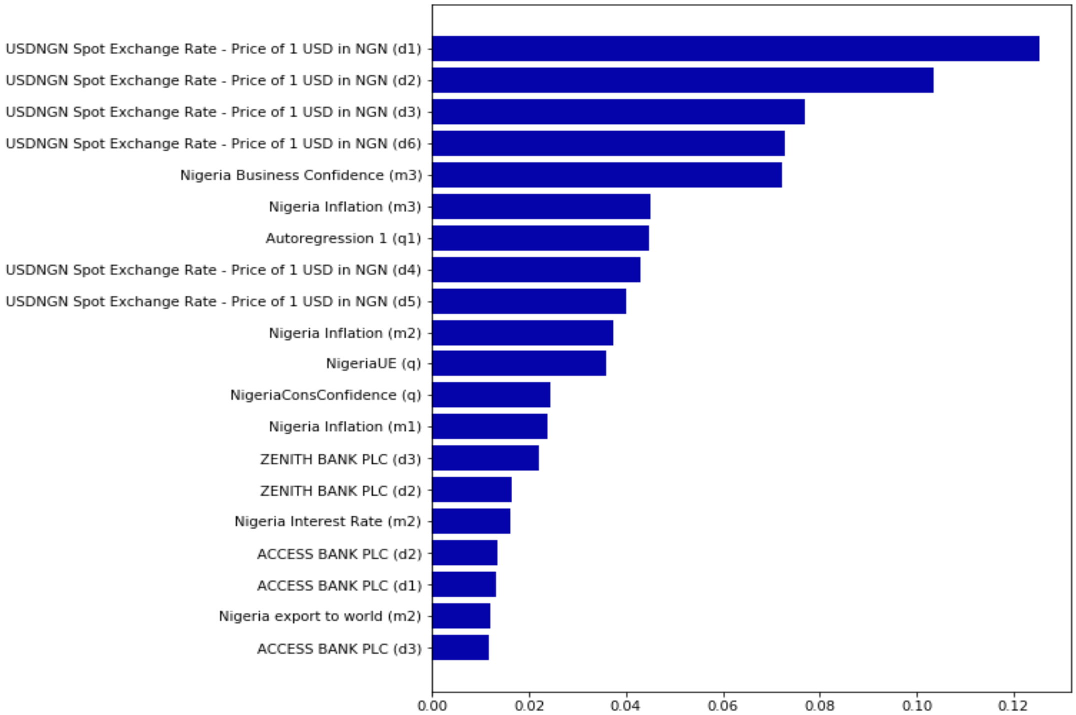
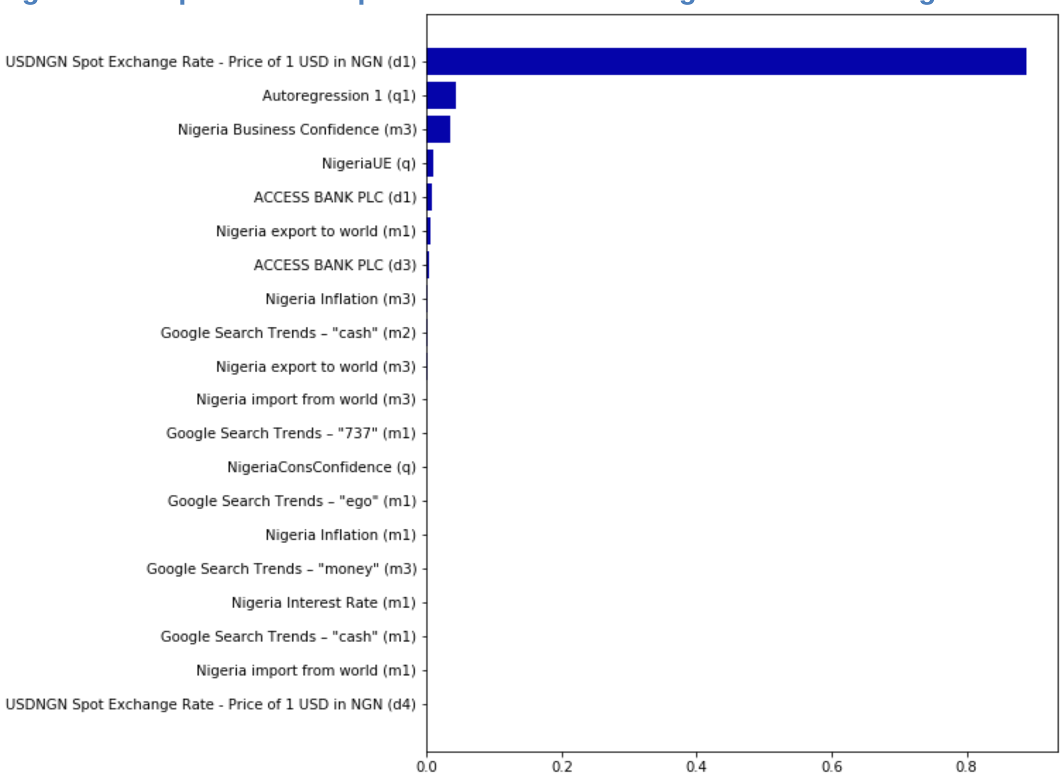


Figure 19. Top 20 most important variables for Nigeria XGBoost regression



Kenya

Figure 20. All non-zero coefficients for Kenya XGBoost regression

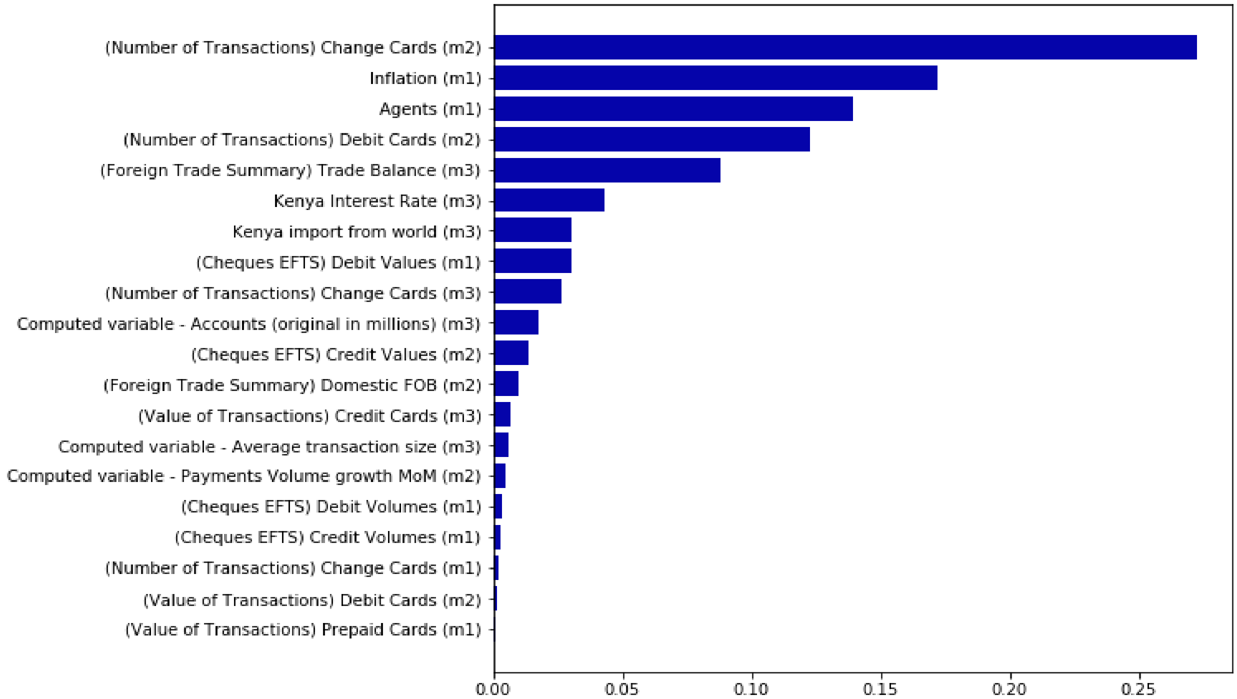
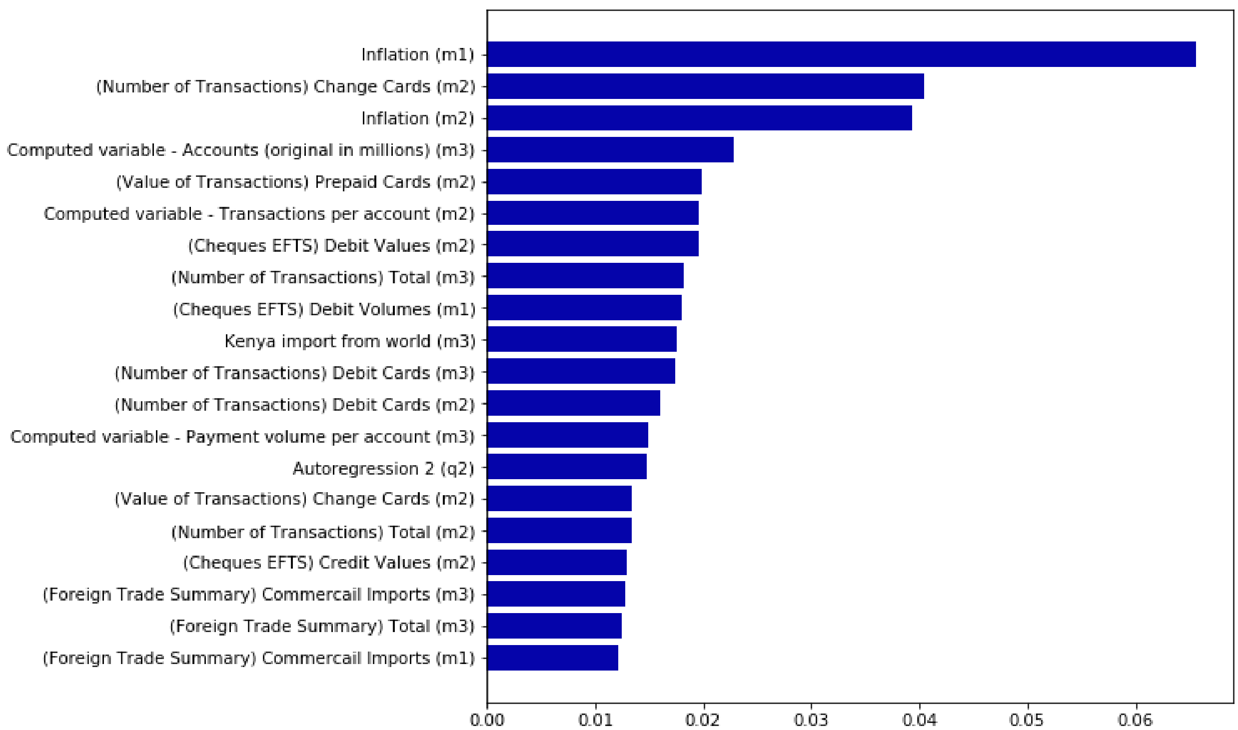


Figure 21. Top 20 most important variables for Kenya random forest regression



Appendix II. Factor Model Supplemental Materials

Figure 22. Uganda GDP: Autocorrelation, Partial Autocorrelation, & Normal Quantile–Quantile Plots of Year-over-Year Quarterly GDP

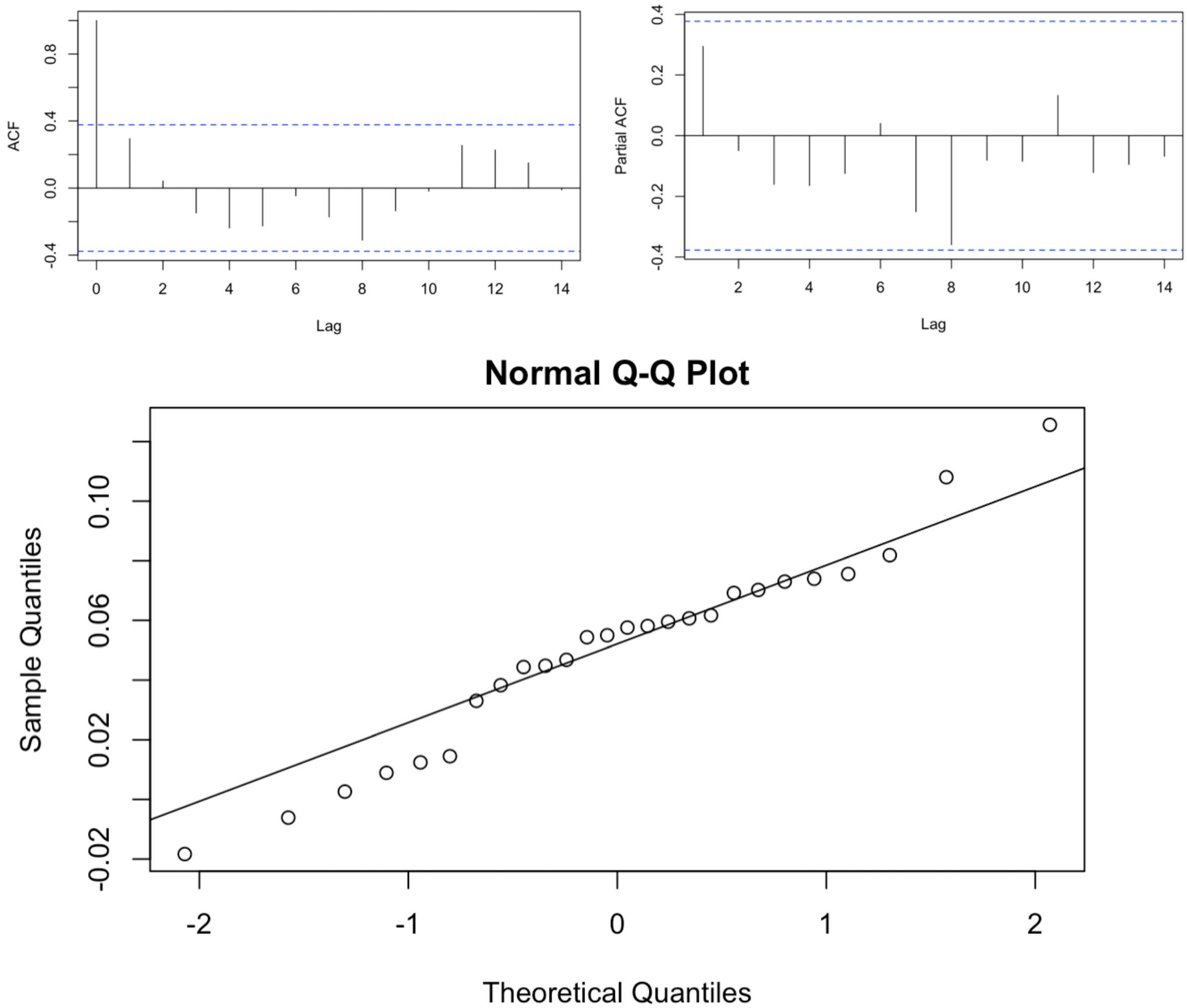


Figure 23. Kenya GDP: Autocorrelation, Partial Autocorrelation, & Normal Quantile–Quantile Plots of Year-over-Year Quarterly GDP

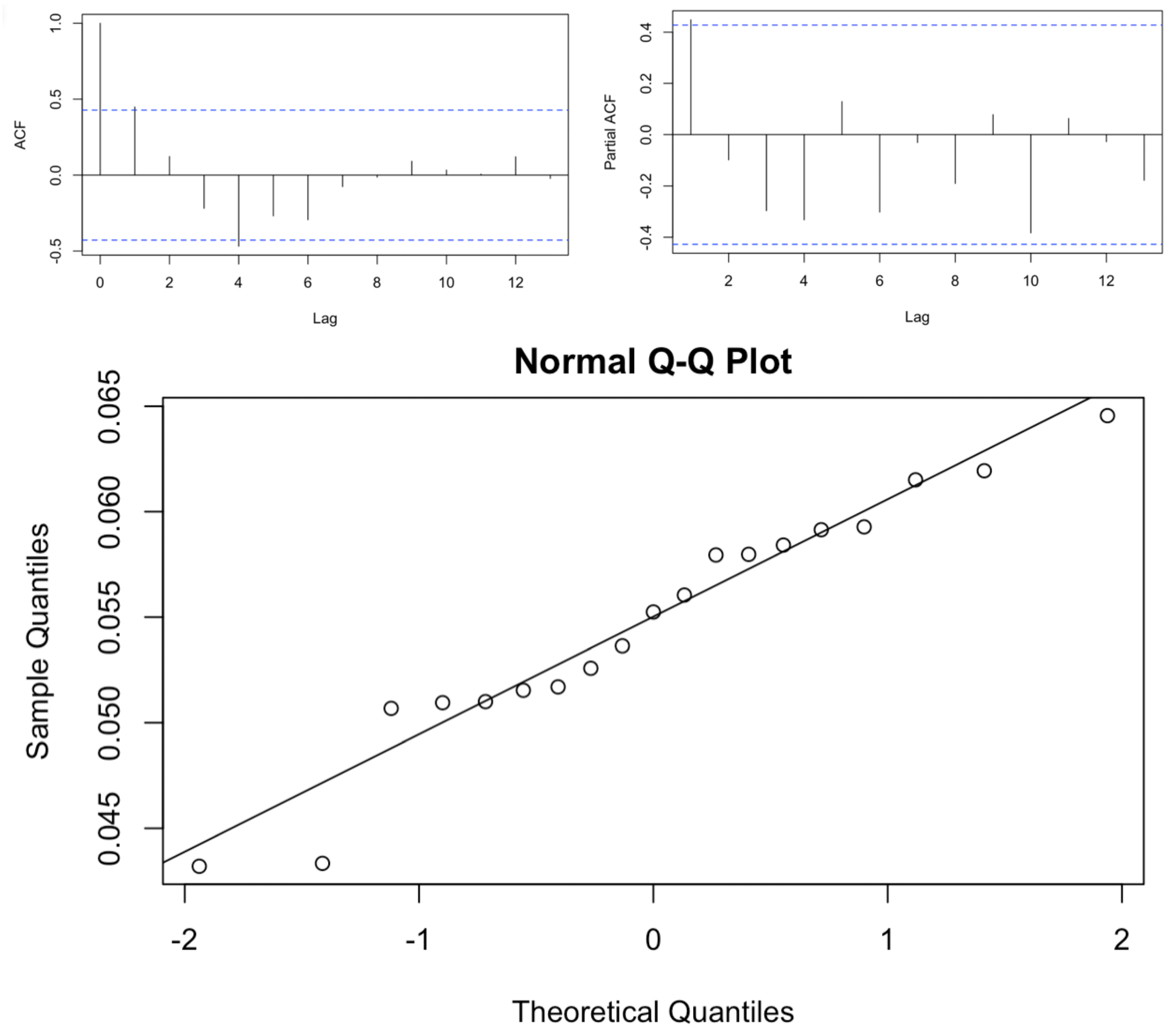


Figure 24. Ghana GDP: Autocorrelation, Partial Autocorrelation, & Normal Quantile–Quantile Plots of Year-over-Year Quarterly GDP

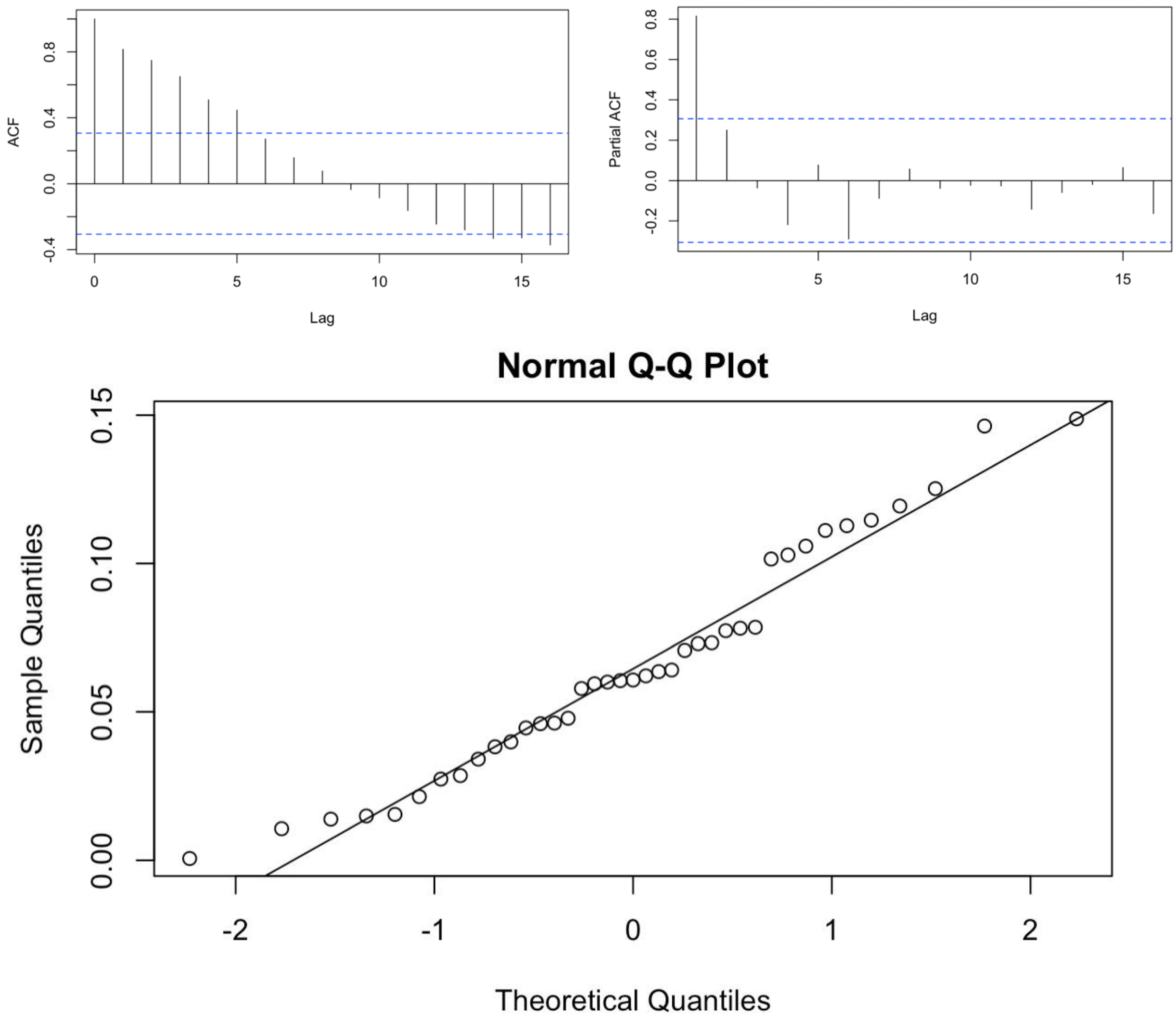


Figure 25. Uganda Residuals: Autocorrelation and Partial Autocorrelation Comparison for Factor Model Pass 3(a) vs. Pass 3(b) Residuals

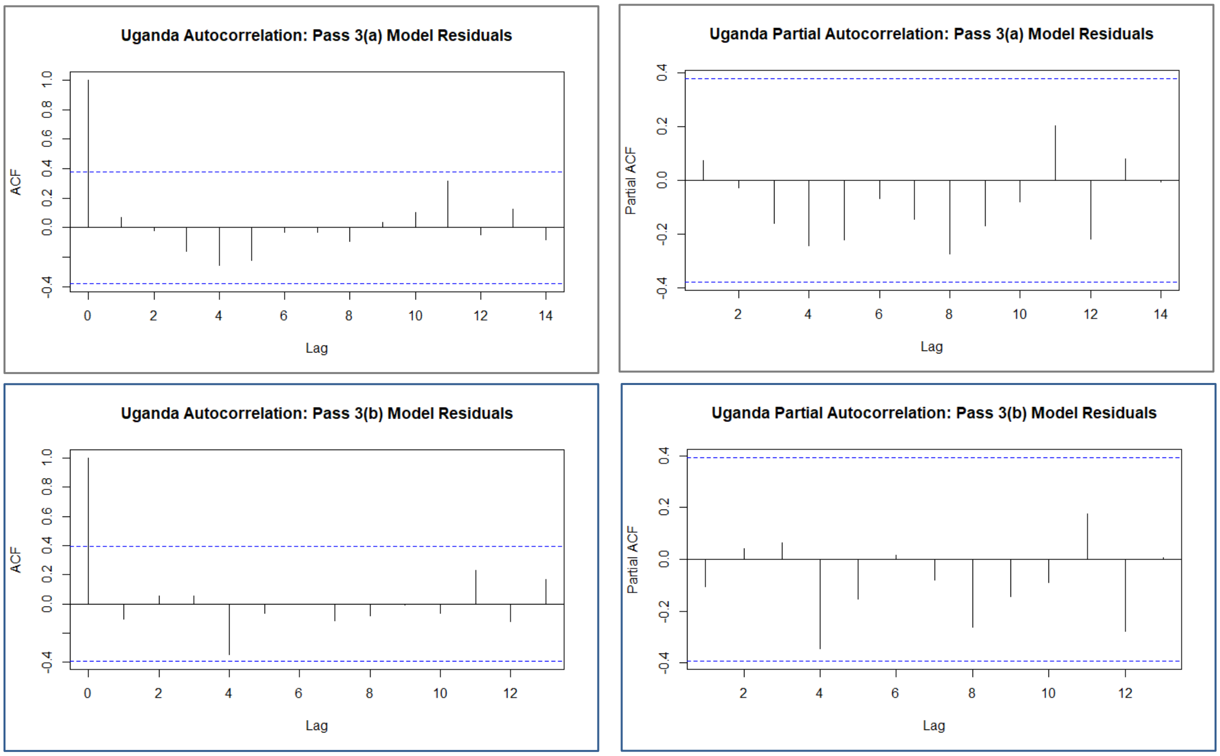


Figure 26. Kenya Residuals: Autocorrelation and Partial Autocorrelation Comparison for Factor Model Pass 3(a) vs. Pass 3(b) Residuals

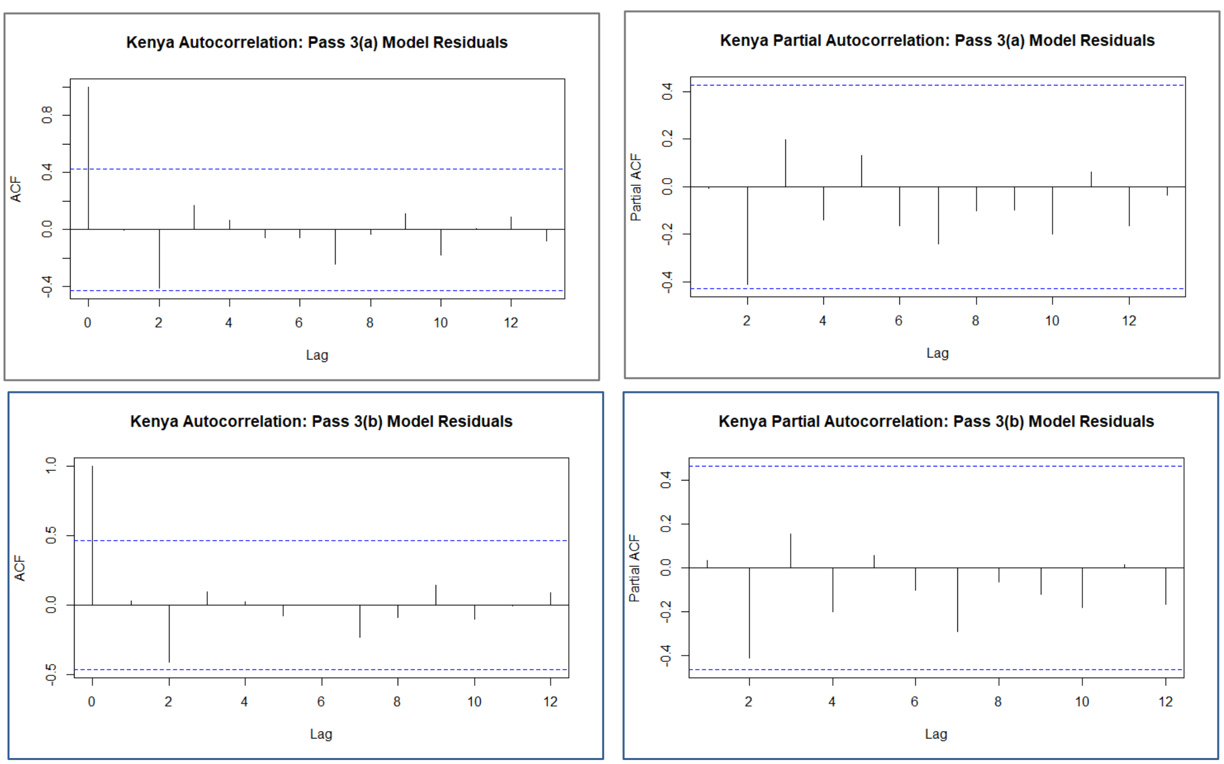
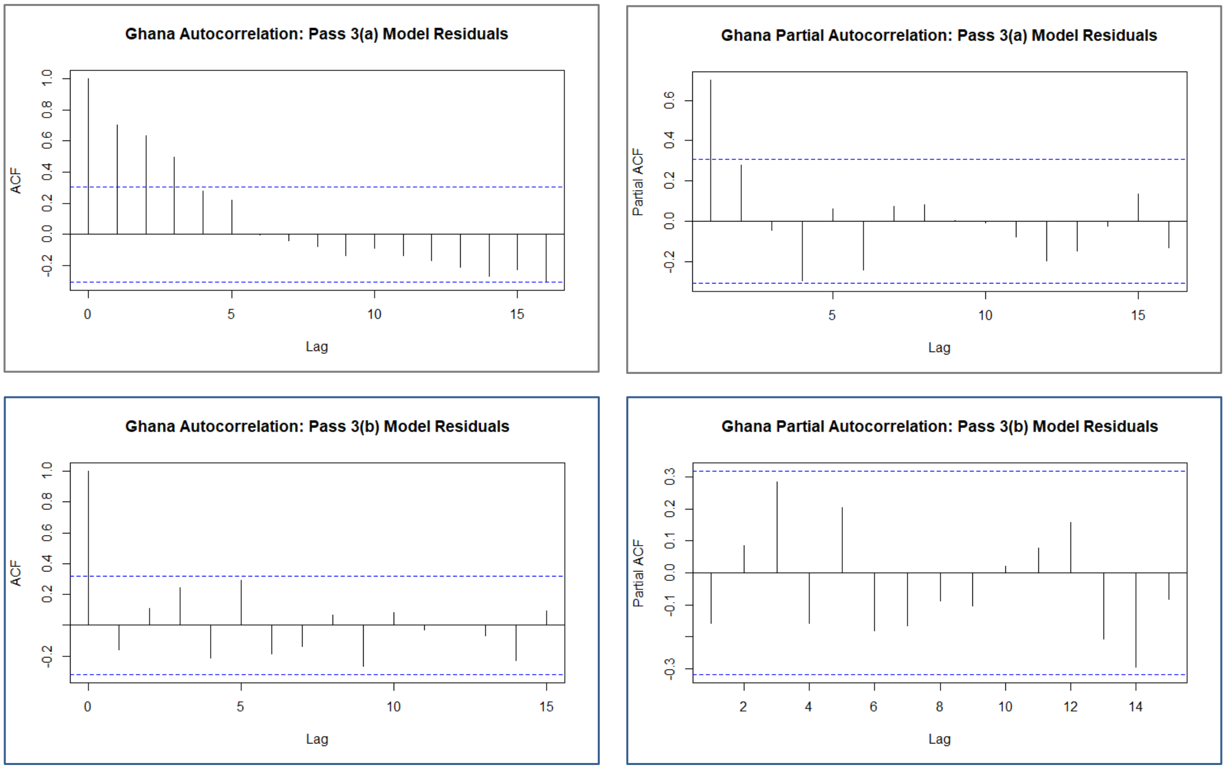
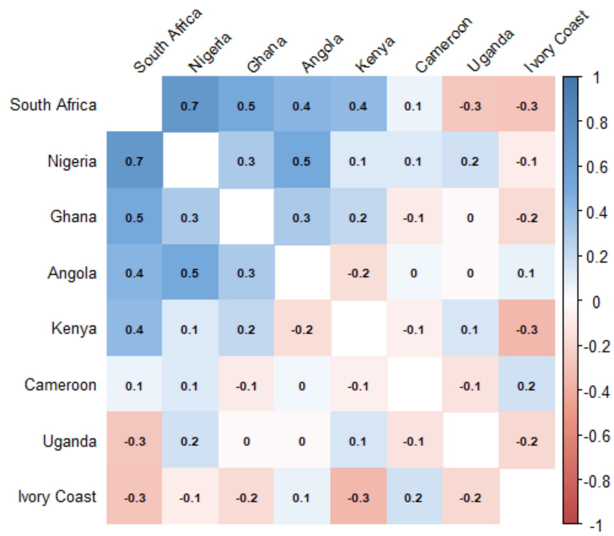


Figure 27. Ghana Residuals: Autocorrelation and Partial Autocorrelation Comparison for Factor Model Pass 3(a) vs. Pass 3(b) Residuals



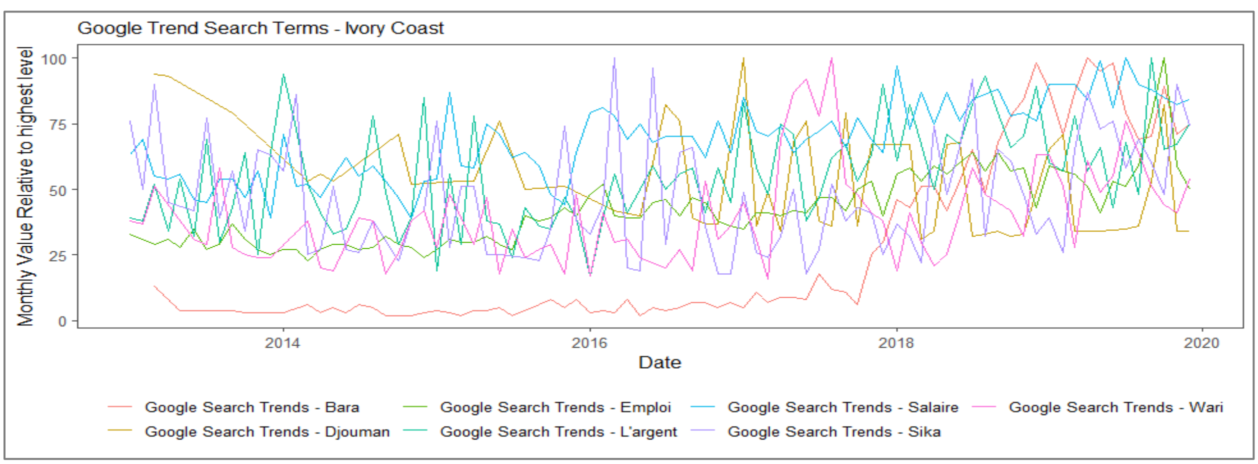
Appendix III. Supplemental Visualizations

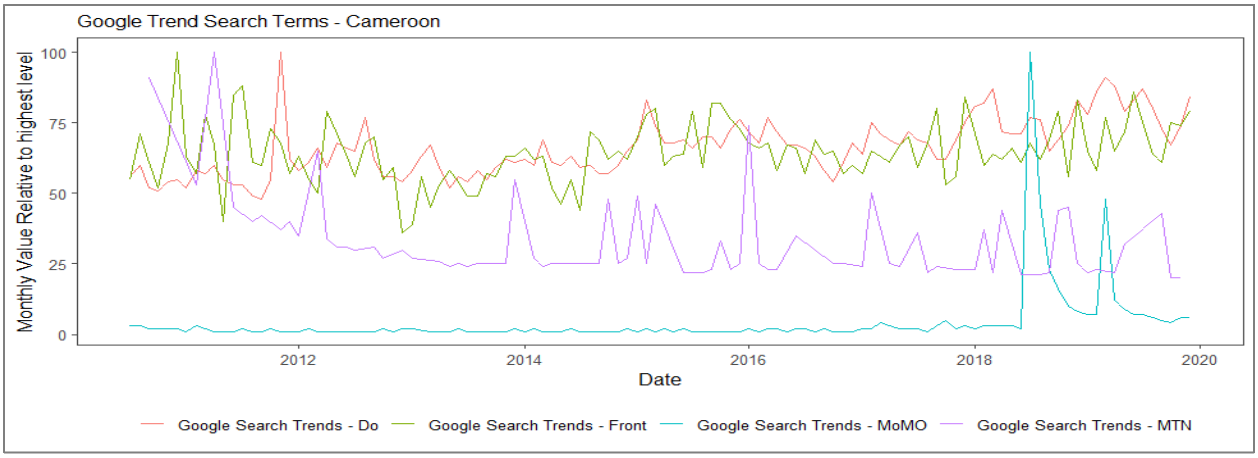
Figure 28. Correlation Matrix of Quarterly GDP YoY Percent Change by Country

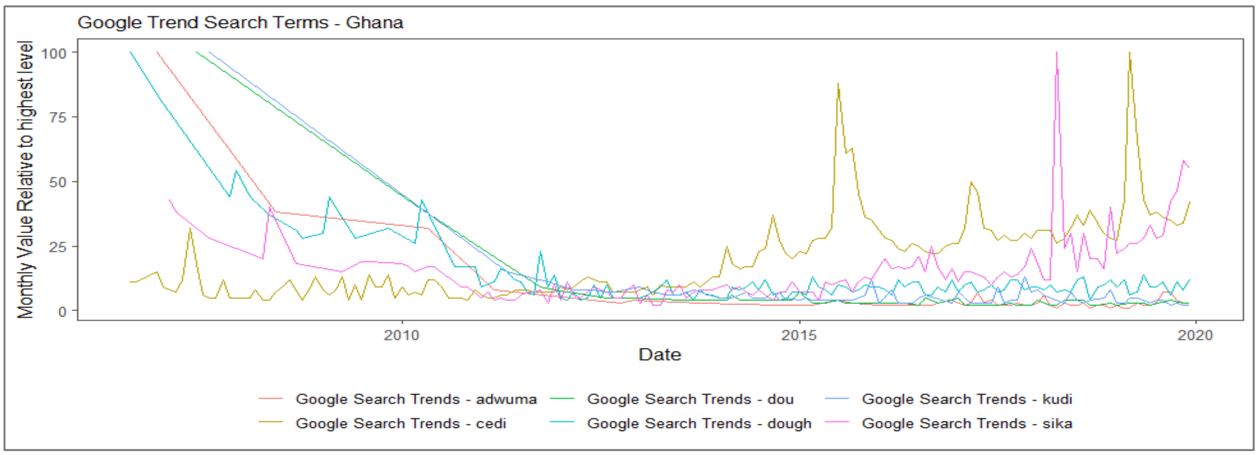


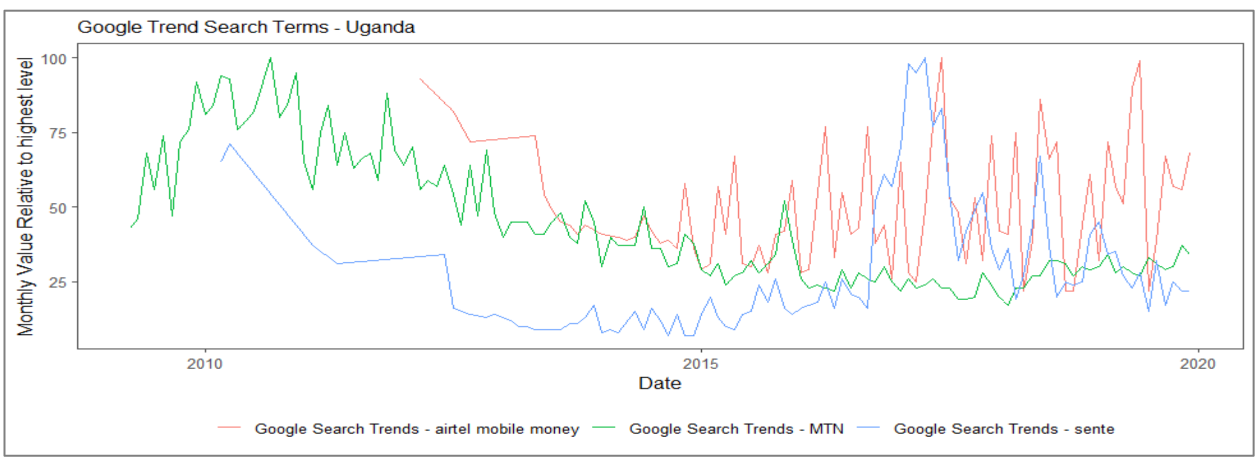
Source: Haver, IMF; Note: Bivariate correlations between GDP and daily, weekly, monthly, and quarterly variables were used to guide variable selection.

Figure 29. Google Trend Search Terms Time Series for Ivory Coast, Cameroon, Ghana, and Uganda









Source: Google Trend; Harvard Project Team analysis

Appendix IV. Data sourcing and aggregation notes

Note on data sourcing for nowcast models: All variables used in Machine Learning and parametric Factor Models are detailed in Appendix V. Data Dictionary. The data was sourced through four different methods:

1. **API:** All Google Trends search term data was obtained using the *pytrends* unofficial API for Google Trends. User can adjust keywords and timeframes used for each country to modify or expand the Google Trends dataset. Financial and macroeconomic variables from Bloomberg were also sourced from the Bloomberg Excel API add-in (all values used are *PX-LAST*)**.** Note that the variables sourced through method (2) that are also available through API (e.g., Trading Economics platform).
2. **Online databases:** The macroeconomic data included in the Data dictionary were sourced from the *Trading Economics* database. The *Trading Economics* database cites the original sources for each of the data variables which are included for completeness.
3. **Country-specific websites:** A select subset of variables sourced directly through CSV file downloads from websites (i.e., Kenya mobile payments and payment card data).
4. **IMF Provided:** Shipping and trade variables were provided by IMF colleagues

Note on data aggregation: Given the large quantity of source data variables with mixed frequencies and update intervals, we first formatted and aggregated all variables together to ensure data files had consistent structure prior to applying the skip-sampling methodology described in Section III.A.. Standardization included date formatting and chronological order of observations. Daily and weekly variables were aggregated into a bi-weekly average frequency first. Data aggregation across mixed frequencies involved sorting variables by country/region and frequency (e.g., all monthly variables for South Africa) and by frequency only (e.g., all daily / weekly / monthly / quarterly variables). For the Factor Models, the method of aggregating lower-frequency data into monthly and quarterly variables is based on categorization of variables as either stock or flow variables (i.e., if a stock variable, the observations are *averaged* and if a flow variable, the observations are *summed*).

Appendix V. Full Data Dictionary Variable List

Table 25. Data Dictionary - Full Variable List[32]

No.	Country	Variable Name	Category	Description	Unit	Frequency	Timeframe	Source
1	Angola	ago_berthvisits_w	Shipping	Shipping Cargo	Metric Tons of Cargo	Weekly	2016/4 - 2020/4	Bloomberg Terminal
2	Angola	ago_buscon_q	Business Confidence	Business Confidence	Points (net difference between positive and negative responses)	Quarterly	2008/9 - 2019/9	Instituto National De Estatica Angola
3	Angola	ago_expdwt_d	Shipping	Exports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
4	Angola	ago_expmtc_d	Shipping	Exports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
5	Angola	ago_expnum_d	Shipping	Exports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
6	Angola	ago_gdp_q	GDP	GDP	Local currency unit	Quarterly	2010/3 - 2019/12	IMF Angola Team
7	Angola	ago_impdwt_d	Shipping	Imports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
8	Angola	ago_impmtc_d	Shipping	Imports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
9	Angola	ago_impnum_d	Shipping	Imports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
10	Angola	ago_indpro_q	Manufacturing	Industrial Production	% (change from previous quarter)	Quarterly	2011/3 - 2019/9	Instituto National De Estatica Angola
11	Angola	ago_inmtc_m	Shipping	Imports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
12	Angola	ago_insa_m	Shipping	Imports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
13	Angola	ago_intrst_d	Interest Rate	Interest Rate (Policy Rate)	% percentage	Daily	2002/1 - 2020/3	National Bank of Angola
14	Angola	ago_lngexport_w	Shipping	Shipping Cargo	Metric Tons of Cargo	Weekly	2014/1 - 2020/4	Bloomberg Terminal
15	Angola	ago_monsup_m	Money Supply M3	Money Supply M3	AOA Million	Monthly	2009/12 - 2020/2	National Bank of Angola
16	Angola	ago_nexport_m	Trade	Trade - Exports	Nominal exports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
17	Angola	ago_nimport_m	Trade	Trade - Imports	Nominal imports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
18	Angola	ago_npltot_a	Debt	Non Performing Loans to Tot Loans	Percent of non-performing loans to total loans	Annual	2000/12 - 2018/12	World Bank
19	Angola	ago_outmtc_m	Shipping	Exports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
20	Angola	ago_outsa_m	Shipping	Exports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
21	Angola	ago_shipload_m	Shipping	Shipping Cargo	Barrels per day	Monthly	2012/1 - 2020/3	Bloomberg Terminal
22	Angola	ago_spotrate_d	Financial Market	Exchange Rate (Spot)	1 USD/AOA	Daily	1993/6 - 2020/4	Bloomberg Terminal
23	Cameroon	cmr_chainv_q	Manufacturing	Inventory	XAF Billion	Quarterly	2016/9 - 2019/6	Institut National De La Statistique du Cameroun

[32] For more details about the Google Search Trend variables, see Section II "alternative data" and Table 2.

24	Cameroon	cmr_expdwt_d	Shipping	Exports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
25	Cameroon	cmr_expmtc_d	Shipping	Exports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
26	Cameroon	cmr_expnum_d	Shipping	Exports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
27	Cameroon	cmr_gdp_q	GDP	GDP	Local currency unit	Quarterly	1999/3 - 2019/6	IMF - Haver
28	Cameroon	cmr_ggldo_m	Google Search Trends	Google Search Trends - Do	Relative to highest level	Monthly	2010/7 - 2019/10	Google Trends
29	Cameroon	cmr_gglfr_m	Google Search Trends	Google Search Trends - Front	Relative to highest level	Monthly	2010/7 - 2019/10	Google Trends
30	Cameroon	cmr_gglmo_m	Google Search Trends	Google Search Trends - MoMO	Relative to highest level	Monthly	2010/7 - 2019/10	Google Trends
31	Cameroon	cmr_gglmt_m	Google Search Trends	Google Search Trends - MTN	Relative to highest level	Monthly	2010/7 - 2019/10	Google Trends
32	Cameroon	cmr_impdwt_d	Shipping	Imports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
33	Cameroon	cmr_impmtc_d	Shipping	Imports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
34	Cameroon	cmr_impnum_d	Shipping	Imports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
35	Cameroon	cmr_indpro_q	Manufacturing	Industrial Production	% (change from previous quarter)	Quarterly	2000/3 - 2019/6	Institut National De La Statistique du Cameroun
36	Cameroon	cmr_inflat_m	Inflation Rate	Inflation Rate	% (change from previous month)	Monthly	2012/1 - 2019/12	Institut National De La Statistique du Cameroun
37	Cameroon	cmr_inmtc_m	Shipping	Imports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
38	Cameroon	cmr_insa_m	Shipping	Imports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
39	Cameroon	cmr_intrst_m	Interest Rate	Interest Rate (Policy Rate)	% percentage	Monthly	2009/6 - 2020/3	Bank of Central African States
40	Cameroon	cmr_nexport_m	Trade	Trade - Exports	Nominal exports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
41	Cameroon	cmr_nimport_m	Trade	Trade - Imports	Nominal imports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
42	Cameroon	cmr_npltot_a	Debt	Non Performing Loans to Tot Loans	Percent of non-performing loans to total loans	Annual	2010/12 - 2018/12	World Bank
43	Cameroon	cmr_outmtc_m	Shipping	Exports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
44	Cameroon	cmr_outsa_m	Shipping	Exports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
45	Cameroon	cmr_spotrate_d	Financial Market	Exchange Rate (Spot)	1 USD/XAF	Daily	1993/6 - 2020/4	Bloomberg Terminal
46	Ethiopia	eth_aqi_d	Air Quality	Air Quality	Index	Daily	2016/8 - 2020/4	AirNow Department of State
47	Ethiopia	eth_inflat_m	Inflation Rate	Inflation Rate	% (YoY)	Monthly	2006/7 - 2020/3	Central Statistical Agency of Ethiopia
48	Ethiopia	eth_intrst_d	Interest Rate	Interest Rate (Policy Rate)	% percentage	Daily	1995/2 - 2019/6	National bank of Ethiopia
49	Ethiopia	eth_nexport_m	Trade	Trade - Exports	Nominal exports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
50	Ethiopia	eth_nimport_m	Trade	Trade - Imports	Nominal imports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
51	Ethiopia	eth_spotrate_d	Financial Market	Exchange Rate (Spot)	1 USD/ETB	Daily	1993/6 - 2020/4	Bloomberg Terminal
52	Ghana	gha_equitygcb_d	Financial Market	Financial - Equity price	ghs	Daily	2006/1 - 2020/4	Bloomberg Terminal

53	Ghana	gha_expdwt_d	Shipping	Exports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
54	Ghana	gha_expmtc_d	Shipping	Exports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
55	Ghana	gha_expnum_d	Shipping	Exports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
56	Ghana	gha_gdp_q	GDP	GDP	Local currency unit	Quarterly	2006/3 - 2019/9	IMF - Haver
57	Ghana	gha_gglad_m	Google Search Trends	Google Search Trends - adwuma	Relative to highest level	Monthly	2006/7 - 2019/10	Google Trends
58	Ghana	gha_gglce_m	Google Search Trends	Google Search Trends - cedi	Relative to highest level	Monthly	2006/7 - 2019/10	Google Trends
59	Ghana	gha_ggldh_m	Google Search Trends	Google Search Trends - dough	Relative to highest level	Monthly	2006/7 - 2019/10	Google Trends
60	Ghana	gha_ggldo_m	Google Search Trends	Google Search Trends - dou	Relative to highest level	Monthly	2006/7 - 2019/10	Google Trends
61	Ghana	gha_gglku_m	Google Search Trends	Google Search Trends - kudi	Relative to highest level	Monthly	2006/7 - 2019/10	Google Trends
62	Ghana	gha_gglsi_m	Google Search Trends	Google Search Trends - sika	Relative to highest level	Monthly	2006/7 - 2019/10	Google Trends
63	Ghana	gha_impdwt_d	Shipping	Imports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
64	Ghana	gha_impmtc_d	Shipping	Imports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
65	Ghana	gha_impnum_d	Shipping	Imports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
66	Ghana	gha_inflat_m	Inflation Rate	Inflation Rate	% (YoY)	Monthly	1998/9 - 2020/2	Ghana Statistical Service
67	Ghana	gha_inmtc_m	Shipping	Imports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
68	Ghana	gha_insa_m	Shipping	Imports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
69	Ghana	gha_intrst_m	Interest Rate	Interest Rate (Policy Rate)	% percentage	Monthly	2002/11 - 2020/3	Bank of Ghana
70	Ghana	gha_lei_m	Leading Economic Index	Leading Economic Index	% (change from same month of previous year)	Monthly	2014/7 - 2019/11	Bank of Ghana
71	Ghana	gha_nexport_m	Trade	Trade - Exports	Nominal exports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
72	Ghana	gha_nimport_m	Trade	Trade - Imports	Nominal imports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
73	Ghana	gha_npltot_a	Debt	Non Performing Loans to Tot Loans	% (NPL/TotLoans)	Annual	2005/12 - 2016/12	FRED
74	Ghana	gha_outmtc_m	Shipping	Exports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
75	Ghana	gha_outsa_m	Shipping	Exports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
76	Ghana	gha_pmi_m	Manufacturing	PMI	Index	Monthly	2017/4 - 2020/3	Bloomberg Terminal
77	Ghana	gha_shipload_m	Shipping	Shipping Cargo	Barrels per day	Monthly	2012/1 - 2020/3	Bloomberg Terminal
78	Ghana	gha_smi_d	Financial Market	Financial - Stock Market	Points (capitalization weighted index with base value 1000 on 12/31/10)	Daily	2016/4 - 2020/4	Bloomberg Markets
79	Ghana	gha_spotrate_d	Financial Market	Exchange Rate (Spot)	1 USD/GHC	Daily	1993/6 - 2020/4	Bloomberg Terminal
80	Ivory_Coast	civ_equitysgbc_d	Financial Market	Financial - Equity price	xaf	Daily	2006/1 - 2020/4	Bloomberg Terminal

81	Ivory_Coast	civ_expdwt_d	Shipping	Exports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
82	Ivory_Coast	civ_expmtc_d	Shipping	Exports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
83	Ivory_Coast	civ_expnum_d	Shipping	Exports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
84	Ivory_Coast	civ_gdp_q	GDP	GDP	Local currency unit	Quarterly	1996/3 - 2018/9	IMF - Haver
85	Ivory_Coast	civ_gglba_m	Google Search Trends	Google Search Trends - Bara	Relative to highest level	Monthly	2013/1 - 2019/10	Google Trends
86	Ivory_Coast	civ_ggldj_m	Google Search Trends	Google Search Trends - Djouman	Relative to highest level	Monthly	2013/1 - 2019/10	Google Trends
87	Ivory_Coast	civ_gglem_m	Google Search Trends	Google Search Trends - Emploi	Relative to highest level	Monthly	2013/1 - 2019/10	Google Trends
88	Ivory_Coast	civ_ggll_m	Google Search Trends	Google Search Trends - L'argent	Relative to highest level	Monthly	2013/1 - 2019/10	Google Trends
89	Ivory_Coast	civ_gglsa_m	Google Search Trends	Google Search Trends - Salaire	Relative to highest level	Monthly	2013/1 - 2019/10	Google Trends
90	Ivory_Coast	civ_gglsi_m	Google Search Trends	Google Search Trends - Sika	Relative to highest level	Monthly	2013/1 - 2019/10	Google Trends
91	Ivory_Coast	civ_gglwa_m	Google Search Trends	Google Search Trends - Wari	Relative to highest level	Monthly	2013/1 - 2019/10	Google Trends
92	Ivory_Coast	civ_impdwt_d	Shipping	Imports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
93	Ivory_Coast	civ_impmtc_d	Shipping	Imports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
94	Ivory_Coast	civ_impnum_d	Shipping	Imports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
95	Ivory_Coast	civ_indpro_m	Manufacturing	Industrial Production	% (YoY)	Monthly	2007/6 - 2019/6	Institut National De La Statistique
96	Ivory_Coast	civ_inflat_m	Inflation Rate	Inflation Rate	% (YoY)	Monthly	2000/1 - 2020/2	Institut National De La Statistique
97	Ivory_Coast	civ_inmtc_m	Shipping	Imports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
98	Ivory_Coast	civ_insa_m	Shipping	Imports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
99	Ivory_Coast	civ_intrst_m	Interest Rate	Interest Rate (Policy Rate)	% percentage	Monthly	2010/12 - 2020/2	Trading Economics
100	Ivory_Coast	civ_nexport_m	Trade	Trade - Exports	Nominal exports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
101	Ivory_Coast	civ_nimport_m	Trade	Trade - Imports	Nominal imports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
102	Ivory_Coast	civ_npltot_a	Debt	Non Performing Loans to Tot Loans	$ (NPl/TotLoans)	Annual	1996/1 - 2017/1	African Open Data
103	Ivory_Coast	civ_outmtc_m	Shipping	Exports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
104	Ivory_Coast	civ_outsa_m	Shipping	Exports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
105	Ivory_Coast	civ_spotrate_d	Financial Market	Exchange Rate (Spot)	1 USD/XOF	Daily	1993/6 - 2020/4	Bloomberg Terminal
106	Ivory_Coast	civ_unemp_a	Unemployment Rate	Unemployment Rate	% (People looking for a job/ tot labor force)	Annual	1991/12 - 2019/12	Institutional Labor Organization
107	Kenya	ken_10yrbd_d	Financial Market	10 Yr Bond Yield	%	Daily	2016/7 - 2020/4	Bloomberg Markets

108	Kenya	ken_eftscredval_m	Check EFTs	Check EFTs	Kshs Billions	Monthly	2007/2 - 2020/2	Kenya Central Bank
109	Kenya	ken_eftscredvol_m	Check EFTs	Check EFTs	Number of Credit Volumes	Monthly	2007/2 - 2020/2	Kenya Central Bank
110	Kenya	ken_eftsdebval_m	Check EFTs	Check EFTs	Kshs Billions	Monthly	2007/2 - 2020/2	Kenya Central Bank
111	Kenya	ken_eftsdebvol_m	Check EFTs	Check EFTs	Number of Debit Volumes	Monthly	2007/2 - 2020/2	Kenya Central Bank
112	Kenya	ken_expdwt_d	Shipping	Exports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
113	Kenya	ken_expmtc_d	Shipping	Exports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
114	Kenya	ken_expnum_d	Shipping	Exports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
115	Kenya	ken_ftscomimp_m	Trade	Trade - Commercial Imports	Ksh Million	Monthly	1998/2 - 2020/2	Kenya Central Bank
116	Kenya	ken_ftsdomfob_m	Trade	Trade - Domestic FOB	Ksh Million	Monthly	1998/2 - 2020/2	Kenya Central Bank
117	Kenya	ken_ftsexp_m	Trade	Trade - Re-exports	Ksh Million	Monthly	1998/2 - 2020/2	Kenya Central Bank
118	Kenya	ken_ftsgvtimp_m	Trade	Trade - Government Imports	Ksh Million	Monthly	1998/2 - 2020/2	Kenya Central Bank
119	Kenya	ken_ftstb_m	Trade	Trade - Trade Balance	Ksh Million	Monthly	1998/2 - 2020/2	Kenya Central Bank
120	Kenya	ken_ftstot_m	Trade	Trade - Foreign Trade Total	Ksh Million	Monthly	1998/2 - 2020/2	Kenya Central Bank
121	Kenya	ken_ftstotfob_m	Trade	Trade - Total FOB	Ksh Million	Monthly	1998/2 - 2020/2	Kenya Central Bank
122	Kenya	ken_gaspr_m	Oil / Gas	Oil / Gas	USD/Liter	Monthly	1990/12 - 2020/1	Kenya National Bureau of Statistics
123	Kenya	ken_gdp_q	GDP	GDP	Local currency unit	Quarterly	2009/3 - 2019/9	IMF - Haver
124	Kenya	ken_gglch_m	Google Search Trends	Google Search Trends - cheddar	Relative to highest level	Monthly	2005/4 - 2019/10	Google Trends
125	Kenya	ken_ggldo_m	Google Search Trends	Google Search Trends - dough	Relative to highest level	Monthly	2005/4 - 2019/10	Google Trends
126	Kenya	ken_gglmt_m	Google Search Trends	Google Search Trends - MTN	Relative to highest level	Monthly	2005/4 - 2019/10	Google Trends
127	Kenya	ken_impdwt_d	Shipping	Imports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
128	Kenya	ken_impmtc_d	Shipping	Imports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
129	Kenya	ken_impnum_d	Shipping	Imports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
130	Kenya	ken_inflat_m	Inflation Rate	Inflation Rate	% (YoY)	Monthly	2005/1 - 2020/3	Kenya Central Bank
131	Kenya	ken_inmtc_m	Shipping	Imports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
132	Kenya	ken_insa_m	Shipping	Imports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
133	Kenya	ken_intrbk_m	Interbank	Interbank - Rate	% (Month over previous Month)	Monthly	1991/7 - 2019/11	Kenya Central Bank
134	Kenya	ken_intrbkvol_d	Interbank	Interbank - Volume	(Could not find units. but assuming amount of interbank loan transactions)	Daily	2011/2 - 2020/4	Kenya Central Bank
135	Kenya	ken_intrbkwbr_d	Interbank	Interbank - Window Borrow Rate	(Could not find units)	Daily	2011/2 - 2020/4	Kenya Central Bank
136	Kenya	ken_intrst_m	Interest Rate	Interest Rate (Policy Rate)	% percentage	Monthly	1991/7 - 2020/3	Kenya Central Bank

137	Kenya	ken_mpaccounts_m	Mobile payments	Mobile payments	Level - Number of accounts	Monthly	2007/3 - 2020/1	Kenya Central Bank
138	Kenya	ken_mpagents_m	Mobile payments	Mobile payments	Level - Number of agents	Monthly	2007/3 - 2020/1	Kenya Central Bank
139	Kenya	ken_mpagentsMOM_m	Mobile payments	Mobile payments	Percent Change - MoM % Change in Agents	Monthly	2007/3 - 2020/1	Kenya Central Bank
140	Kenya	ken_mpavgtxnsz_m	Mobile payments	Mobile payments	Ratio - Ksh per transaction	Monthly	2007/3 - 2020/1	Kenya Central Bank
141	Kenya	ken_mptxnMOM_m	Mobile payments	Mobile payments	Percent Change - MoM % Change in Transactions	Monthly	2007/3 - 2020/1	Kenya Central Bank
142	Kenya	ken_mptxnperacct_m	Mobile payments	Mobile payments	Ratio - Transactions per account	Monthly	2007/3 - 2020/1	Kenya Central Bank
143	Kenya	ken_mptxns_m	Mobile payments	Mobile payments	Level - Number of transactions	Monthly	2007/3 - 2020/1	Kenya Central Bank
144	Kenya	ken_mpvalue_m	Mobile payments	Mobile payments	Level - Ksh	Monthly	2007/3 - 2020/1	Kenya Central Bank
145	Kenya	ken_mpvolacct_m	Mobile payments	Mobile payments	Ratio - Ksh per account	Monthly	2007/3 - 2020/1	Kenya Central Bank
146	Kenya	ken_mpvolacctMOM_m	Mobile payments	Mobile payments	Percent Change - MoM % Change in Payments Volume per Agent	Monthly	2007/3 - 2020/1	Kenya Central Bank
147	Kenya	ken_mpvolagent_m	Mobile payments	Mobile payments	Ratio - Ksh per agent	Monthly	2007/3 - 2020/1	Kenya Central Bank
148	Kenya	ken_mpvolMOM_m	Mobile payments	Mobile payments	Percent Change - MoM % Change in Payments Volume	Monthly	2007/3 - 2020/1	Kenya Central Bank
149	Kenya	ken_nexport_m	Trade	Trade - Exports	Nominal exports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
150	Kenya	ken_nimport_m	Trade	Trade - Imports	Nominal imports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
151	Kenya	ken_npltot_a	Debt	Non Performing Loans to Tot Loans	% (NPL/TotLoans)	Annual	1998/1 - 2017/1	FRED
152	Kenya	ken_numtranschange_m	Payment card transactions	Payment card transactions - Change Card Txn	# of transactions by change cards	Monthly	2009/2 - 2020/2	Kenya Central Bank
153	Kenya	ken_numtranscredit_m	Payment card transactions	Payment card transactions - Credit Card Txn	# of transactions by credit cards	Monthly	2009/2 - 2020/2	Kenya Central Bank
154	Kenya	ken_numtransdebit_m	Payment card transactions	Payment card transactions - Debit Card Txn	# of transactions by debit cards	Monthly	2009/2 - 2020/2	Kenya Central Bank
155	Kenya	ken_numtranspos_m	Payment card transactions	Payment card transactions - POS Machine Txn	# of transactions by pos machines	Monthly	2009/2 - 2020/2	Kenya Central Bank
156	Kenya	ken_numtransprepaid_m	Payment card transactions	Payment card transactions - Prepaid Card Txn	# of transactions by prepaid cards	Monthly	2009/2 - 2020/2	Kenya Central Bank
157	Kenya	ken_numtranstot_m	Payment card transactions	Payment card transactions - Total Txn	# of transactions total	Monthly	2009/2 - 2020/2	Kenya Central Bank
158	Kenya	ken_outmtc_m	Shipping	Exports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
159	Kenya	ken_outsa_m	Shipping	Exports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
160	Kenya	ken_pmi_m	Manufacturing	PMI	Index	Monthly	2017/4 - 2020/3	Bloomberg Terminal
161	Kenya	ken_spotrate_d	Financial Market	Exchange Rate (Spot)	1 USD/KES	Daily	1993/6 - 2020/4	Bloomberg Terminal
162	Kenya	ken_stockindex_d	Financial Market	Financial - Stock Market	Local currency	Daily	2014/9 - 2020/4	Bloomberg Terminal
163	Kenya	ken_unemp_q	Unemployment Rate	Unemployment Rate	% (QoQ)	Quarterly	2019/3 - 2019/12	Kenya National Bureau of Statistics

164	Kenya	ken_valtranschange_m	Payment card transactions	Payment card transactions - Change Card Value	Kshs Millions	Monthly	2009/2 - 2020/2	Kenya Central Bank
165	Kenya	ken_valtranscredit_m	Payment card transactions	Payment card transactions - Credit Card Value	Kshs Millions	Monthly	2009/2 - 2020/2	Kenya Central Bank
166	Kenya	ken_valtransdebit_m	Payment card transactions	Payment card transactions - Debit Card Value	Kshs Millions	Monthly	2009/2 - 2020/2	Kenya Central Bank
167	Kenya	ken_valtranspos_m	Payment card transactions	Payment card transactions - POS Machine Value	Kshs Millions	Monthly	2009/2 - 2020/2	Kenya Central Bank
168	Kenya	ken_valtransprepaid_m	Payment card transactions	Payment card transactions - Prepaid Card Value	Kshs Millions	Monthly	2009/2 - 2020/2	Kenya Central Bank
169	Kenya	ken_valtranstot_m	Payment card transactions	Payment card transactions - Total Value	Kshs Millions	Monthly	2009/2 - 2020/2	Kenya Central Bank
170	Mozambique	moz_expdwt_d	Shipping	Exports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
171	Mozambique	moz_expmtc_d	Shipping	Exports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
172	Mozambique	moz_expnum_d	Shipping	Exports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
173	Mozambique	moz_impdwt_d	Shipping	Imports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
174	Mozambique	moz_impmtc_d	Shipping	Imports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
175	Mozambique	moz_impnum_d	Shipping	Imports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
176	Mozambique	moz_inmtc_m	Shipping	Imports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
177	Mozambique	moz_insa_m	Shipping	Imports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
178	Mozambique	moz_outmtc_m	Shipping	Exports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
179	Mozambique	moz_outsa_m	Shipping	Exports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
180	Namibia	nam_expdwt_d	Shipping	Exports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
181	Namibia	nam_expmtc_d	Shipping	Exports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
182	Namibia	nam_expnum_d	Shipping	Exports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
183	Namibia	nam_impdwt_d	Shipping	Imports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
184	Namibia	nam_impmtc_d	Shipping	Imports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
185	Namibia	nam_impnum_d	Shipping	Imports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
186	Namibia	nam_inmtc_m	Shipping	Imports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
187	Namibia	nam_insa_m	Shipping	Imports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
188	Namibia	nam_outmtc_m	Shipping	Exports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
189	Namibia	nam_outsa_m	Shipping	Exports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
190	Nigeria	nga_10yrbd_d	Financial Market	10 Yr Bond Yield	%	Daily	2016/4 - 2020/4	Trading Economics

191	Nigeria	nga_berthvisits_w	Shipping	Shipping Cargo	Metric Tons of Cargo	Weekly	2015/1 - 2020/4	Bloomberg Terminal
192	Nigeria	nga_buscon_m	Business Confidence	Business Confidence	Points	Monthly	2018/2 - 2020/3	National Bureau of Statistics, Nigeria
193	Nigeria	nga_concon_q	Consumer Confidence	Consumer Confidence	Points (net difference between positive and negative responses)	Quarterly	2008/6 - 2020/3	National Bureau of Statistics, Nigeria
194	Nigeria	nga_equityaccess_d	Financial Market	Financial - Equity price	ngn	Daily	2006/1 - 2020/4	Bloomberg Terminal
195	Nigeria	nga_equityzen_d	Financial Market	Financial - Equity price	ngn	Daily	2006/1 - 2020/4	Bloomberg Terminal
196	Nigeria	nga_expdwt_d	Shipping	Exports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
197	Nigeria	nga_expmtc_d	Shipping	Exports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
198	Nigeria	nga_expnum_d	Shipping	Exports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
199	Nigeria	nga_gdp_q	GDP	GDP	Local currency unit	Quarterly	2010/3 - 2019/12	IMF - Haver
200	Nigeria	nga_ggl73_m	Google Search Trends	Google Search Trends - 737	Relative to highest level	Monthly	2010/7 - 2019/10	Google Trends
201	Nigeria	nga_gglca_m	Google Search Trends	Google Search Trends - cash	Relative to highest level	Monthly	2010/7 - 2019/10	Google Trends
202	Nigeria	nga_ggleg_m	Google Search Trends	Google Search Trends - ego	Relative to highest level	Monthly	2010/7 - 2019/10	Google Trends
203	Nigeria	nga_gglmo_m	Google Search Trends	Google Search Trends - money	Relative to highest level	Monthly	2010/7 - 2019/10	Google Trends
204	Nigeria	nga_gglwo_m	Google Search Trends	Google Search Trends - work	Relative to highest level	Monthly	2010/7 - 2019/10	Google Trends
205	Nigeria	nga_impdwt_d	Shipping	Imports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
206	Nigeria	nga_impmtc_d	Shipping	Imports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
207	Nigeria	nga_impnum_d	Shipping	Imports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
208	Nigeria	nga_inflat_m	Inflation Rate	Inflation Rate	% (YoY)	Monthly	1996/1 - 2020/2	National Bureau of Statistics, Nigeria
209	Nigeria	nga_inmtc_m	Shipping	Imports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
210	Nigeria	nga_insa_m	Shipping	Imports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
211	Nigeria	nga_intrst_m	Interest Rate	Interest Rate (Policy Rate)	% percentage	Monthly	2007/1 - 2020/3	Trading Economics (Central Bank of Nigeria)
212	Nigeria	nga_lngexport_w	Shipping	Shipping Cargo	Metric Tons of Cargo	Weekly	2014/1 - 2020/4	Bloomberg Terminal
213	Nigeria	nga_mpmi_m	Manufacturing	Manufacturing PMI	Index	Monthly	2017/4 - 2020/3	Bloomberg Terminal
214	Nigeria	nga_nexport_m	Trade	Trade - Exports	Nominal exports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
215	Nigeria	nga_nimport_m	Trade	Trade - Imports	Nominal imports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
216	Nigeria	nga_npltot_a	Debt	Non Performing Loans to Tot Loans	% (NPL/TotLoans)	Annual	1998/1 - 2016/1	FRED
217	Nigeria	nga_outmtc_m	Shipping	Exports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)

218	Nigeria	nga_outsa_m	Shipping	Exports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
219	Nigeria	nga_pmi_m	Manufacturing	PMI	Index	Monthly	2017/4 - 2020/3	Bloomberg Terminal
220	Nigeria	nga_shipload_m	Shipping	Shipping Cargo	Barrels per day	Monthly	2012/1 - 2020/3	Bloomberg Terminal
221	Nigeria	nga_smi_d	Financial Market	Financial - Stock Market	Points	Daily	2016/4 - 2020/4	Trading Economics
222	Nigeria	nga_spotrate_d	Financial Market	Exchange Rate (Spot)	1 USD/NGN	Daily	1994/3 - 2020/4	Bloomberg Terminal
223	Nigeria	nga_unemp_q	Unemployment Rate	Unemployment Rate	% (People looking for a job/ tot labor force, QoQ)	Quarterly	2014/3 - 2018/9	National Bureau of Statistics, Nigeria
224	regional	reg_balticdry_d	Shipping	Shipping index	Index	Daily	1993/6 - 2020/4	Bloomberg Terminal
225	regional	reg_brentoil_d	Oil / Gas	Oil / Gas	Index	Daily	1993/6 - 2020/4	Bloomberg Terminal
226	regional	reg_cocoa_d	Commodity Prices	Commodity Prices	Index	Daily	2006/1 - 2020/4	Bloomberg Terminal
227	regional	reg_coffee_d	Commodity Prices	Commodity Prices	Index	Daily	2006/1 - 2020/4	Bloomberg Terminal
228	regional	reg_crudeoil_w	Shipping	Shipping Cargo	Barrels (thousands)	Weekly	2016/1 - 2020/3	Bloomberg Terminal
229	regional	reg_gold_d	Commodity Prices	Commodity Prices	USD/t. oz	Daily	2017/7 - 2020/4	Bloomberg Terminal
230	regional	reg_vix_d	Financial Market	VIX Index	Index	Daily	1993/6 - 2020/4	Bloomberg Terminal
231	regional	reg_wsugar_d	Commodity Prices	Commodity Prices	EUR/MT	Daily	2012/1 - 2020/4	Bloomberg Terminal
232	Senegal	sen_expdwt_d	Shipping	Exports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
233	Senegal	sen_expmtc_d	Shipping	Exports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
234	Senegal	sen_expnum_d	Shipping	Exports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
235	Senegal	sen_impdwt_d	Shipping	Imports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
236	Senegal	sen_impmtc_d	Shipping	Imports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
237	Senegal	sen_impnum_d	Shipping	Imports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
238	Senegal	sen_inmtc_m	Shipping	Imports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
239	Senegal	sen_insa_m	Shipping	Imports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
240	Senegal	sen_outmtc_m	Shipping	Exports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
241	Senegal	sen_outsa_m	Shipping	Exports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
242	South Africa	zaf_10yrbd_d	Financial Market	10 Yr Bond Yield	%	Daily	2016/5 - 2020/4	Trading Economics
243	South Africa	zaf_bci_m	Business Confidence	Business Confidence Index	Index	Monthly	2014/7 - 2020/3	Bloomberg Terminal
244	South Africa	zaf_bnkrp_m	Bankruptcies	Bankruptcies	# of Companies	Monthly	1980/1 - 2020/2	Statistics South Africa
245	South Africa	zaf_buscon_q	Business Confidence	Business Confidence	Points	Quarterly	1975/3 - 2020/3	SA Bureau of Economic Research
246	South Africa	zaf_chainv_q	Manufacturing	Inventory	ZAR Million	Quarterly	1960/3 - 2019/12	Statistics South Africa

247	South Africa	zaf_concon_q	Consumer Confidence	Consumer Confidence	Points	Quarterly	1982/6 - 2020/3	SA Bureau of Economic Research
248	South Africa	zaf_drycoal_w	Shipping	Shipping Cargo	Metric Tons of Cargo	Weekly	2014/1 - 2020/4	Bloomberg Terminal
249	South Africa	zaf_dryiron_w	Shipping	Shipping Cargo	Metric Tons of Cargo	Weekly	2016/7 - 2020/4	Bloomberg Terminal
250	South Africa	zaf_equitysbk_d	Financial Market	Financial - Equity price	zaf	Daily	2006/1 - 2020/4	Bloomberg Terminal
251	South Africa	zaf_expdwt_d	Shipping	Exports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
252	South Africa	zaf_expmtc_d	Shipping	Exports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
253	South Africa	zaf_expnum_d	Shipping	Exports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
254	South Africa	zaf_gdp_q	GDP	GDP	Local currency unit	Quarterly	1990/3 - 2019/12	IMF - Haver
255	South Africa	zaf_gglai_m	Google Search Trends	Google Search Trends - airtime	Relative to highest level	Monthly	2005/7 - 2019/10	Google Trends
256	South Africa	zaf_gglem_m	Google Search Trends	Google Search Trends - employment	Relative to highest level	Monthly	2005/7 - 2019/10	Google Trends
257	South Africa	zaf_gglew_m	Google Search Trends	Google Search Trends - ewallet	Relative to highest level	Monthly	2005/7 - 2019/10	Google Trends
258	South Africa	zaf_ggljo_m	Google Search Trends	Google Search Trends - job	Relative to highest level	Monthly	2005/7 - 2019/10	Google Trends
259	South Africa	zaf_gglmob_m	Google Search Trends	Google Search Trends - mobile money	Relative to highest level	Monthly	2005/7 - 2019/10	Google Trends
260	South Africa	zaf_gglmon_m	Google Search Trends	Google Search Trends - money	Relative to highest level	Monthly	2005/7 - 2019/10	Google Trends
261	South Africa	zaf_hhdgdp_q	Debt	Household Debt to GDP	% of GDP	Quarterly	2008/3 - 2019/9	Bank of International Settlements
262	South Africa	zaf_impdwt_d	Shipping	Imports - Ship Design Capacity Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
263	South Africa	zaf_impmtc_d	Shipping	Imports - Ship Load Daily	Metric Tons of Cargo	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
264	South Africa	zaf_impnum_d	Shipping	Imports - Number of Ships Daily	Number of ships	Daily	2015/4 - 2020/4	IMF (Diego Cerdeiro)
265	South Africa	zaf_indpro_m	Manufacturing	Industrial Production	% (YoY)	Monthly	1974/1 - 2020/1	World Bank
266	South Africa	zaf_inflat_m	Inflation Rate	Inflation Rate	% (YoY)	Monthly	1968/7 - 2020/2	South African Reserve Bank
267	South Africa	zaf_inmtc_m	Shipping	Imports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
268	South Africa	zaf_insa_m	Shipping	Imports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
269	South Africa	zaf_intrbk_d	Interbank	Interbank - Rate	Rate %	Daily	2016/6 - 2020/4	Trading Economics
270	South Africa	zaf_intrst_d	Interest Rate	Interest Rate (Policy Rate)	% percentage	Daily	1998/3 - 2020/3	Trading Economics (South African Reserve Bank)
271	South Africa	zaf_lei_m	Leading Economic Index	Leading Economic Index	% (month over month)	Monthly	1960/2 - 2020/1	South African Reserve Bank
272	South Africa	zaf_nexport_m	Trade	Trade - Exports	Nominal exports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
273	South Africa	zaf_nimport_m	Trade	Trade - Imports	Nominal imports (USD)	Monthly	1998/1 - 2019/12	Bloomberg Terminal
274	South Africa	zaf_npltot_a	Debt	Non Performing Loans to Tot Loans	% (NPL/TotLoans)	Annual	1998/1 - 2016/1	FRED

275	South Africa	zaf_outmtc_m	Shipping	Exports - Ship Load Monthly	Metric Tons of Cargo	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
276	South Africa	zaf_outsa_m	Shipping	Exports - Ship Load Monthly SA	Metric Tons of Cargo - Seasonally Adjusted	Monthly	2015/3 - 2020/2	IMF (Diego Cerdeiro)
277	South Africa	zaf_pmi_m	Manufacturing	PMI	Index	Monthly	2017/4 - 2020/3	Bloomberg Terminal
278	South Africa	zaf_psc_m	Financial Market	Private Sector Credit	ZAR Million	Monthly	1966/3 - 2020/2	South African Reserve Bank
279	South Africa	zaf_retail_m	Retail / Sales	Retail	% (month over month)	Monthly	2002/2 - 2020/1	Statistics South Africa
280	South Africa	zaf_spotrate_d	Financial Market	Exchange Rate (Spot)	1 USD/ZAR	Daily	1993/6 - 2020/4	Bloomberg Terminal
281	South Africa	zaf_stockindex_d	Financial Market	Financial - Stock Market	Local currency	Daily	2006/6 - 2020/4	Bloomberg Terminal
282	South Africa	zaf_unemp_q	Unemployment Rate	Unemployment Rate	% (People looking for a job/ tot labor force)	Quarterly	2000/9 - 2019/12	Statistics South Africa
283	South Africa	zaf_vehic_m	Retail / Sales	Vehicle Sales	Total number of vehicles sold	Monthly	1994/1 - 2020/3	NAAMSA
284	Uganda	uga_agindex_m	Business Tendency Indicator	Business Tendency Indicator - Agriculture	Index	Monthly	2012/7 - 2020/4	IMF
285	Uganda	uga_aqi_d	Air Quality	Air Quality	Index	Daily	2017/2 - 2020/4	AirNow Department of State
286	Uganda	uga_bizindex_m	Business Tendency Indicator	Business Tendency Indicator - Overall	Index	Monthly	2012/7 - 2020/4	IMF
287	Uganda	uga_buscon_m	Business Confidence	Business Confidence	Points	Monthly	2012/7 - 2020/3	Bank of Uganda
288	Uganda	uga_cementexports_m	Trade	Trade - Exports - Cement	Volume	Monthly	2012/7 - 2020/3	IMF
289	Uganda	uga_coffeeexports_m	Trade	Trade - Exports - Coffee	Volume	Monthly	2012/7 - 2020/3	IMF
290	Uganda	uga_contrindex_m	Business Tendency Indicator	Business Tendency Indicator - Construction	Index	Monthly	2012/7 - 2020/4	IMF
291	Uganda	uga_cottonexports_m	Trade	Trade - Exports - Cotton	Volume	Monthly	2012/7 - 2020/3	IMF
292	Uganda	uga_currgdp_a	Trade	Current Account to GDP	% (of GDP, Current Acc measured in USD million)	Annual	1980/12 - 2018/12	Bank of Uganda
293	Uganda	uga_debtgdp_a	Debt	Government Debt to GDP	% (of GDP)	Annual	1997/12 - 2018/12	Trading Economics
294	Uganda	uga_electrexports_m	Trade	Trade - Exports - Electricity	Volume	Monthly	2012/7 - 2020/3	IMF
295	Uganda	uga_equitysb_d	Financial Market	Financial - Equity price	ugx	Daily	2009/1 - 2020/4	Bloomberg Terminal
296	Uganda	uga_fullindex_m	Economic Activity Index	Composite Index of Economic Activity	Index	Monthly	2012/7 - 2020/2	IMF
297	Uganda	uga_fxdeposits_m	Bank Deposits	Private Sector Deposits - FX	USH	Monthly	2012/7 - 2020/3	IMF
298	Uganda	uga_fxloans_m	Private Credit	Private Sector Credit - FX	USH	Monthly	2012/7 - 2020/3	IMF
299	Uganda	uga_gdp_q	GDP	GDP	Local currency unit	Quarterly	2008/9 - 2019/9	IMF - Haver
300	Uganda	uga_gglai_m	Google Search Trends	Google Search Trends - airtel mobile money	Relative to highest level	Monthly	2009/4 - 2019/10	Google Trends
301	Uganda	uga_gglMT_m	Google Search Trends	Google Search Trends - MTN	Relative to highest level	Monthly	2009/4 - 2019/10	Google Trends
302	Uganda	uga_gglse_m	Google Search Trends	Google Search Trends - sente	Relative to highest level	Monthly	2009/4 - 2019/10	Google Trends

303	Uganda	uga_goldexports_m	Trade	Trade - Exports - Gold	Volume	Monthly	2012/7 - 2020/3	IMF
304	Uganda	uga_govtimports_m	Trade	Trade - Imports - Government	USD Millions	Monthly	2012/7 - 2020/3	IMF
305	Uganda	uga_inflat_m	Inflation Rate	Inflation Rate	% (YoY)	Monthly	1998/7 - 2020/3	Bank of Uganda
306	Uganda	uga_intrst_d	Interest Rate	Interest Rate (Policy Rate)	% percentage	Daily	2011/6 - 2020/4	Trading Economics (Bank of Uganda)
307	Uganda	uga_m3_m	Money Supply M3	Money Supply M3	USH	Monthly	2012/7 - 2020/3	IMF
308	Uganda	uga_maizeexports_m	Trade	Trade - Exports - Maize	Volume	Monthly	2012/7 - 2020/3	IMF
309	Uganda	uga_manufindex_m	Business Tendency Indicator	Business Tendency Indicator - Manufacturing	Index	Monthly	2012/7 - 2020/4	IMF
310	Uganda	uga_nexport_m	Trade	Trade - Exports	Nominal exports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
311	Uganda	uga_nimport_m	Trade	Trade - Imports	Nominal imports (USD)	Monthly	1989/8 - 2019/12	Bloomberg Terminal
312	Uganda	uga_nonoilimports_m	Trade	Trade - Imports - Non-oil (Private)	USD Millions	Monthly	2012/7 - 2020/3	IMF
313	Uganda	uga_npltot_a	Debt	Non Performing Loans to Tot Loans	% (NPL/TotLoans)	Annual	1998/1 - 2017/1	FRED
314	Uganda	uga_oilimports_m	Trade	Trade - Imports - Oil (Private)	USD Millions	Monthly	2012/7 - 2020/3	IMF
315	Uganda	uga_pmi_m	Purchasing Managers Index	Purchasing Managers Index	Index	Monthly	2017/3 - 2020/3	IMF
316	Uganda	uga_smi_d	Financial Market	Financial - Stock Market	Points	Daily	2016/4 - 2020/4	Trading Economics
317	Uganda	uga_spotrate_d	Financial Market	Exchange Rate (Spot)	1 USD/UGX	Daily	1993/6 - 2020/4	Bloomberg Terminal
318	Uganda	uga_sugarexports_m	Trade	Trade - Exports - Sugar	Volume	Monthly	2012/7 - 2020/3	IMF
319	Uganda	uga_taxrev_m	Tax Revenue	Tax Revenue	USH Millions	Monthly	2012/7 - 2020/3	IMF
320	Uganda	uga_ushdeposits_m	Bank Deposits	Private Sector Deposits - USH	USH	Monthly	2012/7 - 2020/3	IMF
321	Uganda	uga_ushloans_m	Private Credit	Private Sector Credit - USH	USH	Monthly	2012/7 - 2020/3	IMF
322	Uganda	uga_wholesaleindex_m	Business Tendency Indicator	Business Tendency Indicator - Wholesale Trade	Index	Monthly	2012/7 - 2020/4	IMF