(12) INTERNATIONAL APPLICATION PUBLISHED UNDER THE PATENT COOPERATION TREATY (PCT)

(19) **World Intellectual Property Organization**
International Bureau

(43) **International Publication Date**
14 October 2021 (14.10.2021)

WIPO | PCT

(10) **International Publication Number**
WO 2021/207518 A1

(51) **International Patent Classification:**
G06F 15/18 (2006.01)

(21) **International Application Number:**
PCT/US2021/026417

(22) **International Filing Date:**
08 April 2021 (08.04.2021)

(25) **Filing Language:** English

(26) **Publication Language:** English

(30) **Priority Data:**
63/008,010 10 April 2020 (10.04.2020) US
17/225,461 08 April 2021 (08.04.2021) US

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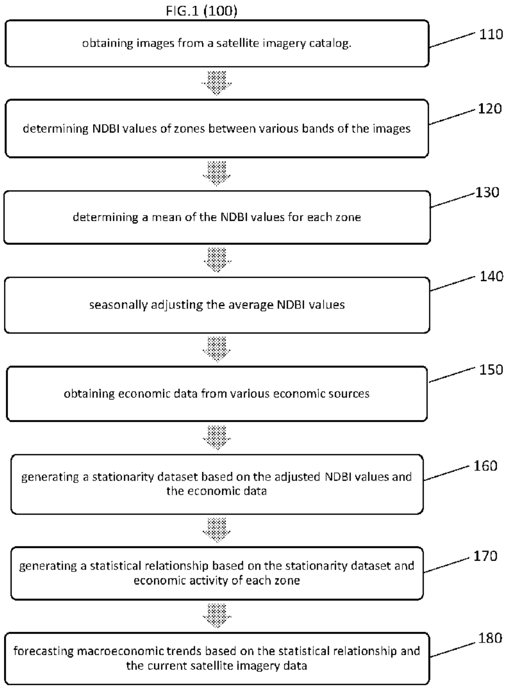
(81) **Designated States** *(unless otherwise indicated, for every kind of national protection available)*: AE, AG, AL, AM, AO, AT, AU, AZ, BA, BB, BG, BH, BN, BR, BW, BY, BZ, CA, CH, CL, CN, CO, CR, CU, CZ, DE, DJ, DK, DM, DO, DZ, EC, EE, EG, ES, FI, GB, GD, GE, GH, GM, GT, HN, HR, HU, ID, IL, IN, IR, IS, IT, JO, JP, KE, KG, KH, KN, KP, KR, KW, KZ, LA, LC, LK, LR, LS, LU, LY, MA, MD, ME, MG, MK, MN, MW, MX, MY, MZ, NA, NG, NI, NO, NZ, OM, PA, PE, PG, PH, PL, PT, QA, RO, RS, RU, RW, SA, SC, SD, SE, SG, SK, SL, ST, SV, SY, TH, TJ, TM, TN, TR, TT, TZ, UA, UG, US, UZ, VC, VN, WS, ZA, ZM, ZW.

(84) **Designated States** *(unless otherwise indicated, for every kind of regional protection available)*: ARIPO (BW, GH, GM, KE, LR, LS, MW, MZ, NA, RW, SD, SL, ST, SZ, TZ, UG, ZM, ZW), Eurasian (AM, AZ, BY, KG, KZ, RU, TJ, TM), European (AL, AT, BE, BG, CH, CY, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HR, HU, IE, IS, IT, LT, LU, LV, MC, MK, MT, NL, NO, PL, PT, RO, RS, SE, SI, SK, SM, TR), OAPI (BF, BJ, CF, CG, CI, CM, GA, GN, GQ, GW, KM, ML, MR, NE, SN, TD, TG).

Published:
— *with international search report (Art. 21(3))*

(54) **Title:** SYSTEMS AND METHODS FOR FORECASTING MACROECONOMIC TRENDS USING GEOSPATIAL DATA AND A MACHINE LEARNING MODEL

FIG.1 (100)



(57) **Abstract:** A system for forecasting macroeconomic trends using geospatial data and a machine learning model. The system may include a server computing device in communication with a user computing device via a network, the server computing device comprising a processor and a memory, the memory storing computer-executable instructions which are executed by the processor to: obtain images from a satellite imagery catalog; determine Normalized-Difference Built-Up Index (NDBI) values of one or more zones between various bands of the images; determine an average of the NDBI values for each zone; seasonally adjust the average NDBI values; obtain economic data from external sources; generate a stationarity dataset based on the adjusted NDBI values and the economic data; generate a statistical relationship model based on the stationarity dataset and economic activity of each zone; and forecast a macroeconomic trend based on the statistical relationship model and the current satellite imagery data.

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SYSTEMS AND METHODS FOR FORECASTING MACROECONOMIC TRENDS USING GEOSPATIAL DATA AND A MACHINE LEARNING MODEL

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] The present disclosure claims priority to U.S. Provisional Patent Application No. 63/008,010 filed April 10, 2020, and U.S. Patent Application No. 17/225,461 filed April 8, 2021, the entirety of which are incorporated herein by reference.

BACKGROUND

[0002] The subject matter discussed in this background section should not be assumed to be prior art merely as a result of its mention herein. Similarly, any problems mentioned in this background section or associated with the subject matter of this background section should not be assumed to have been previously recognized in the prior art.

[0003] Macroeconomics is a branch of economics that studies the behavior of the overall economy operating on a large scale such as national, regional, and global levels. Further, macroeconomics allows entities to determine economy-wide phenomena such as Gross Domestic Product (GDP) for studying economic structure, performance, and behavior of a region(s).

[0004] Generally, the macroeconomic trends (e.g. GDP) of a region is based on factors such as the compensation of employees in a region, consumptions of fixed capital in the region, gross operating surplus in the region, subsidies in the region, and taxes on production in the region. Typically, the macroeconomic trends are measured quarterly and generally subject to three revisions before the frontline numbers for economic output are finalized. As such, current methodologies are inadequate as the macroeconomic trends of a particular quarter, for instance, are not fully known until the end of the succeeding quarter i.e., nearly three months after a particular quarter has ended.

[0005] Currently, the New York and Atlanta Federal Reserve Banks produce estimates of GDP in near real-time (e.g., weekly) in the publicly available service "NowCast" (a statistical model). A short-coming, however, is that such services use extrapolations of past data and small economic data inputs as they become available thereby rendering the estimation rather unreliable, backward looking, and slow/inefficient.

[0006] As an example, the GDP report is published quarterly and revised monthly. The GDP for a given quarter is released in the first month following a quarter as the "advance estimate". The "preliminary estimate" is published in the second month, followed by the "revised" estimate in the third month. Further, various other financial firms use "alternative financial datasets" to, for instance, prognosticate stocks that are likely to be successful or use robotics to analyze crop and weather data to automate daily farming tasks. Such firms provide earth observation data, geo-spatial data, satellite technology and AI, location-based insights on foot traffic patterns, and AI for real-time location of mobile phones, respectively.

[0007] In other examples, financial firms use drones to take pictures of 1) cars in parking lots in order to forecast sales, 2) farm fields at the plant level to identify plant health and/or disease, and 3) building assets to forecast insurance needs, and the like. Where the prior art fails in relation to the present disclosure is that they focus on forecasting for individual companies and not for the macroeconomy where predicting the real-time GDP of a large-scale region such as a city, state, or a country is heretofore unmet.

[0008] Related art, for various aspects contained therewithin, relevant to this disclosure includes, 1) U.S. Patent No. 10, 182, 214 B2 to Amihay Gornik, 2) U.S. Patent No. 10, 319, 107 B2 to Boris Aleksandrovich Babenko, 3) U.S. Patent No. 10, 282, 821 B1 to Michael S. Warren, 4) Chinese Patent Application Publication No. 108416479 A to Liangbing et. al, 5) Chinese Patent Application Publication No. 106503838 A to Chang et. al, 6) Chinese Patent Application Publication No. 106779290 A to MA Congvong, 7) Chinese Patent Application Publication No. 106156894 A to Ling et. al, 8) Chinese Patent Application Publication No. 106600029 A to Jinhua et. al, 9) U.S. Patent No. 8, 364, 569 B1 to Lee, and 10) U.S. Patent Application Publication US2019/0188811 Al to Sasson. The related art is incorporated herein by reference.

[0009] Although a recent addition to the economics literature, the use of satellite imagery for estimating economic activity is already becoming well-established. Doll, Muller, and Morley (2006) proved that nightlight imagery was correlated with GDP for 11 European countries as well as the United States. Numerous other studies have followed that corroborate these results, including Ghosh et al. (2010), Nordhaus and Xi (2011), and Henderson, Storeygard, and Weil (2012). These studies are incorporated herein by reference.

[00010] All of these previous studies utilized night-time luminosity data in order to proxy economic activity. Although this technique is viable, the nightlight methodology is vastly restricted by its ability to discern relative differences in economic activity across geographies. For instance, luminosity is largely binary insofar as a location either has it or it does not, and therefore lumens do not accurately reflect increasing layers of economic complexity. Jean et al. (2016), incorporated herein by reference, provides a different approach: day-time imagery of features in the environment to proxy economic activity.

BRIEF DESCRIPTION OF DRAWINGS

[00011] The file of this patent contains at least one drawing executed in color. Copies of this patent with color drawings will be provided by the Patent and Trademark Office upon request and payment of the necessary fee.

[00012] Other objects and advantages of the present disclosure will become apparent to those skilled in the art upon reading the following detailed description of exemplary embodiments, in conjunction with the accompanying drawings, in which like reference numerals have been used to designate like elements, and in which:

[00013] FIG. 1 shows flowchart for a method for forecasting macroeconomic trends using geospatial data according to an example embodiment of the present disclosure;

[00014] FIG. 2 shows a zone layer, value layer and output layer according to an example embodiment of the present disclosure;

[00015] FIG. 3 shows NDBI zonal statistics for every US state according to an example embodiment of the present disclosure;

[00016] FIG. 4 shows NDBI seasonal adjustment graph for U.S. state of Alabama according to an example embodiment of the present disclosure;

[00017] FIGS. 5A and **5B** illustrate examples of economic data obtained from external sources according to an example embodiment of the present disclosure;

[00018] FIG. 6 shows time-series data and a new first-differenced variable from the underlying values according to an example embodiment of the present disclosure;

[00019] FIG. 7A shows data before being first-differenced according to an example embodiment of the present disclosure;

[00020] FIG. 7B shows data after the first-differencing according to an example embodiment of the present disclosure;

[00021] FIG. 8 shows stationarity for NDBI for US state of Alabama according to an example embodiment of the present disclosure;

[00022] FIG. 9A shows seasonally adjusted NDBI facet graphs according to an example embodiment of the present disclosure;

[00023] FIG. 9B shows real GDP graphs according to an example embodiment of the present disclosure;

[00024] FIG. 10 illustrates a relationship between the percent changes of NDBI and state-level real GDP of AL and AR according to an exemplary embodiment of the present disclosure;

[00025] FIG. 11 shows regression results according to exemplary embodiment of the present disclosure;

[00026] FIG. 12 shows regression results according to exemplary embodiment of the present disclosure;

[00027] FIG. 13 shows regression results according to exemplary embodiment of the present disclosure;

[00028] FIG. 14 illustrates nowcasting technique of prediction according to exemplary embodiment of the present disclosure;

[00029] FIG. 15A shows regression results according to exemplary embodiment of the present disclosure;

[00030] FIG. 15B shows regression results according to exemplary embodiment of the present disclosure;

[00031] FIG. 16 shows a system diagram for forecasting macroeconomic trends using geospatial data according to an exemplary embodiment of the present disclosure; and

[00032] FIG. 17 illustrates a machine configured to perform computing operations according to an embodiment of the present disclosure.

SUMMARY

[00033] A computer-implemented method for forecasting macroeconomic trends using geospatial data and a machine learning model is disclosed. The method may include obtaining images from a satellite imagery catalog; determining Normalized-Difference Built-Up Index (NDBI) values of one or more zones between various bands of the images; determining an average of the NDBI values for each zone; seasonally adjusting the average NDBI values; obtaining economic data from external sources; generating a stationarity dataset based on the adjusted NDBI values and the economic data; generating a statistical relationship model (i.e. machine learning model) based on the stationarity dataset and economic activity of each zone; and forecasting a macroeconomic trend based on the statistical relationship model and the current satellite imagery data.

[00034] In various example embodiments, the macroeconomic trend can be Gross Domestic Product (GDP). The statistical relationship model can be based on at least one machine learning algorithm such as a regression algorithm. The external sources may include Federal Reserve Bank of St. Louis (FRED) and/or the Bureau of Economic Analysis (BEA). The satellite imagery catalog can be Google Earth Engine. Each zone can be a state of the United States.

[00035] In various example embodiments, the method may include compiling and/or exporting the macroeconomic trend to an external destination. The external destination can be a user-access portal that allows authenticated users to view and download the macroeconomic trend. The external destination can be a blockchain based distributed ledger that records the macroeconomic trend.

[00036] A system for forecasting macroeconomic trends using geospatial data and a machine learning model is disclosed. The system may include a processor and a memory, the memory storing computer-executable instructions which are executed by the processor to: obtain images from a satellite imagery catalog; determine NDBI values of one or more zones between various bands of the images; determine an average of the NDBI values for each zone; seasonally adjust the average NDBI values; obtain economic data from external sources; generate a stationarity dataset based on the adjusted NDBI values and the economic data; generate a statistical relationship model (i.e. machine learning model) based on the stationarity dataset

and economic activity of each zone; and forecast a macroeconomic trend based on the statistical relationship model and the current satellite imagery data.

DESCRIPTION

[00037] The present disclosure provides technique that utilizes machine learning models to forecast macroeconomic trends. The disclosed techniques can estimate macroeconomic trends (e.g. Gross Domestic Product (GDP)) continuously and in real-time using daylight imagery from satellites that continuously circumnavigate the globe at high orbit. The disclosed techniques that are based on machine learning consume fewer computing resources, thereby providing improvements in computing technology.

[00038] The methodology underpinning these techniques can be generally encapsulated in a few high-level stages. First, the urbanization data from satellite imagery from past and present snapshots of Earth can be culled, cleaned and transformed into numerical statistics utilizing remote sensing, band math and zonal statistics. Second, a machine learning model can be built that establishes a statistical relationship between the satellite urbanization data and economic activity, as measured by backward-looking macroeconomic estimates. Third, the statistical relationship can be utilized in combination with current satellite images to predict real-time economic activity for a place of interest. Fourth, official economic activity can be predicted prior to formal government statistical releases to confirm the accuracy of the algorithm and further finetune the statistical learning formula for future real-time predictions, as necessary. In various example embodiments, the order of these four stages can be different and some of the stages can be optional. Further, each of the four stages can have various sub-stages and the output of the stages/sub-stages can be exported in real-time to customers through a data portal in human- and machine-readable formats (e.g. CSV, XLSX, APIs, etc.), recorded in a local memory, a cloud based server and/or a blockchain based distributed ledger.

[00039] In an example embodiment, new satellite imagery obtained in stage 1 can continually reinform the statistical learning mathematical model in stage 2, which can be further re-configured by the accuracy of its predictions compared to government releases in stage 4, allowing for better real-time predictions in stage 3. The real-time statistics can then be released to consumers in near real-time (e.g., weekly, daily, and / or sub-daily periods). Each of the stages and sub-stages are subsequently described in detail.

[00040] FIG. 1 shows a flowchart for an example method **100** for forecasting macroeconomic trends using geospatial data based on the disclosed techniques. The method **100** may include a step **110** of obtaining images (e.g. Landsat images from Landsat satellites 4 through 8) from a satellite imagery catalog (e.g. Google Earth Engine (GEE)). Known algorithms to obtain images can be used for step **110**.

[00041] In an example and non-limiting embodiment, the step **110** may entail using daylight imagery from the Landsat Program combined with remote sensing to obtain images. Of course, other known methods can be used to obtain images in step **110**. The obtained images can optionally be filtered based on cloud cover and/or date to obtain Tier 1 (best) imagery.

[00042] The method **100** may include a step **120** of determining Normalized-Difference Built-Up Index (NDBI) values of zones (e.g. geographical areas) between various bands of the images obtained in step **110**. In various example embodiments, the bands in step **120** may be selected from a group including 0.43-0.45 um band, 0.45-0.51 um band, 0.53-0.59 um band, 0.64-0.67 um band, 0.85-0.88 um band, 1.57-1.65 um band, 2.11-2.29 um band, 0.50-0.68 um band, 1.36-1.38 um band, 10.6-11.9 um band, and 11.50-12.51 um band. Further, the bands may be selected based on the type of satellite, without departing from the scope of the disclosure.

[00043] The method **100** may include a step **130** of determining a mean (average) of the NDBI values for each zone. Step **130** can be performed by utilizing the remote sensing technique of a zonal statistic process, as described in https://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/h-how-zonal-statistics-works.htm (April 2021), incorporated herein by reference. The average of the NDBI values can be collated into numerical statistics within a dataset.

[00044] FIG. 2 shows an exemplary zone layer **210**, value layer **220** and output layer **230** that can be used calculate the mean NDBI value for each US state (i.e. the zones). The zone layer **210** may define the zones (e.g. the shapes, values and geographic locations). In an example embodiment, the zone can be a US state. The value layer **220** may contain the input values in calculating the output of each zone. In an example embodiment, value layer can be the NDBI values for each individual geotiff square tile. The output layer **230** can be a result of the aforementioned zonal statistic process applied to the input values.

[00045] The NDBI values determined in step **120** can be based on the short-wave infrared radiation (SWIR) and near infrared radiation (NIR) waves picked up by the sensors on satellites, and the band math between these radiation spectroscopy spectrums. That is, NDBI = (SWIR-NIR)/(SWIR+NIR).

[00046] As an example of determining the NDBI value in step **120**, a single geotiff tile might have a SWIR value of 1.2 microns and NIR value of 0.9 microns, which, when calculated through the aforementioned NDBI formula, would equal an NDBI value of approximately 0.14. Another geotiff tile might have values of 1.1 and 1.6 microns yielding an NDBI score of approximately -0.19, and a third tile might have values of 1.7 and 0.7 microns, yielding a NDBI score of approximately 0.42. The NDBI values are between -1 and 1.

[00047] With all three of these tiles are in the same geographical zone, then, using the zonal statistics described previously, the three NDBI values can be averaged as such utilizing the mean formula:

$$\overline{NDBI} = \frac{\mathrm{NDBI}_1 + \mathrm{NDBI}_2 + \mathrm{NDBI}_3}{3}$$
$$= \frac{0.14 - 0.19 + 0.42}{3} \approx 0.12$$

[00048] This averaging of the individual scores can yield a single score for the entire geographical zone of 0.12. According to the paper on the NDBI from Zha, Gao and Ni (2003), incorporated herein by reference, an average NDBI value of 0.12 may signify an area of modest urbanization. In general, average (mean) NDBI scores above 0 signify more urbanization than vegetation, while values below 0 demonstrate the opposite.

[00049] **FIG. 3** shows exemplary NDBI zonal statistics for every US state in 2015 by overlaying the mean NDBI score for every state of the US over a map of North America's NDBI scores for the first quarter of 2015. While **FIG. 3** is sourced from the Google Earth Engine platform and API to pull the Landsat images and calculate the zonal statistics, there are numerous alternatives for all of the above steps including locating the necessary images on other cloud servers (e.g., Amazon S3, Microsoft Azure) or by purchasing the Landsat images directly from the USGS and NASA. In addition, both the NDBI and zonal statistics can be calculated using other geospatial software (e.g. ArcGIS Pro, QGIS, Global Mapper).

[00050] The method **100** may include a step **140** of seasonally adjusting the average NDBI values determined in step **130** that may have certain seasonal patterns that obscure the true trend of the values. For example, ice cream sales are consistently higher during summer months than the winter, and, therefore, to compare the two periods, seasonal adjustment needs can be conducted to correct for time-consistent differences.

[00051] In an example embodiment, the step **140** can be performed by utilizing the X-13 ARIMA-SEATS, a computer program produced by the US Census Bureau (US Census Bureau 2017). Of course, other similar known programs can be used without departing from the scope of the present disclosure. **FIG. 4** shows NDBI seasonal adjustment graph for U.S. state of Alabama. Similarly, step **140** can be used to generate NDBI seasonal adjustment graph for other U.S. states and zones.

[00052] The method **100** may include a step **150** of obtaining economic data from various economic sources (e.g. official government sources such as the Federal Reserve Bank of St. Louis (FRED) and the Bureau of Economic Analysis (BEA)). In an example embodiment, FRED can provide U.S. national-level statistics and the BEA can provide state-level statistics. Known algorithms to obtain data can be used for step **150**.

[00053] **FIG. 5A** and **5B** provide non-limiting examples of the economic data that can be obtained in step **150**. **FIG. 5A** illustrates economic data obtained from FRED. **FIG. 5B** illustrates economic data obtained from BEA. The economic data in these figures is illustrated by a unique code, type/description of data (aka variable name) and a frequency of recording. It will be apparent to one skilled in the art that such an illustration of the economic data is a non-limiting example.

[00054] The method **100** may include a step **160** of generating a stationarity dataset based on the adjusted NDBI values obtained in step **140** and the economic data obtained in step **150**. The step **160** can include merging the seasonally adjusted NDBI values obtained in step **140** and the economic data in step **150** to obtain a merged dataset that contains multiple variables. The merging can occur along the state, year, and quarter variables. The merged dataset can then be converted from nominal to real (inflation adjusted) values, as necessary. Known techniques (e.g. techniques utilizing common index features) can be used for the merging.

[00055] After the merging, the step **160** can include combining multiple variables in the merged dataset to obtain custom variables such as state-level GDP per capita and national-level yield spreads (e.g., the US 30 Year Constant Maturity Bond less the US 10 Year Constant Maturity Note, etc.). The percent change (PC) and annualized percentage change (APC) can be calculated for all variables, and then the first difference of each of these variations can be calculated for on-the-level, PC and APC.

[00056] A first-differencing of the custom variables can then be performed to obtain the stationarity dataset such that the trend of the data is centered on zero and mean-reverting over time. First-differencing is a technique for achieving stationarity of a time-series variable, which is mean-reverting across time observations. This can allow in achieving consistent forecasts. While many techniques can be used to achieve stationarity, the present disclosure provides a detailed description of the first-differencing technique. Other techniques may include detrending utilizing regression analysis and variable transformations.

[00057] FIG. 6 shows time-series data and a new first-differenced variable from the underlying values. By graphing both 'value' and 'first-differenced value' the point for creating stationarity in the time-series data can be seen. First-differencing can be calculated by subtracting a variable's current period observation by the previous period and continuing this process for all of the previous observations. In mathematical notation, the formula can be:

$\Delta Var_{i,t} = Var_{i,t} - Var_{i,t-1}$, where i is the observation of the variable and t is time

[00058] FIG. 7A shows the data before being first-differenced and it has an upward trend. In contrast, **FIG. 7B** shows the data after the first-differencing and it has nearly no trend. **FIG. 8** shows an example stationarity for NDBI for US state of Alabama using the aforementioned technique. The variables can then be transformed using quadratic terms (squared, cubed, and fourth power), and then all of these forms can be lagged up to 12 quarters. The output in the form of the stationarity dataset can then be saved and/or outputted.

[00059] The method **100** can include a step **170** of generating a statistical relationship model based on the stationarity dataset and economic activity of each zone. **FIG. 9A and FIG. 9B** show seasonally adjusted NDBI facet graphs and real GDP for each of the 50 US states and District of Columbia respectively to be used in step **170**.

[00060] FIG. 10 illustrates a relationship between the percent changes of NDBI and state-level real GDP using the US states of Alabama and Arkansas as examples. Similar relationship can be illustrated for the other states. There can be a strong relationship between the satellite urbanization data and state economic activity levels. To quantify the magnitude, direction and statistical significance of this relationship, various machine learning models can be utilized. The present disclosure describes the regression model in detail, but it will be appreciated by those skilled in the art that other machine learning models such as random forest, boosting, bagging, neural networks, etc. can also be similarly used.

[00061] To avoid spurious models rife with omitted variable bias, the backward selection can be utilized to fit the regression model in order to test individual combinations of different economic data. To forecast accurate prediction, a maximum number of high-frequency data points can be included in the regression specification to maximize both the total predictive capability of the model (as measured by R^2) while simultaneously achieving statistical significance on all variables in the economic data.

[00062] In an example embodiment, over 200 regressions can be implemented to test various combinations of variables, quadratic terms, interaction terms, leads, lags, and fixed effects. Three best regressions can be identified. First, to test the explanatory power and statistical significance of the satellite urbanization data on its own without economic data, the first difference of the seasonally adjusted NDBI ('ndbi_sa_diff1') can be regressed on the first difference of state-level real GDP ('SQGDP9_1_diff1') utilizing a state-level and year fixed effects specification. Through preliminary regressions and statistical tests (e.g. the Hausman-Wu Test), fixed effects can be identified to maximize the statistical variation of the underlying panel data by essentially 'grouping' the individual values according to their underlying state and year groupings.

[00063] FIG. 11 shows example regression results based on a regression that is the baseline analysis showing the relationship between the cleaned NDBI (satellite) data and the cleaned GDP. This regression utilizes dependent (Y) Variable: State-Level Real Seasonally Adjusted GDP, first differenced ('SQGDP_1_diff1') and independent (X) Variable: State-Level Real Seasonally Adjusted NDBI, first differenced ('ndbi_sa_diff1').

[00064] NDBI can be statistically significantly related to GDP when regressed alone as demonstrated by a t-statistic of 2.45 (surpassing the necessary cutoff threshold of 2). In addition, the coefficient on NDBI can be both positive and appropriate in magnitude, further confirming the reliability of this NDBI variable. The most notable value from this regression can be the R^2 ('R-squared') of the model at 41.7%. This value may suggest that the inclusion of NDBI on its own accounted for nearly half of the variation in the GDP data. Finally, other values in the regression output can also suggest an extremely strong model, including an F-statistic of 23.6 (10 is generally considered significant), and a Jarque-Bera (JB) Condition Number of 54.2, suggesting little multicollinearity.

[00065] FIG. 12 shows results of another example regression that may include additional covariates to increase the R^2 of the model while also only utilizing daily variables. This regression utilizes dependent (Y) Variable: State-Level Real Seasonally Adjusted GDP, first differenced ('SQGDP_1_diff1') and independent (X) Variables: Satellite Data: State-Level Real Seasonally Adjusted NDBI, first differenced ('ndbi_sa_diff1'); Past GDP Momentum Factor: Lagged State-Level Real Seasonally Adjusted GDP, first differenced for quarters 1 through 12 (ex. 'SQGDP_1_diff1_lag5'); Yield Spread: Difference between the quarterly average 30 Year Treasury Bond and the 10 Year Treasury Note, first difference ('Spread_30Yr_10yr_diff1'); Yield Spread Squared: Squared difference between the quarterly average 30 Year Treasury Bond and the 10 Year Treasury Note, first difference ('Spread_30Yr_10yr_diff1_2'); and Interaction Term Between Satellite Data & Lagged GDP: Multiplying Satellite Data by Past GDP Momentum Factor as individual variables (ex. 'ndbi_sa_diff1:SQGDP_9_1_diff1_lag5_1').

[00066] Daily data can be important to maintain the ability to run the algorithm in near real-time. After including lagged terms for GDP (e.g., a momentum term), an interaction term between GDP and NDBI, and national-level yield spreads, the predictive capability of the model may increase by nearly 10 percentage points to 52.2%, while also maintaining the statistical significance of the NDBI variable. In fact, NDBI's t-statistic increased to 3.9, well above the threshold of 2. The inclusion of these additional variables may introduce the possibility of multicollinearity.

[00067] FIG. 13 shows results of another example regression based on a technique of including numerous statistically significant covariates. By including additional covariates, such as the yield spread, lagged GDP, population, personal income, construction spending, and several interaction terms, the model yields an R^2 of 87.0%. This suggests that this model explains nearly all of the variation inherent in predicting state-level GDP.

[00068] This regression utilizes Dependent (Y) Variable: State-Level Real Seasonally Adjusted GDP, first differenced ('SQGDP_1_diff1') and Independent (X) Variables: Satellite Data: State-Level Real Seasonally Adjusted NDBI, first differenced ('ndbi_sa_diff1'); Past GDP Momentum Factor: Lagged State-Level Real Seasonally Adjusted GDP, first differenced for quarters 1 through 12 (ex. 'SQGDP_1_diff1_lag5'); Yield Spread: Difference between the quarterly average 30 Year Treasury Bond and the 10 Year Treasury Note, first difference ('Spread_30Yr_10yr_diff1'); Yield Spread Squared: Squared difference between the quarterly average 30 Year Treasury Bond and the 10 Year Treasury Note, first difference ('Spread_30Yr_10yr_diff1_2'); and Interaction Term Between Satellite Data & Lagged GDP: Multiplying Satellite Data by Past GDP Momentum Factor as individual variables (ex. 'ndbi_sa_diff1:SQGDP_9_1_diff1_lag5_1'). Other explanatory variables may include state population, personal income and construction.

[00069] The method **100** may include a step **180** of forecasting macroeconomic trends (e.g. GDP) based on the statistical relationship model and the current satellite imagery data. The step **180** can be based on a Nowcasting technique illustrated in **FIG. 14** and described in detail as follows. Using weekly data and previously described regression specifications a statistical learning model can be built. This model can relate the two leftmost columns (variables X and Z) to the center column of Y from 1984 Week 1 to 2020 Week 52. This may build a mathematical relationship between state-level GDP (Y) and the satellite urbanization data (X), including the covariates (Z). As official GDP is not a weekly statistic, a linear interpolation can be used to transform the current quarterly GDP statistics into weekly data for the backward-looking models.

[00070] In an example embodiment, to nowcast GDP, the algorithm continues utilizing the weekly statistical learning model culled from the officially released, backward-looking data and carries forward the mathematical specifications to predict present GDP. As the Landsat satellites continue to orbit the Earth photographing the surface in real-time, the inventor continues to run the Region Reducer Function up to the present moment and then plugs these urbanization values into the algorithm to forecast current GDP. Thus, as the satellites circumnavigate the globe every 20 minutes, the algorithm can proxy economic activity continuously, in near real-time (US Geological Survey n.d.).

[00071] In an example embodiment, one or more steps of method **100** can be retuned to be modulated with the newest official GDP releases from the BEA or other sources. To verify the predictive accuracy of the algorithm, the statistical learning model can be utilized to predict backward-looking state-level GDP values. For example, **FIG. 15A** shows results by US state for 2019, Quarter 4 using a regression technique similar to the one used for **FIG. 12**'s results. **FIG. 15B** shows regression results by US state for 2019, Quarter 4 using a regression technique similar to the one used for **FIG. 13**'s results.

[00072] In an example embodiment, when the results from columns 'SQGDP9_1_apc' to 'gdp_pred2_apc' are compared for **FIG. 15A** and **FIG. 15B**, the predicted values can be similar to the actual BEA values. The precision of these estimates can improve when more complicated machine learning algorithms such as random forest and neural networks are employed.

[00073] In an example embodiment, the macroeconomic trends forecasted by the method **100** can be compiled and exported using known techniques. For example, a user-access portal can be used that will allow authenticated users to view and download the products that they subscribe to onto their local devices (e.g. CSV, XLSX, etc. files). In addition, authenticated users may access the forecasts via known programs such as Microsoft Excel or computer programming languages such as Python and R. The trends can also reach users via weekly or monthly newsletters.

[00074] In an example embodiment, the macroeconomic trends forecasted by the method **100** can be recorded in a local memory, a cloud-based server and/or a blockchain based distributed ledger. In a blockchain, the records can be stored in the order that the records are received. Each node in the blockchain network has a complete replica of the entire blockchain. To verify that the transactions in a ledger stored at a node are correct, the blocks in the blockchain can be accessed from oldest to newest, generating a new hash of the block and comparing the new hash to the hash generated when the block was created. If the hashes are the same, then the transactions in the block are verified.

[00075] FIG. 16 shows a system **1600** for forecasting macroeconomic trends using geospatial data, the system **1600** comprising a processor **1610** and a memory **1620**, the memory **1620** storing computer-executable instructions which are executed by the processor **1610**.

[00076] In an example embodiment, these computer-executable instructions cause the processor **1610** to obtain images from a satellite imagery catalog, determine NDBI values of one or more zones between various bands of the images, and determine an average of the NDBI values for each zone. This is similar to aspects of previously described steps **110**, **120** and **130** respectively.

[00077] The computer-executable instructions may further cause the processor **1610** to seasonally adjust the average NDBI values, obtain economic data from external sources and generate a stationarity dataset based on the adjusted NDBI values and the economic data. This is similar to aspects of previously described steps **140**, **150** and **160** respectively

[00078] The computer-executable instructions may further cause the processor **1610** to generate a statistical relationship model based on the stationarity dataset and economic activity of each zone; and forecast a macroeconomic trend based on the statistical relationship model and the current satellite imagery data. This is similar to aspects of previously described steps **170** and **180** respectively.

[00079] FIG. 17 is a block diagram illustrating an example computer system **1700** upon which any one or more of the methodologies (e.g. method **100** and/or system **1600**) herein discussed may be run according to an example described herein. Computer system **1700** may be embodied as a computing device, providing operations of the components featured in the various figures, including components of the system **1600**, method **100**, or any other processing or computing platform or component described or referred to herein.

[00080] In alternative embodiments, the computer system **1700** can operate as a standalone device or may be connected (e.g., networked) to other machines. In a networked deployment, the computing system **1700** may operate in the capacity of either a server or a client machine in server-client network environments, or it may act as a peer machine in peer-to-peer (or distributed) network environments.

[00081] Example computer system **1700** includes a processor **1702** (e.g., a central processing unit (CPU), a graphics processing unit (GPU) or both), a main memory **1704** and a static memory **1706**, which communicate with each other via an interconnect **1708** (e.g., a link, a bus, etc.). The computer system **1700** may further include a video display unit **1710**, an input device **1712** (e.g. keyboard) and a user interface (UI) navigation device **1714** (e.g., a mouse). In one embodiment, the video display unit **1710**, input device **1712** and UI navigation device **1714** are a touch screen display. The computer system **1700** may additionally include a storage device **1716** (e.g., a drive unit), a signal generation device **1718** (e.g., a speaker), an output controller **1732**, and a network interface device **1720** (which may include or operably communicate with one or more antennas **1730**, transceivers, or other wireless communications hardware), and one or more sensors **1728**.

[00082] The storage device **1716** includes a machine-readable medium **1722** on which is stored one or more sets of data structures and instructions **1724** (e.g., software) embodying or utilized by any one or more of the methodologies or functions described herein. The instructions **1724** may also reside, completely or at least partially, within the main memory **1704**, static memory **1706**, and/or within the processor **1702** during execution thereof by the computer system **1700**, with the main memory **1704**, static memory **1706**, and the processor **1702** constituting machine-readable media.

[00083] While the machine-readable medium **1722** (or computer-readable medium) is illustrated in an example embodiment to be a single medium, the term “machine-readable medium” may include a single medium or multiple medium (e.g., a centralized or distributed database, and/or associated caches and servers) that store the one or more instructions **1724**.

[00084] The term “machine-readable medium” shall also be taken to include any tangible medium that is capable of storing, encoding or carrying instructions for execution by the machine and that cause the machine to perform any one or more of the methodologies of the present disclosure or that is capable of storing, encoding or carrying data structures utilized by or associated with such instructions.

[00085] The term “machine-readable medium” shall accordingly be taken to include, but not be limited to, solid-state memories, optical media, magnetic media or other non-transitory media. Specific examples of machine-readable media include non-volatile memory, including, by way of example, semiconductor memory devices (e.g., Electrically Programmable Read-Only Memory (EPROM), Electrically Erasable Programmable Read-Only Memory (EEPROM)) and flash memory devices;

magnetic disks such as internal hard disks and removable disks; magneto-optical disks; and CD-ROM and DVD-ROM disks.

[00086] The instructions **1724** may further be transmitted or received over a communications network **1726** using a transmission medium via the network interface device **1720** utilizing any one of several well-known transfer protocols (e.g., HTTP). Examples of communication networks include a local area network (LAN), wide area network (WAN), the Internet, mobile telephone networks, Plain Old Telephone (POTS) networks, and wireless data networks (e.g., Wi-Fi, 3G, and 4G LTE/LTE-A or WiMAX networks). The term “transmission medium” shall be taken to include any intangible medium that can store, encoding, or carrying instructions for execution by the machine, and includes digital or analog communications signals or other intangible medium to facilitate communication of such software.

[00087] Other applicable network configurations may be included within the scope of the presently described communication networks. Although examples were provided with reference to a local area wireless network configuration and a wide area Internet network connection, it will be understood that communications may also be facilitated using any number of personal area networks, LANs, and WANs, using any combination of wired or wireless transmission mediums.

[00088] The embodiments described above may be implemented in one or a combination of hardware, firmware, and software. For example, the features in the system architecture **1700** of the processing system may be client-operated software or be embodied on a server running an operating system with software running thereon. While some embodiments described herein illustrate only a single machine or device, the terms “system”, “machine”, or “device” shall also be taken to include any collection of machines or devices that individually or jointly execute a set (or multiple sets) of instructions to perform any one or more of the methodologies discussed herein.

[00089] Examples, as described herein, may include, or may operate on, logic or several components, modules, features, or mechanisms. Such items are tangible entities (e.g., hardware) capable of performing specified operations and may be configured or arranged in a certain manner. In an example, circuits may be arranged (e.g., internally or with respect to external entities such as other circuits) in a specified manner as a module, component, or feature. In an example, the whole or part of one or more computer systems (e.g., a standalone, client or server computer system) or one or more hardware processors may be configured by firmware or software (e.g., instructions, an application portion, or an application) as an item that operates to perform specified operations. In an example, the software may reside on a machine readable medium. In an example, the software, when executed by underlying hardware, causes the hardware to perform the specified operations.

[00090] Accordingly, such modules, components, and features are understood to encompass a tangible entity, be that an entity that is physically constructed, specifically configured (e.g., hardwired), or temporarily (e.g., transitorily) configured (e.g., programmed) to operate in a specified manner or to perform part or all operations described herein. Considering examples in which modules, components, and features are temporarily configured, each of the items need not be instantiated at any one moment in time. For example, where the modules, components, and features comprise a general-purpose hardware processor configured using software, the general-purpose hardware processor may be configured as respective different items at different times. Software may accordingly configure a hardware processor, for example, to constitute a particular item at one instance of time and to constitute a different item at a different instance of time.

[00091] Additional examples of the presently described method (e.g. **700**), system (e.g. **100**), and device embodiments are suggested according to the structures and techniques described herein. Other non-limiting examples may be configured to operate separately or can be combined in any permutation or combination with any one or more of the other examples provided above or throughout the present disclosure.

[00092] It will be appreciated by those skilled in the art that the present disclosure can be embodied in other specific forms without departing from the spirit or essential characteristics thereof. The presently disclosed embodiments are therefore considered in all respects to be illustrative and not restricted. The scope of the disclosure is indicated by the appended claims rather than the foregoing description and all changes that come within the meaning and range and equivalence thereof are intended to be embraced therein.

[00093] It should be noted that the terms “including” and “comprising” should be interpreted as meaning “including, but not limited to”. If not already set forth explicitly in the claims, the term “a” should be interpreted as “at least one” and “the”, “said”, etc. should be interpreted as “the at least one”, “said at least one”, etc. Furthermore, it is the Applicant's intent that only claims that include the express language "means for" or "step for" be interpreted under 35 U.S.C. 112(f). Claims that do not expressly include the phrase "means for" or "step for" are not to be interpreted under 35 U.S.C. 112(f).

[00094] The present disclosure incorporates the following publications/articles by reference:

1. Doll, Christopher N. H., Jan-Peter Muller, and Jeremy G. Morley. 2006. "Mapping Regional Economic Activity from Night-Time Light Satellite Imagery." *Ecological Economics* 75-92.
2. ESRI. n.d. *How Zonal Statistics Work.* Accessed March 7, 2021. https://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/h-how-zonal-statistics-works.htm.
3. Ghosh, T., R. Powell, C. D. Elvidge, K. E. Baugh, P. C. Sutton, and S. Anderson. 2010. "Shedding Light on the Global Distribution of Economic Activity." *The Open Geography Journal* 148-161.
4. He, Chunyang, Peijun Shi, Dingyong Xie, and Yuanyuan Zhao. 2010. "Improving the Normalized Difference Built Up Index to Map Urban Built-Up Areas Using a Semiautomatic Segmentation Approach." *Remote Sensing Letters* 213-221.
5. Henderson, J. Vernon, Adam Storeygard, and David N. Weil. 2012. "Measuring Economic Growth from Outer Space." *American Economic Association* 994-1028.
6. Jean, Neal, Marshall Burke, Michael Xie, W. Matthew Davis, David B. Lobell, and Stefano Ermon. 2016. "Combining Satellite Imagery and Machine Learning to Predict Poverty." *Science* 790-794.
7. US Census Bureau. 2017. *X-13 ARIMA-SEATS Seasonal Adjustment Program.* March 10. Accessed March 4, 2021. census.gov/srd/www/x13as/.
8. US Geological Survey. n.d. *USGS Landsat 4 Surface Reflection Tier.* Accessed March 4, 2021. https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LT04_C01_T1_SR.
9. Xi, Chen, and William D. Nordhaus. 2011. "Using Luminosity Data as a Proxy for Economic Statistics." *PNAS* 8589-9504.

10. Zha, Y., J. Gao, and S. Ni. 2003. "Use of Normalized Difference Built-Up Index in Automatically Mapping Urban Areas from TM Imagery." *International Journal of Remote Sensing* 583-594

CLAIMS

1. A computer-implemented method for forecasting macroeconomic trends using geospatial data and a machine learning model, the method comprising:

obtaining images from a satellite imagery catalog;

determining Normalized-Difference Built-Up Index (NDBI) values of one or more zones between various bands of the images;

determining an average of the NDBI values for each zone;

seasonally adjusting the average NDBI values;

obtaining economic data from external sources;

generating a stationarity dataset based on the adjusted NDBI values and the economic data;

generating a statistical relationship model based on the stationarity dataset and economic activity of each zone; and

forecasting a macroeconomic trend based on the statistical relationship model and the current satellite imagery data.

2. The method of claim 1, wherein the macroeconomic trend is Gross Domestic Product (GDP).

3. The method of claim 1, wherein the statistical relationship model is based on at least one machine learning algorithm.

4. The method of claim 3, wherein the machine learning algorithm is a regression algorithm.

5. The method of claim 1, wherein the external sources include Federal Reserve Bank of St. Louis (FRED) and the Bureau of Economic Analysis (BEA).

6. The method of claim 1, wherein the satellite imagery catalog is Google Earth Engine.

7. The method of claim 1, wherein each zone is a state of the United States.

8. The method of claim 1, comprising:

compiling and/or exporting the macroeconomic trend to an external destination.

9. The method of claim 8, wherein the external destination is a user-access portal that allows authenticated users to view and download the macroeconomic trend.

10. The method of claim 8, wherein the external destination is a blockchain based distributed ledger that records the macroeconomic trend.

11. A system for forecasting macroeconomic trends using geospatial data a machine learning model, the system comprising a processor and a memory, the memory storing computer-executable instructions which are executed by the processor to:

obtain images from a satellite imagery catalog;

determine Normalized-Difference Built-Up Index (NDBI) values of one or more zones between various bands of the images;

determine an average of the NDBI values for each zone;

seasonally adjust the average NDBI values;

obtain economic data from external sources;

generate a stationarity dataset based on the adjusted NDBI values and the economic data;

generate a statistical relationship model based on the stationarity dataset and economic activity of each zone; and

forecast a macroeconomic trend based on the statistical relationship model and the current satellite imagery data.

12. The system of claim 11, wherein the macroeconomic trend is Gross Domestic Product (GDP).

13. The system of claim 11, wherein the statistical relationship model is based on at least one machine learning algorithm.

14. The system of claim 11, wherein the machine learning algorithm is a regression algorithm.

15. The system of claim 11, wherein the external sources include Federal Reserve Bank of St. Louis (FRED) and the Bureau of Economic Analysis (BEA).

16. The system of claim 11, wherein the satellite imagery catalog is Google Earth Engine.

17. The system of claim 11, wherein each zone is a state of the United States.

18. The system of claim 11, wherein the macroeconomic trend is compiled and/or exported to an external destination.

19. The system of claim 18, wherein the external destination is a user-access portal that allows authenticated users to view and download the macroeconomic trend.

20. The system of claim 19, wherein the external destination is a blockchain based distributed ledger that records the macroeconomic trend.

FIG.1 (100)

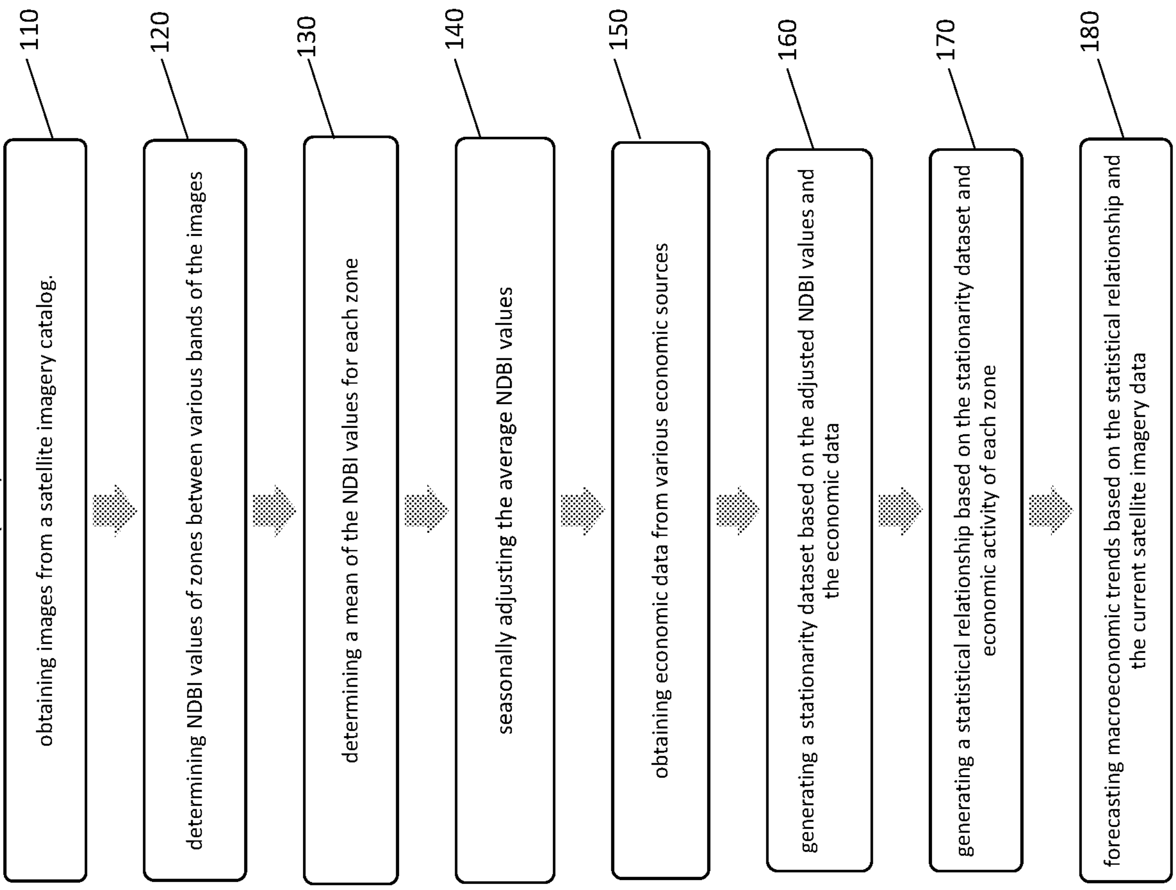

110
obtaining images from a satellite imagery catalog.
120
determining NDBI values of zones between various bands of the images
130
determining a mean of the NDBI values for each zone
140
seasonally adjusting the average NDBI values
150
obtaining economic data from various economic sources
160
generating a stationarity dataset based on the adjusted NDBI values and the economic data
170
generating a statistical relationship based on the stationarity dataset and economic activity of each zone
180
forecasting macroeconomic trends based on the statistical relationship and the current satellite imagery data

FIG.2 (200)

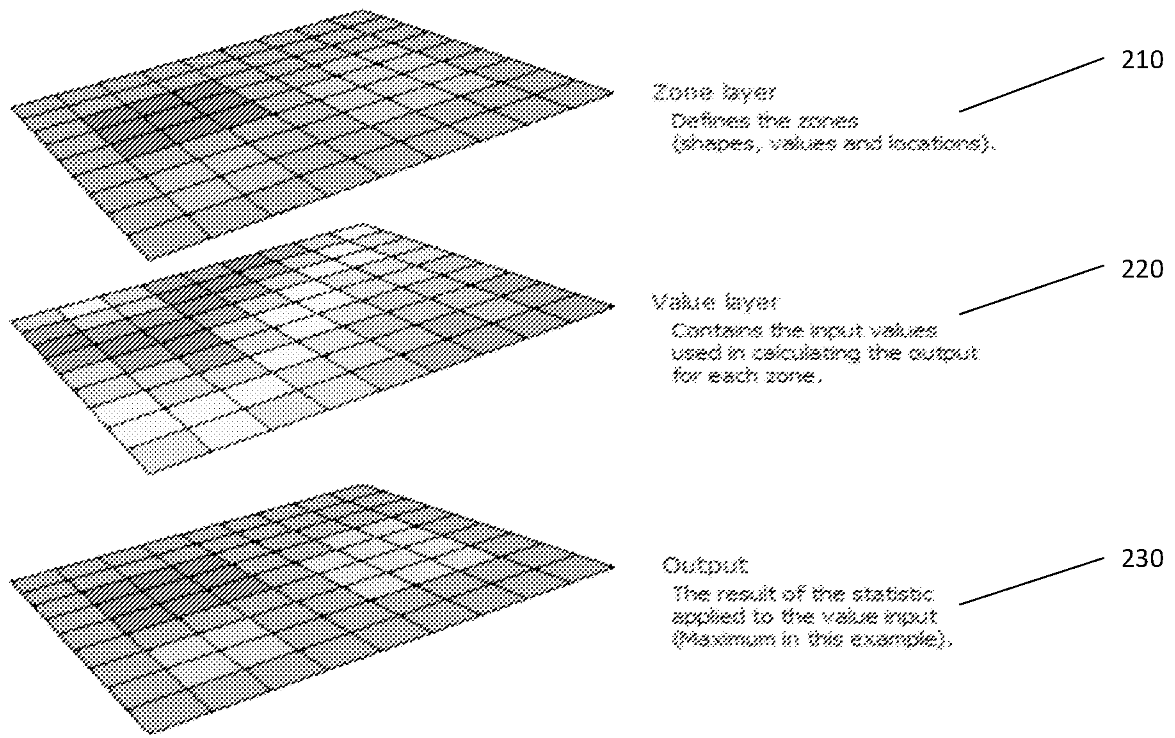

Zone layer
Defines the zones
(shapes, values and locations).
210
Value layer
Contains the input values
used in calculating the output
for each zone.
220
Output
The result of the statistic
applied to the value input
(Maximum in this example).
230

FIG.3

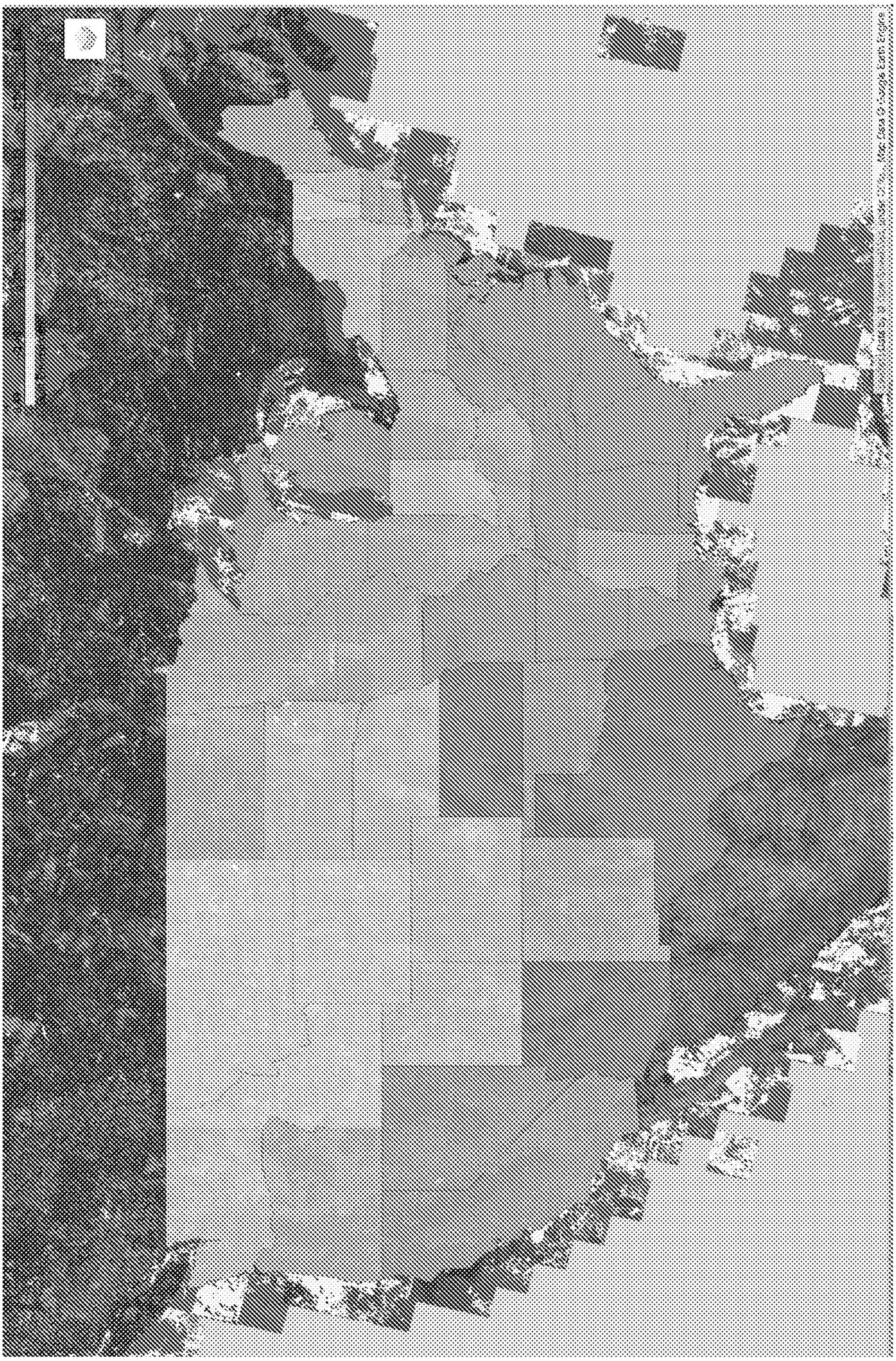


FIG.4

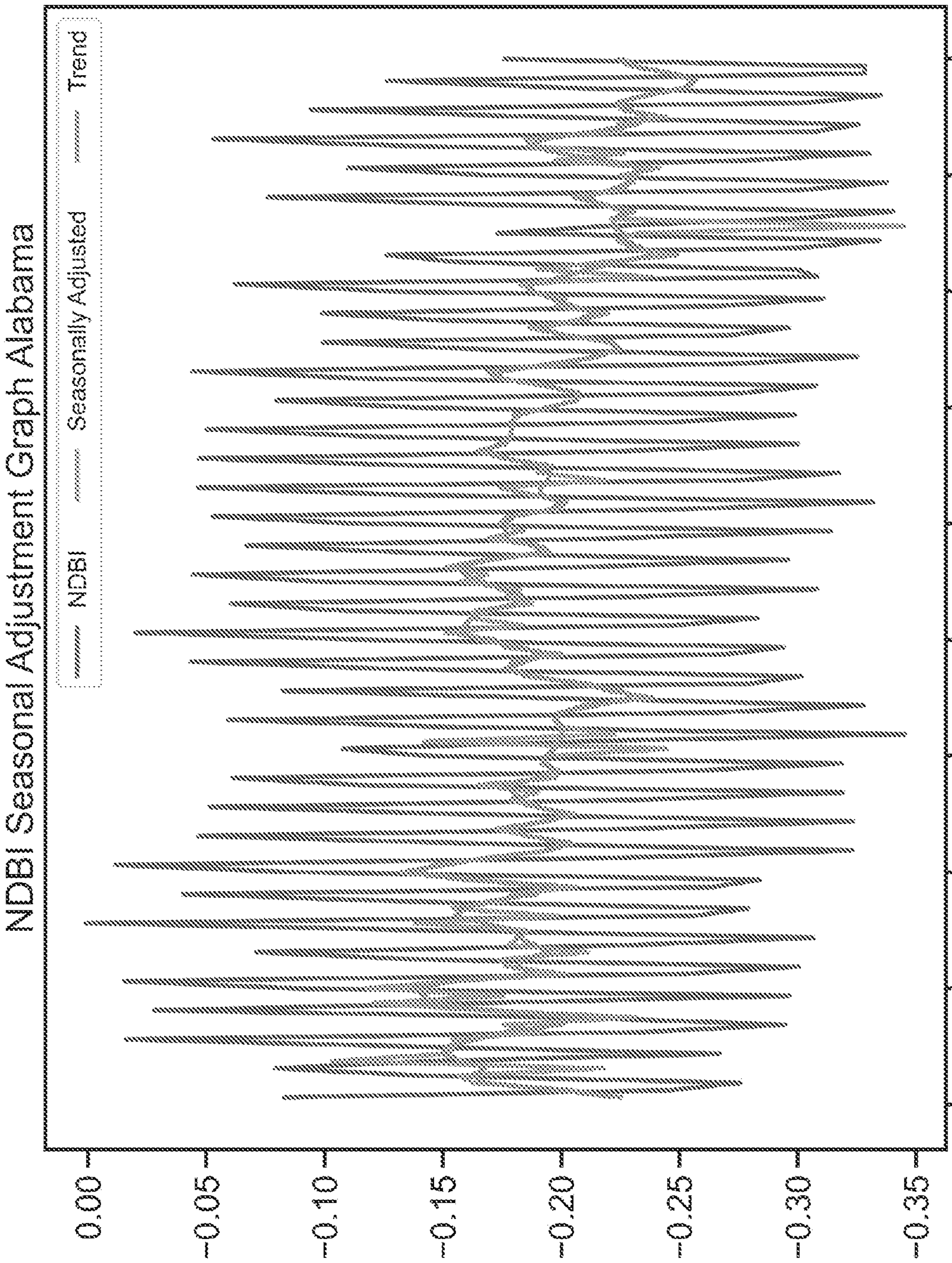

NDBI Seasonal Adjustment Graph Alabama
NDBI
Seasonally Adjusted
Trend
0.00
-0.05
-0.10
-0.15
-0.20
-0.25
-0.30
-0.35
1984
1988
1992
1996
2000
2004
2008
2012
2016
2020

FIG.5A

Code	Variable Name	Periodicity
GDPC1	Real Gross Domestic Product (Chained 2012)	Quarterly
A191RL1Q225SBEA	Real Gross Domestic Product (% Change from Proceeding Period)	Quarterly
A191RO1Q156NBEA	Real Gross Domestic Product from Quarter One Year Ago	Quarterly
A939RX0Q0417SBEA	Real GDP per capita (Chained 2012)	Quarterly
GDPDEF	GDP Deflator	Quarterly
GPDIC1	Real Gross Private Domestic Investment (Chained 2012)	Quarterly
A006RL1Q225SBEA	Real Gross Private Domestic Investment (% Change from Proceeding Period)	Quarterly
CPIAUCSL	CPI with energy and food	Monthly
CPILFESL	CPI without energy and food	Monthly
RECPROUSM156N	Recession Probability	Monthly
EFFR	Effective Federal Funds Rate	Daily
DGS30	30 Year Treasury Constant Maturity	Daily
DGS20	20 Year Treasury Constant Maturity	Daily
DGS10	10 Year Treasury Constant Maturity	Daily
DGS5	5 Year Treasury Constant Maturity	Daily
DGS6MO	6-Month Treasury Constant Maturity	Daily
DGS3MO	3-Month Treasury Constant Maturity	Daily

FIG.5B

Code	Variable Name	Periodicity
SQGDP9	Real GDP by State, Line 1, Personal income (millions of dollars, seasonally adjusted)	Quarterly
SQINC1	GDP and Personal Income, Line 1, Population (midperiod, persons)	Quarterly
SQINC1	GDP and Personal Income, Line 2, Per capita personal income, (dollars)	Quarterly
SQINC1	GDP and Personal Income, Line 3, Personal income (millions of dollars, seasonally adjusted)	Quarterly
SQINC4	GDP and Personal Income, Line 10, Nonfarm personal income	Quarterly
SQINC4	GDP and Personal Income, Line 11, Equals: Net earnings by place of residence	Quarterly
SQINC4	GDP and Personal Income, Line 45, Equals: Net earnings by place of residence	Quarterly
SQINC4	GDP and Personal Income, Line 50, Wages and salaries	Quarterly
SQINC6N	Compensation of Employees by NAICS Industry, Line 172, Nonfarm compensation	Quarterly
SQINC6N	Compensation of Employees by NAICS Industry, Line 400, Construction	Quarterly
SQINC35	Personal Current Transfer Receipts, Line 1000, Personal current transfer receipts	Quarterly
SQINC35	Personal Current Transfer Receipts, Line 2110, Social Security benefits	Quarterly
SQINC35	Personal Current Transfer Receipts, Line 2210, Medicare benefits	Quarterly
SQINC35	Personal Current Transfer Receipts, Line 2221, Medicaid	Quarterly
SQINC35	Personal Current Transfer Receipts, Line 2410, State unemployment insurance compensation	Quarterly
SQINC35	Personal Current Transfer Receipts, Line 6000, All other personal current transfer receipts	Quarterly

FIG.6

Year	Quarter	Value	First-Differenced Value
2021	3	7.3	3.6
2021	2	3.7	-1.9
2021	1	5.6	-4.5
2020	4	10.1	7.6
2020	3	2.5	-4.2
2020	2	6.7	3.2
2020	1	3.5	-0.5
2019	4	4	-

FIG.7A

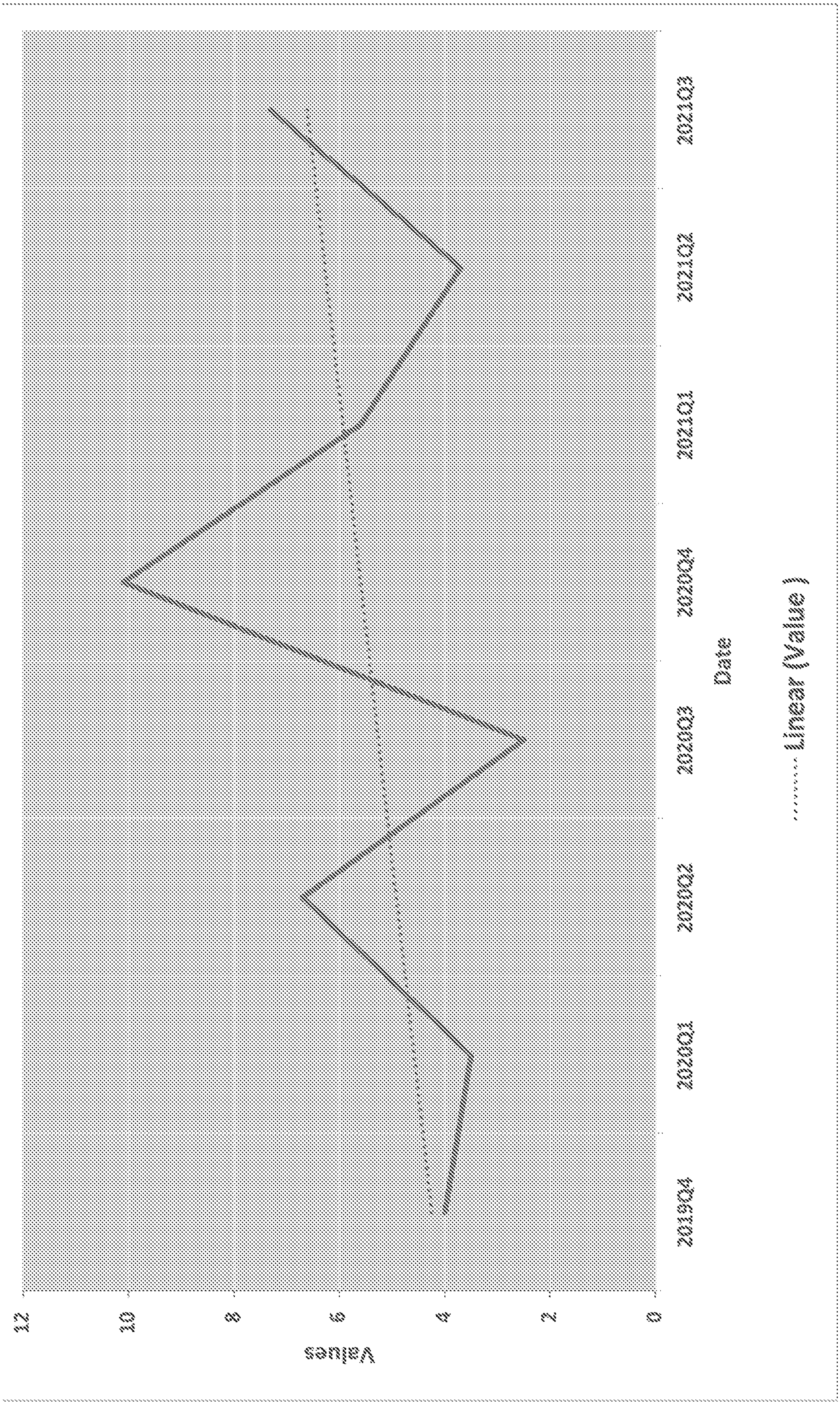
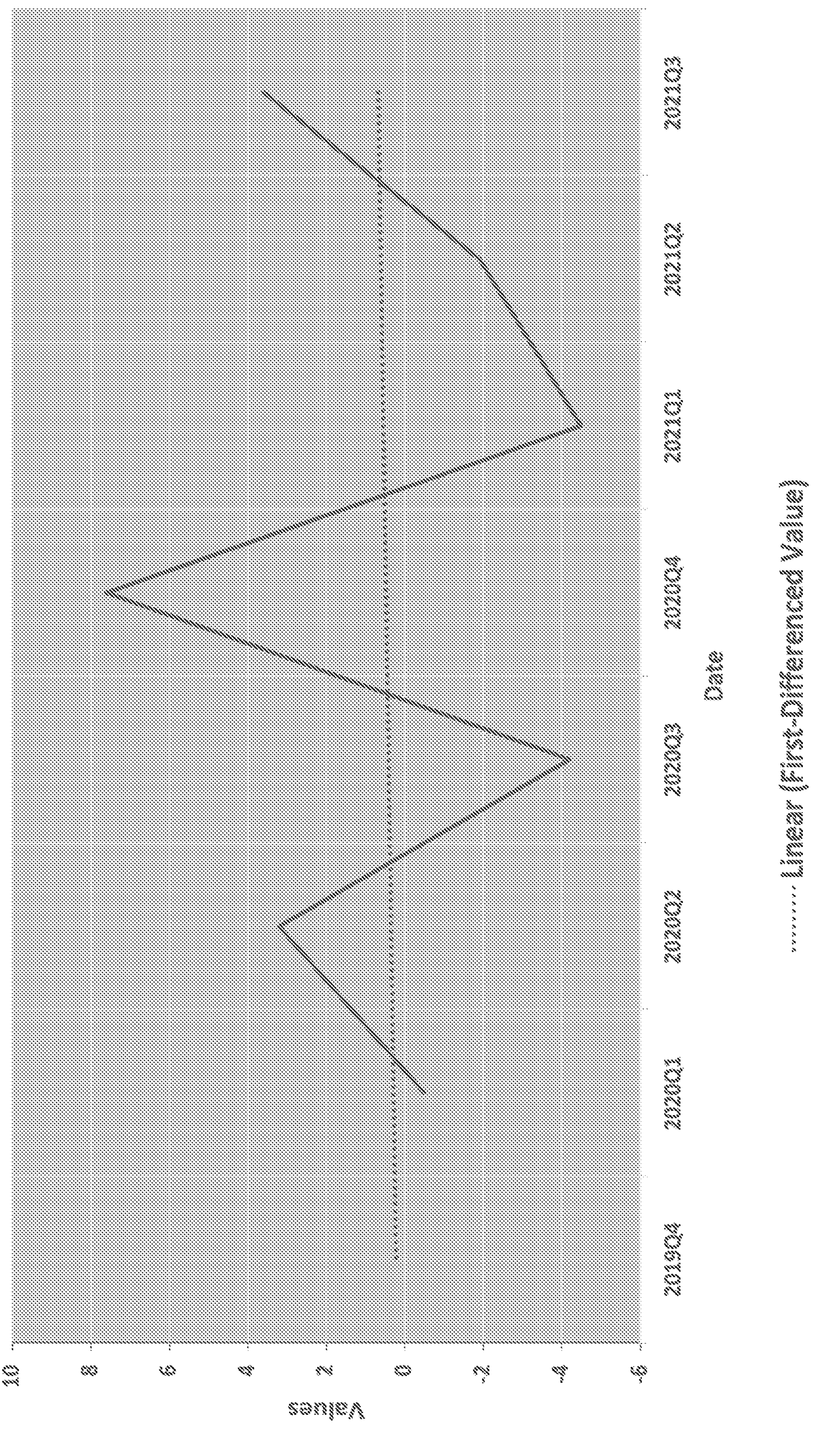

Values
0
2
4
6
8
10
12
2019Q4
2020Q1
2020Q2
2020Q3
2020Q4
2021Q1
2021Q2
2021Q3
Date
Linear (Value)

FIG.7B



Values
10
8
6
4
2
0
-2
-4
-6
Date
2019Q4
2020Q1
2020Q2
2020Q3
2020Q4
2021Q1
2021Q2
2021Q3
Linear (First-Differenced Value)

FIG.8

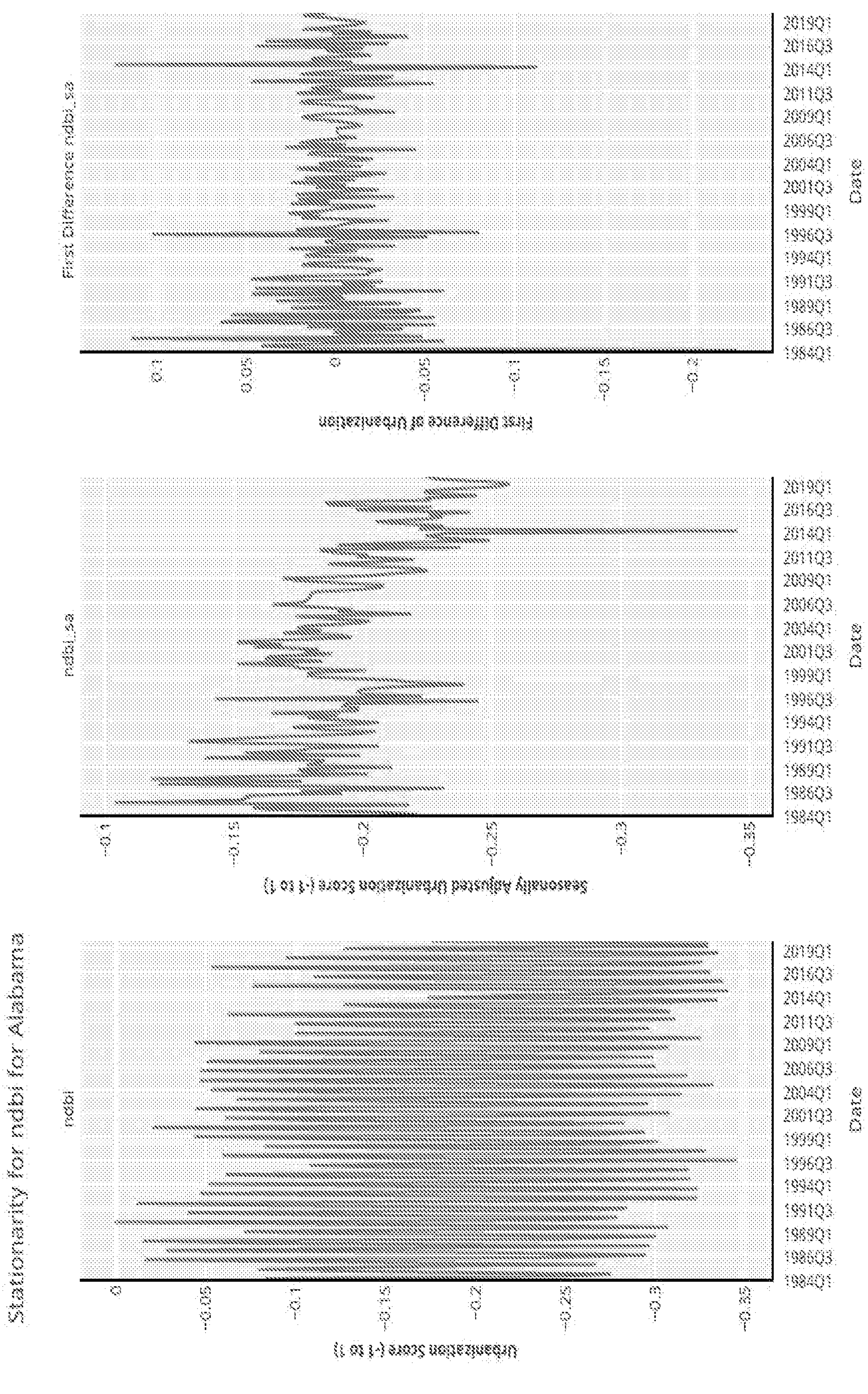

Stationarity for ndbi for Alabama
ndbi
Urbanization Score (-1 to 1)
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
-0.35
ndbi_sa
Seasonally Adjusted Urbanization Score (-1 to 1)
-0.1
-0.15
-0.2
-0.25
-0.3
-0.35
First Difference ndbi_sa
First Difference of Urbanization
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
1984Q1
1986Q3
1989Q1
1991Q3
1994Q1
1996Q3
1999Q1
2001Q3
2004Q1
2006Q3
2009Q1
2011Q3
2014Q1
2016Q3
2019Q1
Date

FIG.9A

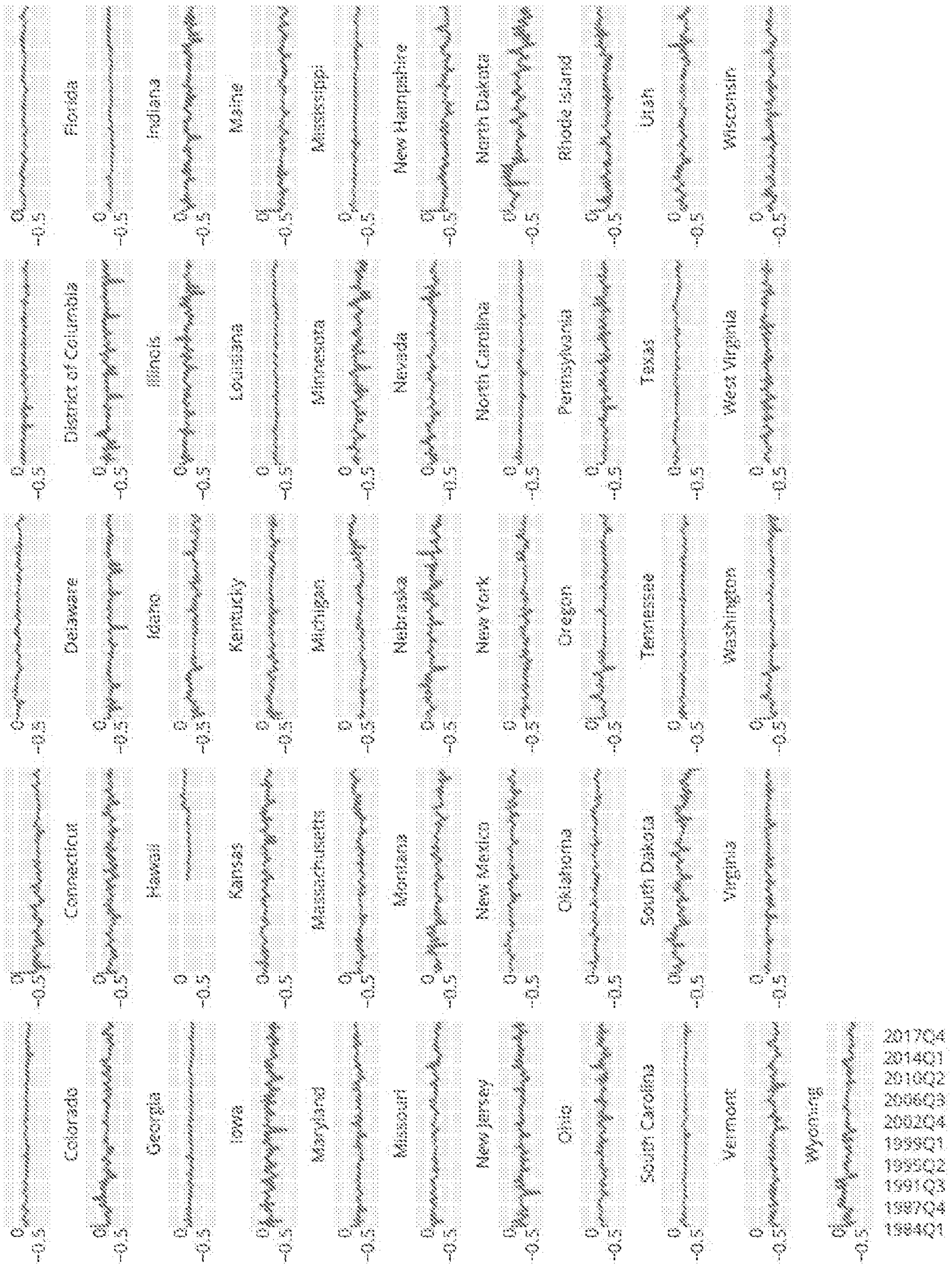

Alabama
Alaska
Arizona
Arkansas
California
Colorado
Connecticut
Delaware
District of Columbia
Florida
Georgia
Hawaii
Idaho
Illinois
Indiana
Iowa
Kansas
Kentucky
Louisiana
Maine
Maryland
Massachusetts
Michigan
Minnesota
Mississippi
Missouri
Montana
Nebraska
Nevada
New Hampshire
New Jersey
New Mexico
New York
North Carolina
North Dakota
Ohio
Oklahoma
Oregon
Pennsylvania
Rhode Island
South Carolina
South Dakota
Tennessee
Texas
Utah
Vermont
Virginia
Washington
West Virginia
Wisconsin
Wyoming
0
-0.5
1984Q1
1987Q4
1991Q3
1995Q2
1999Q1
2002Q4
2006Q3
2010Q2
2014Q1
2017Q4

FIG.9B

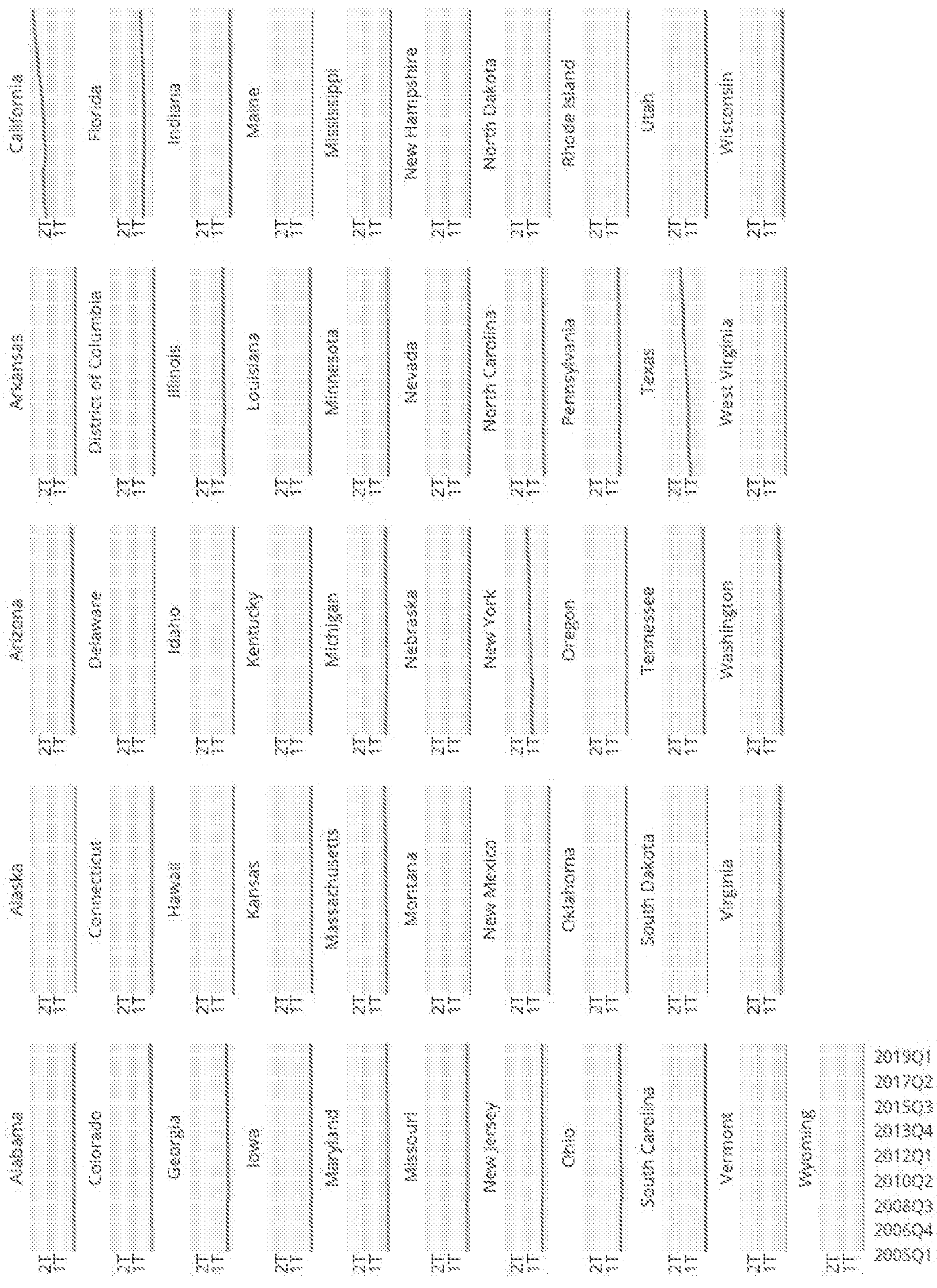

Alabama
Alaska
Arizona
Arkansas
California
Colorado
Connecticut
Delaware
District of Columbia
Florida
Georgia
Hawaii
Idaho
Illinois
Indiana
Iowa
Kansas
Kentucky
Louisiana
Maine
Maryland
Massachusetts
Michigan
Minnesota
Mississippi
Missouri
Montana
Nebraska
Nevada
New Hampshire
New Jersey
New Mexico
New York
North Carolina
North Dakota
Ohio
Oklahoma
Oregon
Pennsylvania
Rhode Island
South Carolina
South Dakota
Tennessee
Texas
Utah
Vermont
Virginia
Washington
West Virginia
Wisconsin
Wyoming
2T
1T
2005Q1
2006Q4
2008Q3
2010Q2
2012Q1
2013Q4
2015Q3
2017Q2
2019Q1

FIG.10

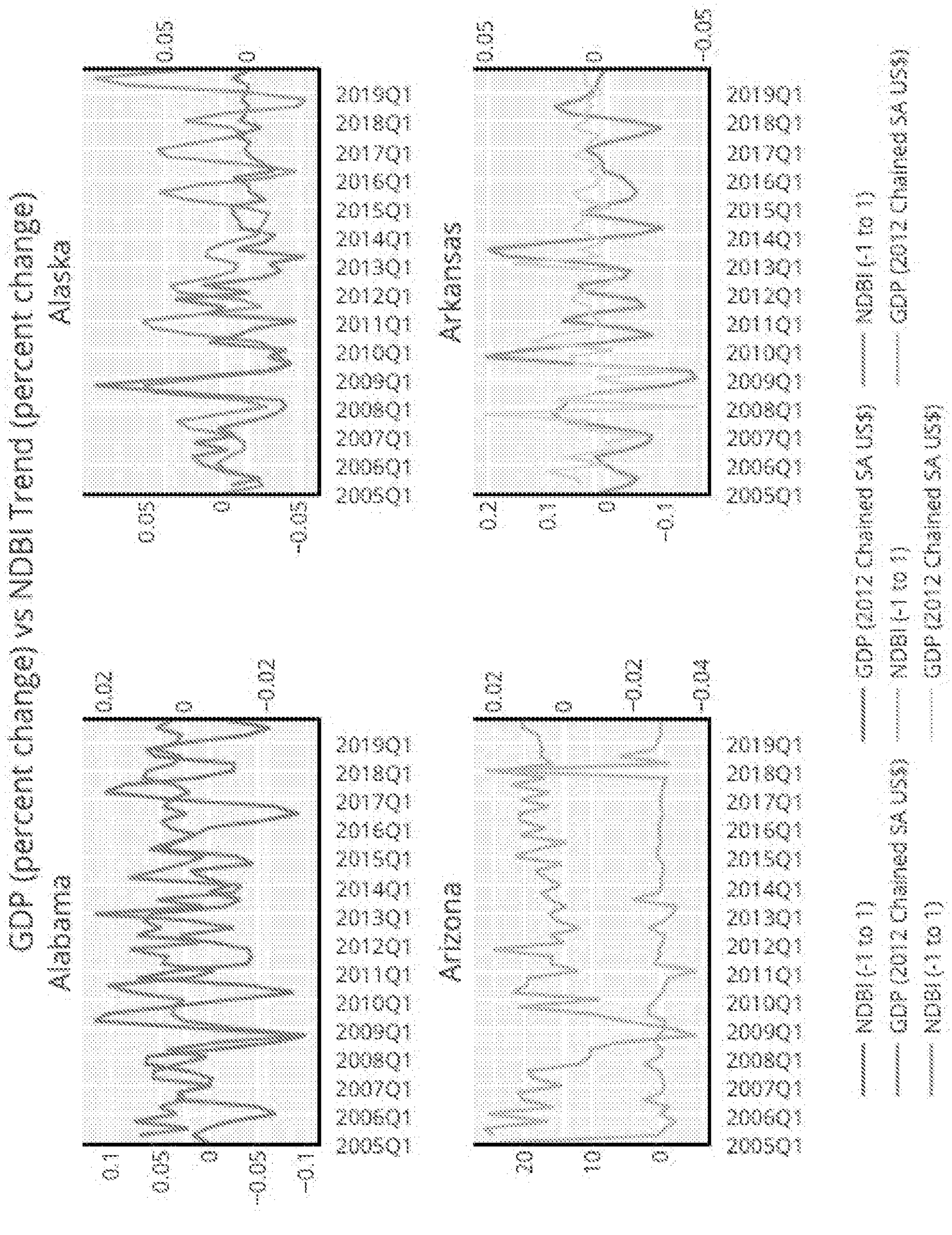

GDP (percent change) vs NDBI Trend (percent change)
Alabama
Alaska
Arizona
Arkansas
2005Q1
2006Q1
2007Q1
2008Q1
2009Q1
2010Q1
2011Q1
2012Q1
2013Q1
2014Q1
2015Q1
2016Q1
2017Q1
2018Q1
2019Q1
0.1
0.05
0
−0.05
−0.1
0.02
−0.02
−0.04
30
10
0.2
NDBI (-1 to 1)
GDP (2012 Chained SA US$)

FIG.11

OLS Regression Results

Dep. Variable:	SQGDP9_1_diff1	R-squared:	0.417
Model:	OLS	Adj. R-squared:	0.399
Method:	Least Squares	F-statistic:	23.59
Date:	Sun, 07 Mar 2021	Prob (F-statistic):	1.68e-187
Time:	17:48:33	Log-Likelihood:	-48011.
No. Observations:	2040	AIC:	9.614e+04
Df Residuals:	1979	BIC:	9.649e+04
Df Model:	60		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025
Intercept	5.595e+08	7.01e+08	0.798	0.425	-8.15e+08
C(State)[T.Alaska]	-5.805e+08	9.14e+08	-0.635	0.525	-2.37e+09
C(State)[T.Arizona]	1.283e+09	9.14e+08	1.404	0.160	-5.09e+08
C(State)[T.Arkansas]	-1.737e+08	9.14e+08	-0.190	0.849	-1.97e+09
C(State)[T.California]	2.018e+10	9.14e+08	22.080	0.000	1.84e+10
C(State)[T.Colorado]	1.901e+09	9.14e+08	2.080	0.038	1.09e+08
C(State)[T.Connecticut]	-4.801e+08	9.14e+08	-0.525	0.599	-2.27e+09
C(State)[T.Delaware]	-4.612e+08	9.14e+08	-0.505	0.614	-2.25e+09
C(State)[T.District of Columbia]	-1.06e+08	9.14e+08	-0.116	0.908	-1.9e+09
C(State)[T.Florida]	4.709e+09	9.14e+08	5.152	0.000	2.92e+09
C(State)[T.Georgia]	2.561e+09	9.14e+08	2.802	0.005	7.69e+08
C(State)[T.Hawaii]	-2.227e+08	9.14e+08	-0.244	0.808	-2.02e+09
C(State)[T.Idaho]	-8.326e+07	9.14e+08	-0.091	0.927	-1.88e+09
C(State)[T.Illinois]	1.537e+09	9.14e+08	1.681	0.093	-2.56e+08
C(State)[T.Indiana]	8.184e+08	9.14e+08	0.895	0.371	-9.74e+08
C(State)[T.Iowa]	2.729e+07	9.14e+08	0.030	0.976	-1.77e+09
C(State)[T.Kansas]	8.838e+07	9.14e+08	0.097	0.923	-1.7e+09
C(State)[T.Kentucky]	4.411e+07	9.14e+08	0.048	0.962	-1.75e+09
C(State)[T.Louisiana]	-5.573e+08	9.14e+08	-0.610	0.542	-2.35e+09
C(State)[T.Maine]	-4.29e+08	9.14e+08	-0.469	0.639	-2.22e+09
C(State)[T.Maryland]	8.755e+08	9.14e+08	0.958	0.338	-9.17e+08
C(State)[T.Massachusetts]	2.164e+09	9.14e+08	2.368	0.018	3.71e+08
C(State)[T.Michigan]	1.622e+09	9.14e+08	1.775	0.076	-1.7e+08
C(State)[T.Minnesota]	1.049e+09	9.14e+08	1.148	0.251	-7.44e+08
C(State)[T.Mississippi]	-4.45e+08	9.14e+08	-0.487	0.626	-2.24e+09
C(State)[T.Missouri]	3.127e+07	9.14e+08	0.034	0.973	-1.76e+09
C(State)[T.Montana]	-3.274e+08	9.14e+08	-0.358	0.720	-2.12e+09
C(State)[T.Nebraska]	3.914e+07	9.14e+08	0.043	0.966	-1.75e+09
C(State)[T.Nevada]	1.782e+08	9.14e+08	0.195	0.845	-1.61e+09
C(State)[T.New Hampshire]	-2.834e+08	9.14e+08	-0.310	0.757	-2.08e+09
C(State)[T.New Jersey]	5.481e+08	9.14e+08	0.600	0.549	-1.24e+09
C(State)[T.New Mexico]	-2.436e+08	9.14e+08	-0.266	0.790	-2.04e+09
C(State)[T.New York]	5.511e+09	9.14e+08	6.030	0.000	3.72e+09
C(State)[T.North Carolina]	1.425e+09	9.14e+08	1.559	0.119	-3.67e+08
C(State)[T.North Dakota]	-9.302e+07	9.14e+08	-0.102	0.919	-1.89e+09
C(State)[T.Ohio]	2.216e+09	9.14e+08	2.425	0.015	4.24e+08
C(State)[T.Oklahoma]	4.53e+08	9.14e+08	0.496	0.620	-1.34e+09
C(State)[T.Oregon]	9.963e+08	9.14e+08	1.090	0.276	-7.96e+08
C(State)[T.Pennsylvania]	2.287e+09	9.14e+08	2.502	0.012	4.94e+08
C(State)[T.Rhode Island]	-5.076e+08	9.14e+08	-0.555	0.579	-2.3e+09
C(State)[T.South Carolina]	6.531e+08	9.14e+08	0.715	0.475	-1.14e+09
C(State)[T.South Dakota]	-3.311e+08	9.14e+08	-0.362	0.717	-2.12e+09
C(State)[T.Tennessee]	1.079e+09	9.14e+08	1.180	0.238	-7.14e+08
C(State)[T.Texas]	1.192e+10	9.14e+08	13.041	0.000	1.01e+10
C(State)[T.Utah]	7.015e+08	9.14e+08	0.768	0.443	-1.09e+09
C(State)[T.Vermont]	-5.03e+08	9.14e+08	-0.550	0.582	-2.3e+09
C(State)[T.Virginia]	1.009e+09	9.14e+08	1.104	0.270	-7.83e+08
C(State)[T.Washington]	3.914e+09	9.14e+08	4.283	0.000	2.12e+09
C(State)[T.West Virginia]	-4.446e+08	9.14e+08	-0.486	0.627	-2.24e+09
C(State)[T.Wisconsin]	6.474e+08	9.14e+08	0.708	0.479	-1.14e+09
C(State)[T.Wyoming]	-5.431e+08	9.14e+08	-0.594	0.552	-2.34e+09
C(Year)[T.2011.0]	-6.862e+08	4.05e+08	-1.696	0.090	-1.48e+09
C(Year)[T.2012.0]	-1.022e+09	4.05e+08	-2.525	0.012	-1.82e+09
C(Year)[T.2013.0]	6.681e+07	4.05e+08	0.165	0.869	-7.28e+08
C(Year)[T.2014.0]	5.537e+08	4.05e+08	1.368	0.171	-2.4e+08
C(Year)[T.2015.0]	-5.257e+06	4.05e+08	-0.013	0.990	-7.99e+08
C(Year)[T.2016.0]	-8.14e+07	4.05e+08	-0.201	0.841	-8.75e+08
C(Year)[T.2017.0]	4.728e+08	4.05e+08	1.168	0.243	-3.21e+08
C(Year)[T.2018.0]	3.582e+08	4.05e+08	0.885	0.377	-4.36e+08
C(Year)[T.2019.0]	3.819e+08	4.05e+08	0.944	0.346	-4.12e+08
ndbi_sa_diff1	2.793e+09	1.14e+09	2.452	0.014	5.59e+08

Omnibus:	652.864	Durbin-Watson:	2.343
Prob(Omnibus):	0.000	Jarque-Bera (JB):	51443.227
Skew:	-0.569	Prob(JB):	0.00
Kurtosis:	27.575	Cond. No.	54.2

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi

FIG.12

OLS Regression Results

Dep. Variable:	SQGDP9_1_diff1	R-squared:	0.522
Model:	OLS	Adj. R-squared:	0.501
Method:	Least Squares	F-statistic:	25.13
Date:	Sun, 07 Mar 2021	Prob (F-statistic):	1.11e-251
Time:	18:33:39	Log-Likelihood:	-47808.
No. Observations:	2040	AIC:	9.579e+04
Df Residuals:	1954	BIC:	9.627e+04
Df Model:	85		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0
Intercept	4.124e+08	6.84e+08	0.603	0.546	-9.28
C(State)[T.Alaska]	-6.279e+08	8.33e+08	-0.754	0.451	-2.26
C(State)[T.Arizona]	1.328e+09	8.34e+08	1.592	0.111	-3.08
C(State)[T.Arkansas]	-1.689e+08	8.33e+08	-0.203	0.839	-1.8
C(State)[T.California]	1.861e+10	1.17e+09	15.932	0.000	1.63
C(State)[T.Colorado]	1.687e+09	8.37e+08	2.016	0.044	4.59
C(State)[T.Connecticut]	-4.024e+08	8.34e+08	-0.483	0.629	-2.04
C(State)[T.Delaware]	-4.952e+08	8.33e+08	-0.594	0.552	-2.13
C(State)[T.District of Columbia]	-3.234e+08	8.33e+08	-0.388	0.698	-1.96
C(State)[T.Florida]	4.751e+09	8.54e+08	5.561	0.000	3.08
C(State)[T.Georgia]	2.426e+09	8.4e+08	2.888	0.004	7.79
C(State)[T.Hawaii]	-2.748e+08	8.33e+08	-0.330	0.741	-1.91
C(State)[T.Idaho]	-1.58e+08	8.33e+08	-0.190	0.850	-1.79
C(State)[T.Illinois]	1.236e+09	8.44e+08	1.465	0.143	-4.19
C(State)[T.Indiana]	5.949e+08	8.38e+08	0.710	0.478	-1.85
C(State)[T.Iowa]	-7.05e+07	8.33e+08	-0.085	0.933	-1.7
C(State)[T.Kansas]	-1.328e+08	8.34e+08	-0.159	0.873	-1.77
C(State)[T.Kentucky]	-1.474e+07	8.33e+08	-0.018	0.986	-1.65
C(State)[T.Louisiana]	-5.099e+08	8.33e+08	-0.612	0.541	-2.14
C(State)[T.Maine]	-4.756e+08	8.33e+08	-0.571	0.568	-2.11
C(State)[T.Maryland]	6.246e+08	8.35e+08	0.748	0.454	-1.01
C(State)[T.Massachusetts]	1.823e+09	8.42e+08	2.166	0.030	1.72
C(State)[T.Michigan]	1.669e+09	8.4e+08	1.988	0.047	2.22
C(State)[T.Minnesota]	9.237e+08	8.35e+08	1.106	0.269	-7.14
C(State)[T.Mississippi]	-4.414e+08	8.33e+08	-0.530	0.596	-2.07
C(State)[T.Missouri]	3.565e+06	8.33e+08	0.004	0.996	-1.63
C(State)[T.Montana]	-3.859e+08	8.33e+08	-0.463	0.643	-2.02
C(State)[T.Nebraska]	-1.647e+08	8.34e+08	-0.198	0.843	-1.8
C(State)[T.Nevada]	1.467e+08	8.33e+08	0.176	0.860	-1.49
C(State)[T.New Hampshire]	-3.515e+08	8.33e+08	-0.422	0.673	-1.98
C(State)[T.New Jersey]	2.899e+08	8.37e+08	0.347	0.729	-1.35
C(State)[T.New Mexico]	-3.019e+08	8.33e+08	-0.362	0.717	-1.94
C(State)[T.New York]	4.446e+09	9.08e+08	4.897	0.000	2.67
C(State)[T.North Carolina]	1.284e+09	8.36e+08	1.536	0.125	-3.55
C(State)[T.North Dakota]	-3.071e+08	8.33e+08	-0.369	0.712	-1.94
C(State)[T.Ohio]	2.233e+09	8.41e+08	2.654	0.008	5.83
C(State)[T.Oklahoma]	3.623e+08	8.33e+08	0.435	0.664	-1.27
C(State)[T.Oregon]	8.265e+08	8.34e+08	0.984	0.325	-8.15
C(State)[T.Pennsylvania]	1.736e+09	8.45e+08	2.055	0.040	7.9
C(State)[T.Rhode Island]	-5.358e+08	8.33e+08	-0.643	0.520	-2.17
C(State)[T.South Carolina]	5.624e+08	8.33e+08	0.675	0.500	-1.07
C(State)[T.South Dakota]	-3.399e+08	8.33e+08	-0.408	0.683	-1.97
C(State)[T.Tennessee]	9.396e+08	8.34e+08	1.126	0.260	-6.97
C(State)[T.Texas]	1.057e+10	9.94e+08	10.639	0.000	8.62
C(State)[T.Utah]	5.958e+08	8.33e+08	0.715	0.475	-1.04
C(State)[T.Vermont]	-5.397e+08	8.33e+08	-0.648	0.517	-2.17
C(State)[T.Virginia]	8.959e+08	8.35e+08	1.073	0.283	-7.41
C(State)[T.Washington]	3.532e+09	8.52e+08	4.147	0.000	1.86
C(State)[T.West Virginia]	-4.494e+08	8.33e+08	-0.540	0.590	-2.08
C(State)[T.Wisconsin]	4.907e+08	8.34e+08	0.589	0.556	-1.14
C(State)[T.Wyoming]	-5.507e+08	8.33e+08	-0.661	0.509	-2.18
C(Year)[T.2011.0]	-6.81e+08	4.48e+08	-1.518	0.129	-1.56
C(Year)[T.2012.0]	-1.046e+09	4.22e+08	-2.481	0.013	-1.87
C(Year)[T.2013.0]	-1.772e+08	4.44e+08	-0.399	0.690	-1.05
C(Year)[T.2014.0]	2.818e+08	4.6e+08	0.612	0.540	-6.21
C(Year)[T.2015.0]	7.669e+06	4.26e+08	0.018	0.986	-8.28
C(Year)[T.2016.0]	-4.08e+08	4.58e+08	-0.891	0.373	-1.31
C(Year)[T.2017.0]	-2.85e+08	4.51e+08	-0.631	0.528	-1.17
C(Year)[T.2018.0]	6.227e+07	4.42e+08	0.141	0.888	-8.05
C(Year)[T.2019.0]	2.678e+08	4.22e+08	0.635	0.526	-5.59
ndbi_sa_diff1	4.816e+09	1.22e+09	3.941	0.000	2.42
SQGDP9_1_diff1_lag1_1	-0.2044	0.023	-8.973	0.000	-0
SQGDP9_1_diff1_lag2_1	-0.0501	0.022	-2.230	0.026	-0
SQGDP9_1_diff1_lag3_1	0.1357	0.020	5.642	0.000	0
SQGDP9_1_diff1_lag4_1	0.0721	0.020	3.665	0.000	0
SQGDP9_1_diff1_lag5_1	-0.0731	0.017	-4.221	0.000	-0
SQGDP9_1_diff1_lag6_1	-0.0224	0.017	-1.292	0.197	-0
SQGDP9_1_diff1_lag7_1	0.0617	0.017	3.651	0.000	0
SQGDP9_1_diff1_lag8_1	-0.0609	0.016	-3.704	0.000	-0
SQGDP9_1_diff1_lag9_1	0.0758	0.016	4.605	0.000	0
SQGDP9_1_diff1_lag10_1	0.1145	0.016	6.970	0.000	0
SQGDP9_1_diff1_lag11_1	0.0770	0.017	4.642	0.000	0
SQGDP9_1_diff1_lag12_1	0.0641	0.016	3.909	0.000	0
Spread_30yr_10yr_diff1	-2.618e+09	1.05e+09	-2.485	0.013	-4.68
Spread_30yr_10yr_diff1_2	3.063e+10	6.92e+09	4.429	0.000	1.71
ndbi_sa_diff1:SQGDP9_1_diff1_lag2_1	0.2196	0.365	0.602	0.547	-0
ndbi_sa_diff1:SQGDP9_1_diff1_lag3_1	-1.2685	0.398	-3.186	0.001	-2
ndbi_sa_diff1:SQGDP9_1_diff1_lag4_1	-0.4043	0.292	-1.384	0.166	-0
ndbi_sa_diff1:SQGDP9_1_diff1_lag5_1	0.6791	0.272	2.499	0.013	0
ndbi_sa_diff1:SQGDP9_1_diff1_lag6_1	0.1092	0.360	0.303	0.762	-0
ndbi_sa_diff1:SQGDP9_1_diff1_lag7_1	1.0497	0.355	2.959	0.003	0
ndbi_sa_diff1:SQGDP9_1_diff1_lag8_1	-1.3370	0.287	-4.666	0.000	-1
ndbi_sa_diff1:SQGDP9_1_diff1_lag9_1	-0.2766	0.256	-1.081	0.280	-0
ndbi_sa_diff1:SQGDP9_1_diff1_lag10_1	-0.3464	0.312	-1.110	0.267	-0
ndbi_sa_diff1:SQGDP9_1_diff1_lag11_1	0.4953	0.289	1.714	0.087	-0
ndbi_sa_diff1:SQGDP9_1_diff1_lag12_1	-0.7246	0.270	-2.679	0.007	-1

Omnibus:	550.369	Durbin-Watson:	2.022
Prob(Omnibus):	0.000	Jarque-Bera (JB):	38604.454
Skew:	0.269	Prob(JB):	0.00
Kurtosis:	24.304	Cond. No.	1.04e+12

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
[2] The condition number is large, 1.04e+12. This might indicate that there are
strong multicollinearity or other numerical problems.

OLS Regression Results

Dep. Variable:	SQGDP9_1_diff1	R-squared:	0.876
Model:	OLS	Adj. R-squared:	0.855
Method:	Least Squares	F-statistic:	55.57
Date:	Sun, 07 Mar 2021	Prob (F-statistic):	0.00
Time:	17:49:17	Log-Likelihood:	-30864.
No. Observations:	1353	AIC:	6.202e+04
Df Residuals:	1205	BIC:	6.280e+04
Df Model:	147		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.
Intercept	-1.795e+09	5.546e+08	-3.240	0.001	-2.88
C(State)[T.Alaska]	1.618e+08	6.49e+08	0.249	0.803	-1.11
C(State)[T.Arizona]	5.07e+08	7.29e+08	0.696	0.487	-9.23
C(State)[T.Arkansas]	2.668e+08	5.92e+08	0.455	0.647	-8.74
C(State)[T.California]	5.624e+09	4.23e+09	1.274	0.203	1.32
C(State)[T.Colorado]	5.448e+08	6.87e+08	0.793	0.428	-8.04
C(State)[T.Connecticut]	-4.31e+08	6.03e+08	-0.715	0.475	-1.61
C(State)[T.Delaware]	3.490e+08	6.31e+08	0.554	0.580	-8.89
C(State)[T.District of Columbia]	-2.136e+08	7.7e+08	-0.277	0.782	-1.72
C(State)[T.Florida]	-1.007e+08	2.19e+09	-0.050	0.960	-4.39
C(State)[T.Georgia]	1.305e+09	9.66e+08	1.352	0.177	-5.9
C(State)[T.Hawaii]	4.512e+07	6.29e+08	0.072	0.942	-1.19
C(State)[T.Idaho]	6.184e+08	5.97e+08	1.036	0.300	-5.53
C(State)[T.Illinois]	-1.001e+09	9.52e+08	-1.078	0.281	-3.27
C(State)[T.Indiana]	2.854e+08	6.07e+08	0.470	0.638	-9.06
C(State)[T.Iowa]	2.781e+08	5.8e+08	0.405	0.632	-8.8
C(State)[T.Kansas]	7.251e+08	5.85e+08	1.240	0.215	-4.22
C(State)[T.Kentucky]	9.093e+07	5.64e+08	0.172	0.864	-1.01
C(State)[T.Louisiana]	-3.280e+08	6.08e+08	-0.541	0.589	-1.52
C(State)[T.Maine]	3.215e+08	5.28e+08	0.571	0.568	-8.1
C(State)[T.Maryland]	-2.056e+08	5.98e+08	-0.344	0.731	-1.38
C(State)[T.Massachusetts]	-2.947e+08	7.51e+08	-0.393	0.695	-1.77
C(State)[T.Michigan]	-2.384e+07	7.07e+08	-0.034	0.973	-1.41
C(State)[T.Minnesota]	2.018e+08	6.15e+08	0.328	0.743	-1.0
C(State)[T.Mississippi]	5.059e+08	5.39e+08	0.938	0.348	-5.77
C(State)[T.Missouri]	-2.943e+08	3.81e+08	-0.826	0.409	-1.53
C(State)[T.Montana]	4.425e+08	6.3e+08	0.703	0.482	-7.93
C(State)[T.Nebraska]	5.553e+08	6e+08	0.925	0.355	-6.23
C(State)[T.Nevada]	7.936e+07	5.81e+08	0.136	0.891	-1.06
C(State)[T.New Hampshire]	1.109e+08	6.35e+08	0.175	0.861	-1.13
C(State)[T.New Jersey]	-1.717e+09	7.04e+08	-2.445	0.015	-3.1
C(State)[T.New Mexico]	8.114e+08	6.09e+08	1.333	0.183	-3.83
C(State)[T.New York]	-7.617e+08	1.61e+09	-0.472	0.637	-3.93
C(State)[T.North Carolina]	2.382e+08	9.33e+08	0.255	0.799	-1.59
C(State)[T.North Dakota]	6.253e+08	5.34e+08	1.303	0.193	-4.10
C(State)[T.Ohio]	2.159e+08	7.84e+08	0.277	0.782	-1.32
C(State)[T.Oklahoma]	9.627e+08	5.7e+08	1.689	0.092	-1.56
C(State)[T.Oregon]	6.945e+08	5.91e+08	1.174	0.241	-4.66
C(State)[T.Pennsylvania]	-1.762e+08	8.3e+08	-0.212	0.832	-1.81
C(State)[T.Rhode Island]	3.365e+08	7.29e+08	0.462	0.644	-1.09
C(State)[T.South Carolina]	6.063e+08	5.95e+08	1.019	0.308	-5.61
C(State)[T.South Dakota]	5.657e+08	6.32e+08	0.894	0.371	-6.75
C(State)[T.Tennessee]	4.409e+08	6.48e+08	0.681	0.496	-8.3
C(State)[T.Texas]	3.557e+09	3.31e+09	1.073	0.284	-2.95
C(State)[T.Utah]	5.735e+08	5.82e+08	0.985	0.325	-5.69
C(State)[T.Vermont]	3.514e+08	6.56e+08	0.535	0.592	-9.36
C(State)[T.Virginia]	-8.427e+08	7.28e+08	-1.158	0.247	-2.27
C(State)[T.Washington]	2.149e+09	8.79e+08	2.444	0.015	4.24
C(State)[T.West Virginia]	5.087e+08	6.35e+08	0.799	0.425	-7.39
C(State)[T.Wisconsin]	1.535e+08	5.73e+08	0.268	0.789	-9.7
C(State)[T.Wyoming]	2.579e+08	6.61e+08	0.390	0.696	-1.04
C(Year)[T.2011.0]	-5019.0311	6112.516	-0.821	0.412	-1.7
C(Year)[T.2012.0]	-1.066e+04	1.1e+04	-0.969	0.333	-3.22
C(Year)[T.2013.0]	-5.284e+08	2.45e+08	-2.161	0.031	-1.01
C(Year)[T.2014.0]	1.452e+08	2.41e+08	0.602	0.547	-3.28
C(Year)[T.2015.0]	-3.008e+08	2.30e+08	-1.631	0.103	-6.57
C(Year)[T.2016.0]	3.232e+08	2.39e+08	1.352	0.177	-1.46
C(Year)[T.2017.0]	-2.393e+08	2.11e+08	-1.134	0.257	-6.53
C(Year)[T.2018.0]	-4.037e+08	2.89e+08	-1.396	0.163	-9.71
C(Year)[T.2019.0]	-7.015e+08	2.87e+08	-2.445	0.015	-1.27
ndbi_sa_diff1	1.614e+09	9.43e+08	1.712	0.087	-2.35
Spread_30yr_10yr_diff1	-1.857e+09	1.41e+09	-1.314	0.189	-4.6
Spread_30yr_10yr_diff1_2	1.2e+10	1.43e+10	0.839	0.402	-1.61
SQGDP9_1_diff1_lag1_1	-0.0545	0.030	-1.855	0.064	-0
SQGDP9_1_diff1_lag2_1	0.0634	0.026	2.439	0.015	0
SQGDP9_1_diff1_lag3_1	-0.0457	0.025	-1.857	0.064	-0
SQGDP9_1_diff1_lag4_1	-0.0794	0.025	-3.205	0.001	-0
SQGDP9_1_diff1_lag5_1	-0.0006	0.024	-0.023	0.981	-0
SQGDP9_1_diff1_lag6_1	-0.0296	0.024	-1.221	0.222	-0
SQGDP9_1_diff1_lag7_1	-0.0927	0.025	-3.685	0.000	-0
SQGDP9_1_diff1_lag8_1	-0.0517	0.027	-1.891	0.059	-0
SQGDP9_1_diff1_lag9_1	-0.0456	0.023	-1.980	0.048	-0
SQGDP9_1_diff1_lag10_1	-0.0077	0.022	-0.351	0.725	-0
SQGDP9_1_diff1_lag11_1	0.1023	0.022	4.628	0.000	0
SQGDP9_1_diff1_lag12_1	-0.0245	0.022	-1.105	0.269	-0
real_SQINC1_1_diff1	0.2507	0.050	5.007	0.000	0
real_SQINC1_1_diff1_lag1_1	-0.1342	0.033	-4.035	0.000	-0
real_SQINC1_1_diff1_lag2_1	-0.2887	0.035	-8.250	0.000	-0
real_SQINC1_1_diff1_lag3_1	0.0119	0.035	0.339	0.735	-0
real_SQINC1_1_diff1_lag4_1	0.4497	0.035	12.858	0.000	0
real_SQINC1_1_diff1_lag5_1	-0.0276	0.034	-0.818	0.413	-0
real_SQINC1_1_diff1_lag6_1	-0.1025	0.032	-3.155	0.002	-0
real_SQINC1_1_diff1_lag7_1	0.0748	0.033	2.265	0.024	0
real_SQINC1_1_diff1_lag8_1	-0.1287	0.035	-3.679	0.000	-0
real_SQINC1_1_diff1_lag9_1	-0.0787	0.033	-2.354	0.019	-0
real_SQINC1_1_diff1_lag10_1	0.1266	0.031	4.036	0.000	0
real_SQINC1_1_diff1_lag11_1	0.0423	0.031	1.363	0.173	-0
real_SQINC1_1_diff1_lag12_1	-0.0184	0.034	-0.540	0.589	-0
real_SQINC1_2_diff1	-2.723e+04	5563.583	-4.894	0.000	-3.81
real_SQINC1_2_diff1_lag1_1	-2161.8536	5011.442	-0.431	0.666	-1.2
real_SQINC1_2_diff1_lag2_1	6596.6856	4912.907	1.341	0.180	-3052
real_SQINC1_2_diff1_lag3_1	-1.302e+04	5241.141	-2.483	0.013	-2.33
real_SQINC1_2_diff1_lag4_1	-3.534e+04	5593.710	-6.499	0.000	-4.73
real_SQINC1_2_diff1_lag5_1	2.027e+04	5483.325	3.747	0.000	1.75
real_SQINC1_2_diff1_lag6_1	-2927.7823	5460.962	-0.542	0.588	-1.35
real_SQINC1_2_diff1_lag7_1	2.314e+04	6257.080	3.698	0.000	1.08
real_SQINC1_2_diff1_lag8_1	1.039e+04	6185.445	1.680	0.093	-6407
real_SQINC1_2_diff1_lag9_1	1709.6373	5519.565	0.301	0.763	-9230
real_SQINC1_2_diff1_lag10_1	8451.7435	5772.444	1.464	0.143	-2865
real_SQINC1_2_diff1_lag11_1	-1.489e+04	5981.317	-2.489	0.013	-2.66
real_SQINC1_2_diff1_lag12_1	2.666e+04	5723.169	4.658	0.000	1.54
real_SQINC1_3_diff1	3.331e+05	2.08e+05	1.601	0.110	-7.52
real_SQINC1_3_diff1_lag1_1	2.4e+05	1.71e+05	1.406	0.160	-9.5
real_SQINC1_3_diff1_lag2_1	3.422e+05	1.64e+05	2.083	0.037	1.99
real_SQINC1_3_diff1_lag3_1	2.270e+05	1.5e+05	1.514	0.130	-6.72
real_SQINC1_3_diff1_lag4_1	-5974.6686	1.57e+05	-0.038	0.970	-3.15
real_SQINC1_3_diff1_lag5_1	1.976e+05	1.5e+05	1.316	0.188	-9.69
real_SQINC1_3_diff1_lag6_1	5.460e+05	1.46e+05	3.743	0.000	2.6
real_SQINC1_3_diff1_lag7_1	1.376e+05	1.44e+05	0.953	0.341	-1.46
real_SQINC1_3_diff1_lag8_1	2.733e+05	1.64e+05	1.667	0.096	-5.03
real_SQINC1_3_diff1_lag9_1	-1.332e+04	1.49e+05	-0.089	0.929	-3.03
real_SQINC1_3_diff1_lag10_1	2.065e+04	1.51e+05	0.137	0.891	-2.75
real_SQINC1_3_diff1_lag11_1	6.041e+04	1.35e+05	0.446	0.656	-2.05
real_SQINC1_3_diff1_lag12_1	7.586e+04	1.51e+05	0.504	0.615	-2.2
real_SQINC4_50_diff1	0.8199	0.061	13.500	0.000	0
real_SQINC4_50_diff1_lag1_1	0.2013	0.065	3.098	0.002	0
real_SQINC4_50_diff1_lag2_1	0.1633	0.066	2.487	0.013	0
real_SQINC4_50_diff1_lag3_1	-0.0530	0.066	-0.813	0.416	-0
real_SQINC4_50_diff1_lag4_1	-0.4139	0.067	-6.154	0.000	-0
real_SQINC4_50_diff1_lag5_1	-0.2738	0.063	-4.346	0.000	-0
real_SQINC4_50_diff1_lag6_1	-0.0262	0.061	-0.429	0.668	-0
real_SQINC4_50_diff1_lag7_1	-0.2401	0.061	-3.917	0.000	-0
real_SQINC4_50_diff1_lag8_1	0.0402	0.067	0.599	0.549	-0
real_SQINC4_50_diff1_lag9_1	0.2494	0.066	3.757	0.000	0
real_SQINC4_50_diff1_lag10_1	-0.0480	0.065	-0.740	0.459	-0
real_SQINC4_50_diff1_lag11_1	-0.1411	0.068	-2.050	0.041	-0
real_SQINC4_50_diff1_lag12_1	-0.2236	0.060	-3.701	0.000	-0
real_SQINC6N_400_diff1	-1.2666	3.391	-0.373	0.709	-7
real_SQINC6N_400_diff1_lag1_1	0.2974	3.336	0.089	0.929	-6
real_SQINC6N_400_diff1_lag2_1	10.6532	3.290	3.238	0.001	3
real_SQINC6N_400_diff1_lag3_1	12.9838	3.318	3.913	0.000	6
real_SQINC6N_400_diff1_lag4_1	-1.9260	3.404	-0.566	0.571	-9
real_SQINC6N_400_diff1_lag5_1	-6.3714	3.453	-1.845	0.065	-13
real_SQINC6N_400_diff1_lag6_1	14.0631	3.391	4.147	0.000	7
real_SQINC6N_400_diff1_lag7_1	0.4943	3.392	0.143	0.887	-6
real_SQINC6N_400_diff1_lag8_1	-4.4801	3.559	-1.259	0.208	-11
real_SQINC6N_400_diff1_lag9_1	11.8400	3.494	3.389	0.001	4
real_SQINC6N_400_diff1_lag10_1	-3.1409	3.402	-0.923	0.356	-9
real_SQINC6N_400_diff1_lag11_1	2.0110	3.355	0.599	0.549	-4
real_SQINC6N_400_diff1_lag12_1	1.2549	3.441	0.365	0.715	-5
ndbi_sa_diff1:SQGDP9_1_diff1_lag2_1	0.8096	0.322	2.516	0.012	0
ndbi_sa_diff1:SQGDP9_1_diff1_lag3_1	-0.3303	0.340	-0.972	0.331	-0
ndbi_sa_diff1:SQGDP9_1_diff1_lag4_1	-0.2422	0.257	-0.965	0.335	-0
ndbi_sa_diff1:SQGDP9_1_diff1_lag5_1	0.9421	0.253	3.726	0.000	0
ndbi_sa_diff1:SQGDP9_1_diff1_lag6_1	0.1483	0.339	0.437	0.662	-0
ndbi_sa_diff1:SQGDP9_1_diff1_lag7_1	-0.3732	0.317	-1.178	0.239	-0
ndbi_sa_diff1:SQGDP9_1_diff1_lag8_1	-0.2755	0.265	-1.041	0.298	-0
ndbi_sa_diff1:SQGDP9_1_diff1_lag9_1	-0.7780	0.226	-3.439	0.001	-1
ndbi_sa_diff1:SQGDP9_1_diff1_lag10_1	0.0795	0.256	0.310	0.756	-0
ndbi_sa_diff1:SQGDP9_1_diff1_lag11_1	-0.5428	0.258	-2.106	0.035	-1
ndbi_sa_diff1:SQGDP9_1_diff1_lag12_1	-0.6096	0.238	-2.567	0.010	-1

Omnibus:	435.195	Durbin-Watson:	1.973
Prob(Omnibus):	0.000	Jarque-Bera (JB):	34008.044
Skew:	0.029	Prob(JB):	0.00
Kurtosis:	16.168	Cond. No.	2.60e+19

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifi
[2] The smallest eigenvalue is 2.47e-15. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

FIG.14

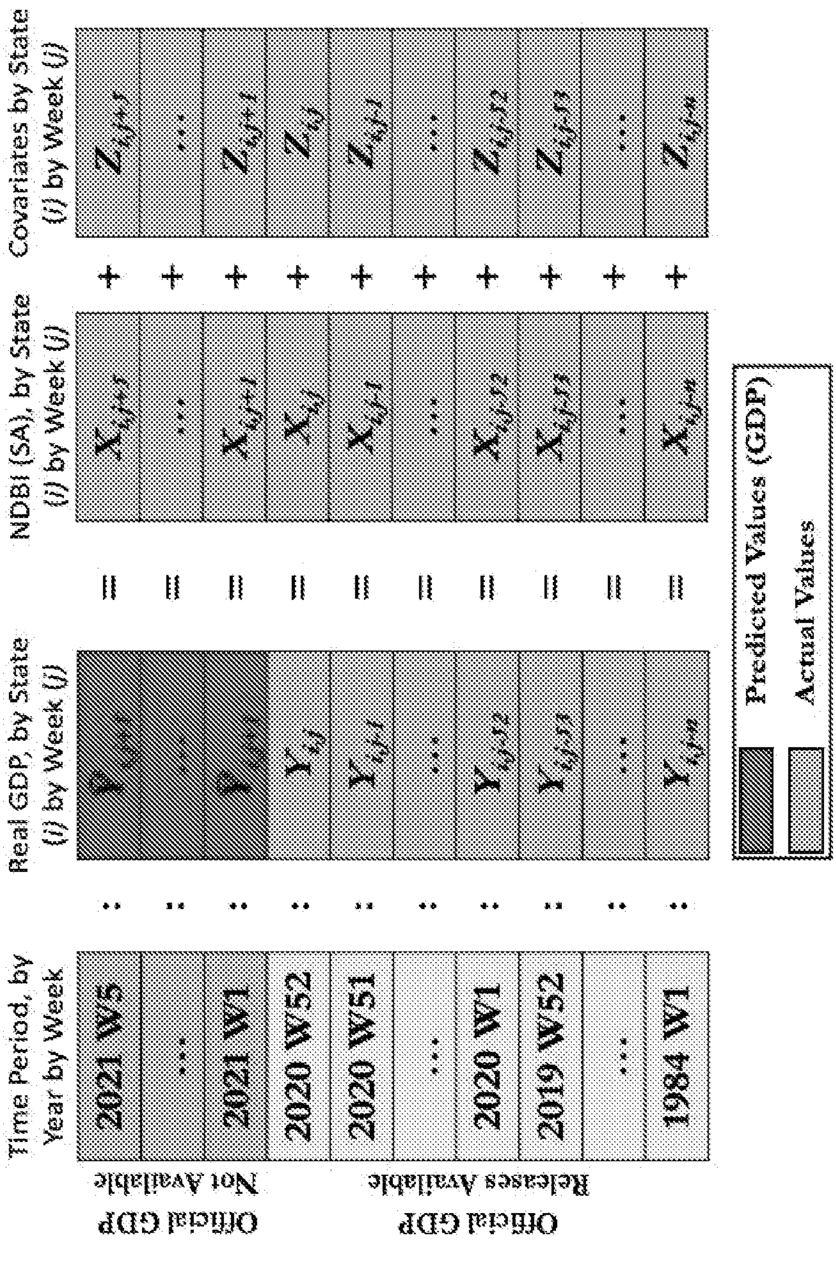

Time Period, by Year by Week
Real GDP, by State (i) by Week (j)
NDBI (SA), by State (i) by Week (j)
Covariates by State (i) by Week (j)
Official GDP Not Available
Official GDP Releases Available
2021 W5
2021 W1
2020 W52
2020 W51
2020 W1
2019 W52
1984 W1
Predicted Values (GDP)
Actual Values

FIG.15A

State	Year	Quarter	SQGDP8_1	gdp_pred2	SQGDP8_1_spc	gdp_pred2_spc	predicted_deviation	predicted_deviation_spc
Alabama	2019.0	4.0	202675500000.0	202152600080.0	1.32	2.25	77180080.0	2.24
Alaska	2019.0	4.0	53440300000.0	53250843371.0	-0.47	2.95	-189356620.0	2.95
Arizona	2019.0	4.0	330007500000.0	327575547495.0	5.92	5.07	-1438952505.0	5.06
Arkansas	2019.0	4.0	118245300000.0	118179623814.0	1.91	1.76	-65776186.0	1.74
California	2019.0	4.0	2846387100000.0	2829443953920.0	6.03	1.94	-18921110007.0	1.87
Colorado	2019.0	4.0	381367300000.0	382455445931.0	2.49	6.77	1088145931.0	6.75
Connecticut	2019.0	4.0	252214600000.0	251853541466.0	1.87	0.74	-361058534.0	0.72
Delaware	2019.0	4.0	54503600000.0	53820914957.0	1.72	-2.74	-682685043.0	-2.78
District of Columbia	2019.0	4.0	124940800000.0	124328930309.0	2.71	2.7	-613069691.0	2.67
Florida	2019.0	4.0	973507200000.0	972488241512.0	3.42	2.87	-1018958488.0	2.84
Georgia	2019.0	4.0	551120400000.0	552152702791.0	1.82	1.45	1032302791.0	1.41
Hawaii	2019.0	4.0	22953400000.0	22648101648.0	2.65	5.15	-194298352.0	5.12
Idaho	2019.0	4.0	78250200000.0	78434080585.0	5.56	7.81	183180585.0	7.75
Illinois	2019.0	4.0	774597900000.0	777393857426.0	-0.15	2.8	2795957426.0	2.8
Indiana	2019.0	4.0	340545700000.0	340317821062.0	1.93	2.7	-227878938.0	2.66
Iowa	2019.0	4.0	173558800000.0	174533892121.0	-1.34	2.98	1174092121.0	2.97
Kansas	2019.0	4.0	181115800000.0	180958870489.0	2.44	2.58	-156729511.0	2.52
Kentucky	2019.0	4.0	192380000000.0	191860920351.0	2.28	2.38	-492079649.0	2.34
Louisiana	2019.0	4.0	241835400000.0	241571191126.0	1.45	4.34	-264208874.0	4.33
Maine	2019.0	4.0	68476800000.0	68658362604.0	3.35	6.02	181762604.0	5.99
Maryland	2019.0	4.0	377229300000.0	375941593117.0	2.77	1.96	-1287306883.0	1.93
Massachusetts	2019.0	4.0	522215300000.0	525614981042.0	0.36	3.39	3399681042.0	3.36
Michigan	2019.0	4.0	474492000000.0	475509040409.0	0.87	2.05	1017040409.0	2.04
Minnesota	2019.0	4.0	343848000000.0	342380303740.0	2.4	1.32	-1468696260.0	1.3
Mississippi	2019.0	4.0	103662200000.0	102576891840.0	2.9	1.0	-785308160.0	0.97
Missouri	2019.0	4.0	289578100000.0	289262471821.0	1.89	3.87	-115628302.0	3.85
Montana	2019.0	4.0	48620900000.0	48775094109.0	3.49	2.88	150294106.0	2.85
Nebraska	2019.0	4.0	118428000000.0	118001736045.0	4.05	5.25	-426263954.0	5.22
Nevada	2019.0	4.0	155549200000.0	155215782555.0	2.7	4.81	266586568.0	4.85
New Hampshire	2019.0	4.0	77048400000.0	78473812915.0	-0.54	5.04	1425412915.0	5.05
New Jersey	2019.0	4.0	580216800000.0	568823380091.0	1.52	2.5	-1393338909.0	2.48
New Mexico	2019.0	4.0	100228800000.0	100070924104.0	1.7	7.21	-157875896.0	7.19
New York	2019.0	4.0	1405605700000.0	1408909680045.0	1.29	0.42	3303980045.0	0.41
North Carolina	2019.0	4.0	616523800000.0	615276191254.0	2.74	2.58	-1247608746.0	2.55
North Dakota	2019.0	4.0	53902400000.0	54306632152.0	-0.35	2.46	404232152.0	2.43
Ohio	2019.0	4.0	619258700000.0	620076667490.0	1.5	2.84	818967490.0	2.82
Oklahoma	2019.0	4.0	197205900000.0	200335347855.0	-2.81	2.59	3129447855.0	2.52
Oregon	2019.0	4.0	228411300000.0	227815573529.0	4.94	3.39	-595726471.0	3.34
Pennsylvania	2019.0	4.0	731065100000.0	731274078841.0	1.37	3.39	208978841.0	3.36
Rhode Island	2019.0	4.0	53680800000.0	53988446523.0	2.5	2.52	308140523.0	2.5
South Carolina	2019.0	4.0	217572700000.0	217908792656.0	2.75	4.09	336032656.0	4.06
South Dakota	2019.0	4.0	48105000000.0	46059274500.0	2.44	-14.08	-2045725500.0	-14.1
Tennessee	2019.0	4.0	329751700000.0	331130297540.0	-0.06	1.43	1378597540.0	1.42
Texas	2019.0	4.0	1777395800000.0	1788089810040.0	0.72	4.72	10694010040.0	4.71
Utah	2019.0	4.0	171289500000.0	171515113615.0	4.04	7.51	223212515.0	7.47
Vermont	2019.0	4.0	28550000000.0	30401102514.0	5.93	7.8	641102514.5	7.79
Virginia	2019.0	4.0	494365500000.0	492832622079.0	2.06	4.02	-1532877921.0	3.96
Washington	2019.0	4.0	556200100000.0	557943428742.0	2.92	6.16	1693328742.0	6.13
West Virginia	2019.0	4.0	71658700000.0	72649774076.0	-4.93	-1.46	991074076.0	-1.41
Wisconsin	2019.0	4.0	309808300000.0	309307891862.0	2.68	1.05	-500408138.0	1.02
Wyoming	2019.0	4.0	38387100000.0	38493518832.0	-0.2	4.58	106418832.0	4.53

State	Year	Quarter	SQGDP9_1	gdp_pred2	SQGDP9_1_apc	gdp_pred2_apc	predicted_deviation	predicted_deviation_apc
Alabama	2019.0	4.0	202075600000.0	201604630464.0	1.32	2.51	-470969536.0	2.5
Alaska	2019.0	4.0	53440200000.0	53592043248.0	-0.47	-0.62	151843248.0	-0.62
Arizona	2019.0	4.0	329007500000.0	328608683613.0	4.82	4.57	-397815887.0	4.32
Arkansas	2019.0	4.0	118245600000.0	117712247525.0	1.81	1.26	-533352475.0	1.24
California	2019.0	4.0	2848287100000.0	2845528932349.0	6.53	5.82	-2758157651.0	5.75
Colorado	2019.0	4.0	381357300000.0	380611330504.0	3.49	0.19	-759862496.0	0.16
Connecticut	2019.0	4.0	282214500000.0	283656094650.0	1.27	2.65	641494650.0	2.63
Delaware	2019.0	4.0	84503000000.0	84003208611.0	1.72	-1.70	-499791389.0	-1.70
District of Columbia	2019.0	4.0	124840810000.0	nan	2.71	0.5	nan	-0.03
Florida	2019.0	4.0	973507300000.0	974071503222.0	3.42	3.53	563803522.0	3.5
Georgia	2019.0	4.0	551120400000.0	551426207577.0	1.82	1.47	305807577.0	1.45
Hawaii	2019.0	4.0	82963400000.0	82845902823.0	2.85	2.95	-137497377.0	2.92
Idaho	2019.0	4.0	78290000000.0	78208450835.0	5.50	5.62	-74449035.0	5.56
Illinois	2019.0	4.0	774597300000.0	773548691707.0	-0.15	0.42	-1050808293.0	0.42
Indiana	2019.0	4.0	340045700000.0	340559583723.0	1.53	3.85	13953723.0	3.83
Iowa	2019.0	4.0	173639500000.0	175376859508.0	-1.34	2.63	1716259508.0	2.64
Kansas	2019.0	4.0	161115000000.0	162331440177.0	2.44	3.76	1216840177.0	3.74
Kentucky	2019.0	4.0	192350010000.0	192784551895.0	2.26	2.81	434341592.0	2.79
Louisiana	2019.0	4.0	241835400000.0	242705510891.0	1.43	10.47	870110981.0	10.46
Maine	2019.0	4.0	59476000000.0	59673757544.0	3.36	4.54	197157545.0	4.51
Maryland	2019.0	4.0	377229300000.0	376448412531.0	2.77	3.33	-780887989.0	3.3
Massachusetts	2019.0	4.0	622215310000.0	623939436074.0	0.36	3.57	1724136074.0	3.57
Michigan	2019.0	4.0	474492000000.0	475359517581.0	0.57	3.34	867517581.0	3.33
Minnesota	2019.0	4.0	343049000000.0	343781515961.0	2.4	3.44	-87484039.0	3.42
Mississippi	2019.0	4.0	103822200000.0	103653884579.0	2.9	4.35	121494379.0	4.32
Missouri	2019.0	4.0	289370100000.0	289362741867.0	1.80	4.34	-10358133.0	4.32
Montana	2019.0	4.0	49625500000.0	48345858758.0	3.49	1.7	-282443232.5	1.67
Nebraska	2019.0	4.0	119428000000.0	119804036365.0	4.06	3.33	376036365.0	3.31
Nevada	2019.0	4.0	155549200000.0	156326982396.0	2.7	5.79	777782395.0	5.75
New Hampshire	2019.0	4.0	77049400000.0	77175917804.0	-0.64	-1.82	126517804.0	-1.21
New Jersey	2019.0	4.0	580216610000.0	555760556435.0	1.52	2.72	-1435843582.0	2.7
New Mexico	2019.0	4.0	100228600000.0	100171359820.0	1.7	2.27	-57240180.0	2.25
New York	2019.0	4.0	1456500700000.0	1456248231743.0	1.39	1.2	-300469257.0	1.19
North Carolina	2019.0	4.0	515629500000.0	517069182359.0	2.74	4.74	445362359.0	4.71
North Dakota	2019.0	4.0	53902400000.0	54482213825.0	-0.25	-5.47	559813825.0	-5.47
Ohio	2019.0	4.0	619256700000.0	615517422441.0	1.6	1.88	250722441.0	1.84
Oklahoma	2019.0	4.0	197208900000.0	198829533504.0	-2.01	-0.39	1720633504.0	-0.38
Oregon	2019.0	4.0	226411500000.0	228705627119.0	4.34	4.65	259257119.0	4.61
Pennsylvania	2019.0	4.0	731035100000.0	733991714219.0	1.37	3.87	2956614219.0	3.86
Rhode Island	2019.0	4.0	63660500000.0	nan	2.3	0.5	nan	-0.02
South Carolina	2019.0	4.0	217072700000.0	217174878112.0	3.75	3.13	102178112.0	3.1
South Dakota	2019.0	4.0	48155000000.0	48232261104.0	2.44	-4.26	127261104.0	-4.3
Tennessee	2019.0	4.0	329721700000.0	330550102500.0	-0.02	3.16	728402800.0	3.15
Texas	2019.0	4.0	1777396900000.0	1783447969491.0	0.73	2.18	6052069491.0	2.17
Utah	2019.0	4.0	171258900000.0	171510501389.0	4.94	5.86	220861382.0	5.82
Vermont	2019.0	4.0	29860000000.0	29870875897.0	0.83	3.89	10075897.0	3.85
Virginia	2019.0	4.0	494525500000.0	492794389530.0	2.88	3.85	-1771110451.5	3.82
Washington	2019.0	4.0	656250100000.0	654810503703.0	2.32	2.83	-1439810297.0	2.8
West Virginia	2019.0	4.0	71659700000.0	70542380813.0	-4.93	-2.35	-1116339187.0	-2.3
Wisconsin	2019.0	4.0	309898300000.0	309414086248.0	2.88	2.39	-484211052.0	2.35
Wyoming	2019.0	4.0	36857100000.0	36878152340.0	-5.2	-4.36	311052340.0	-4.38

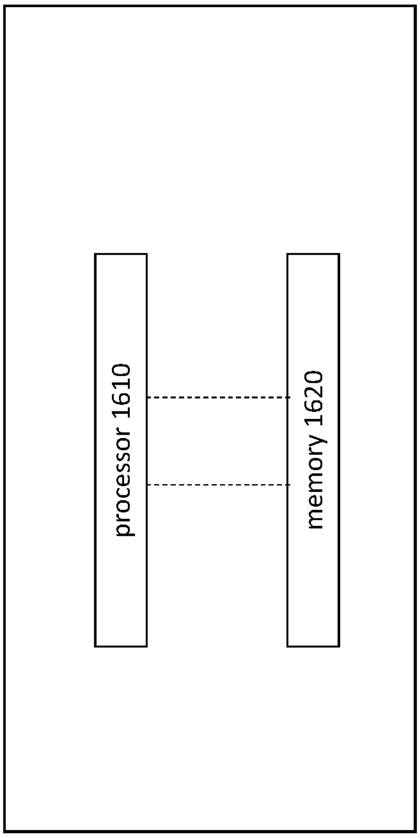
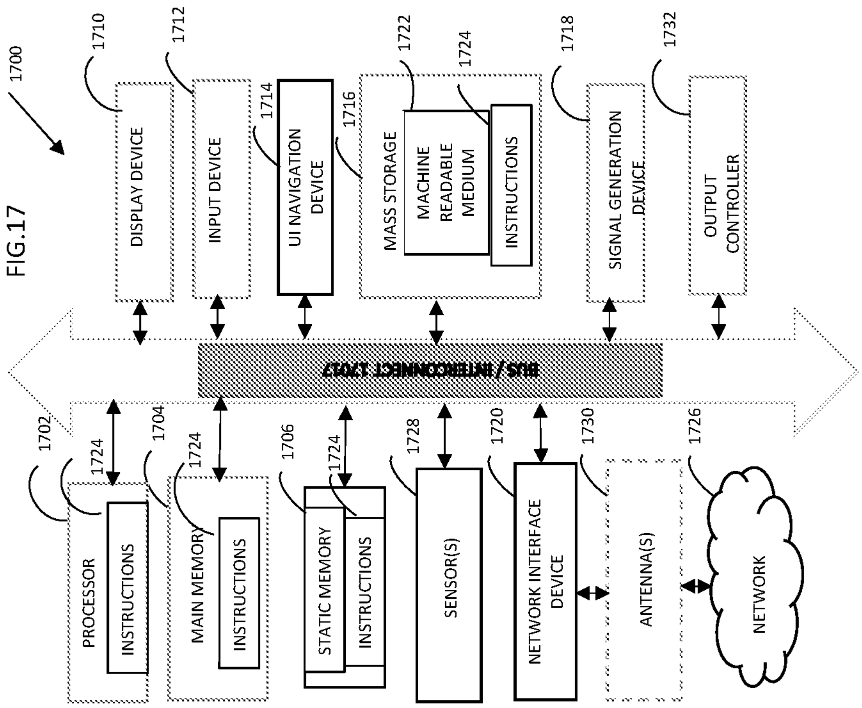


FIG.16 (1600)

FIG.17


1700
1710
DISPLAY DEVICE
1712
INPUT DEVICE
1714
UI NAVIGATION DEVICE
1716
MASS STORAGE
1722
MACHINE READABLE MEDIUM
1724
INSTRUCTIONS
1718
SIGNAL GENERATION DEVICE
1732
OUTPUT CONTROLLER
BUS / INTERCONNECT 17017
1702
PROCESSOR
1724
INSTRUCTIONS
1704
MAIN MEMORY
1724
INSTRUCTIONS
1706
STATIC MEMORY
1724
INSTRUCTIONS
1728
SENSOR(S)
1720
NETWORK INTERFACE DEVICE
1730
ANTENNA(S)
1726
NETWORK

INTERNATIONAL SEARCH REPORT

International application No.
PCT/US 21/26417

A. CLASSIFICATION OF SUBJECT MATTER
IPC - G06F 15/18 (2021.01)

CPC - G06N 99/005, G06K 9/6256, G06K 9/6269, G06N 5/025, G06N 7/005, G06N 3/049, G06N 3/02, G05B 13/027, G05B 13/048, G06Q 10/10, G06Q 10/06, G06Q 30/0201, G06Q 30/02, G06Q 40/00

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
See Search History document

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched
See Search History document

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)
See Search History document

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X ----- Y	US 2014/0201126 A1 (ZADEH et al.) 17 July 2014 (17.07.2014), entire document, especially Fig. B5, B6, 108, 149; para [0174], [0181], [0599], [1023], [1327], [1328], [1420], [1793], [1823], [2006], [2198], [2466], [2961]	1-4, 6-9, 11-14, 16-19 ----------------------------- 5, 10, 15, 20
Y	US 2015/0371224 A1 (LINGAPPA) 24 December 2015 (24.12.2015), entire document, especially para [0032], [0109]	5, 10, 15, 20
A	US 2017/0213280 A1 (KAZNADY) 27 July 2017 (27.07.2017), entire document	1-20
A	US 2016/0224951 A1 (HOFFBERG) 04 August 2016 (04.08.2016), entire document	1-20
A	US 8,954,361 B1 (C4CAST.COM, INC.) 10 February 2015 (10.02.2015), entire document	1-20

☐ Further documents are listed in the continuation of Box C. ☐ See patent family annex.

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"P" document published prior to the international filing date but later than the priority date claimed
"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention
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"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art
"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
24 May 2021 (24.05.2021)	JUN 29 2021

Name and mailing address of the ISA/US	Authorized officer
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