Kevin O'Connor : U1344805

MODELING CORONAVIRUS RECESSION DEPTH IN THE UNITED STATES USING CHANGES IN LEADING ENERGY INDICATORS AS PROXY FOR ECONOMIC ACTIVITY

Key Definitions:

Energy Intensity – The quantity of energy required per unit output or activity

Total Energy Consumption – All primary energy sources used directly by the energy-consuming sectors (residential, commercial, industrial, transportation, and electric power), as well as net imports of electricity.

1. Introduction

In this paper, I will estimate the depth of the COVID recession using annual time-series data from 1949 to 2011 for GDP, total energy consumption, and energy intensity. While there are certainly more definitive and accurate ways to model changes in GDP, there are some benefits in this parsimonious approach. Firstly, energy consumption is a leading indicator. In-depth data is provided by the US. Energy Information Administration on a monthly basis. GDP is reported quarterly. It could be beneficial to have a reliable estimation of how GDP will change before it is reported officially. Secondly, in theory, much of total economic activity is captured by energy consumption, as most economic activities heavily involve the consumption or transfer of energy. That is to say, changes in energy consumption may relate to changes in GDP. In this paper, we do a full econometric treatment of the relationships between these variables in the United States, establishing a model for estimating the depth of a recession based on the delta of total energy expenditures. If successful, monthly energy consumption data provided by the U.S. Energy Information Administration may prove to be a leading indicator of GDP trends. If properly demonstrated, this leading information could be useful to investors, researchers, and policymakers.

2. Brief Literature Review

In the past four decades, there has been substantial exploration of the relationship between GDP and energy consumption. From here forward, when referring to causality, we will be referring specifically to Granger-type causality. (4) In energy economics is, there are four hypothetical relationships between energy consumption and GDP. Unidirectional causality from GDP to energy, unidirectional causality from energy to GDP, also known as the growth argument, bidirectional causality between GDP and energy consumption, and the neutral case, where any correlation between GDP and energy consumption is spurious. (7)

This work was pioneered by Kraft and Kraft in the 1978 study on the unidirectional causality from GDP to energy consumption in the United States. (3) Kraft's findings were put into question by Akarca and Long in 1980. As proponents of the neutral argument, they found that by changing the time period from Kraft's study by two years, the original results seemed apparently spurious. (6) This was followed by several studies in the 80s and 90s that either confirmed or contradicted Kraft and Kraft's results. (5) There clearly exists some controversy on the matter.

In 2003, Ugur Soytas and Ramazan Sari found bi-directional causality in Argentina, unidirectional causality from GDP to energy in Italy and Korea, and unidirectional causality from energy consumption to GDP in Turkey, France, Germany, and Japan. The main bend of their study was the implications of energy conservation policy on economic growth. (5) There remains no definitive answer on the direction of causality, despite the intuitive logic of GDP being in part, a function of energy consumption. Much of this work has been done to demonstrate the direction of causality, and using the surface level interpretation of causality on implications of energy policy on economic growth. Further on in this paper, while we will compare the causal results from this data set to the results of previous authors. After, we will dig in deeper for what these relationships can infer about macroeconomic trends.

In regards to the energy intensity of GDP in the United States, there has been a consistent 1 - 2% decline in energy intensity in the past several decades. We want to include this in our model, as the energy input required to produce a dollar of GDP growth has been, and will be consistently decreasing as efficiency of producing and consuming energy improves with technological innovation. Looking solely at GDP over a 60-year time frame fails to capture the whole picture of how increasing energy efficiency ties into economic growth. "Although growth of energy consumption in the United States is closely tied to growth in GDP and other economic assumptions, it is partially offset by improvements in energy efficiency and other changes in the economy that result in lower energy use per unit of economic output." (8) Clearly, we should expect a negative correlation between energy intensity of GDP and GDP.

3. Data, Model, and Interpretations

We will analyze GDP, indexed in 1985 years, as a function of total energy expenditures (TEC) in quadrillions BTU, and Energy Intensity (EI), which is ratio of GDP over total energy consumption, indexed in 1985 years. GDP will be our dependent variable, a function of energy intensity and total energy consumption. See equation below. (I) After we establish our model, and validate our classical assumptions, making the model as sounds as we can, we will test for granger causality. If we can establish precedence from energy consumption to GDP, we will use simple modeling to test impacts of energy consumption declines on the new data from the coronavirus pandemic.

$$(I)\ GDP = \beta_0 + \beta_1(TEC) + \beta_2(EI) + u_i$$

All data in the model is from 1949 to 2011. The time periods are all annual. Total energy consumption is not indexed, as the control for this variable is the energy intensity of GDP. Data on GDP and energy intensity indicators were sourced from the Office of Energy Efficiency and Renewable Energy. The data on energy consumption was sourced from the U.S. Energy Information Administration.

From the literature, we will expect that there will be a positive correlation between TEC and GDP, and a negative correlation between EI and GDP.

	Dependent variable:
	gdp
energy	0.005***
	(0.001)
ei	-1.410***
	(0.106)
Constant	2.179***
	(0.222)
Observations	63
R2	0.965
Adjusted R2	0.964
Residual Std. Error	0.103 (df = 60)
F Statistic	829.889*** (df = 2; 60)

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Note: *p<0.1; **p<0.05; ***p<0.01

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Regression Output

(Table 1.0) – Regression Summary for Model (I)

The results of the regression show some promise, and some areas of concern. The signs of our coefficients are as we would expect from the literature, and the adjusted R-Squared suggests that 96% of variation in GDP, around it's mean, adjusted for degrees of freedom is explained by the model. As it is typical for a high R-Squared value in time-series regression analysis, the positive results seen do not preclude any violations of the classical assumptions. We will first assess whether the model is correctly specified before making any other adjustments. This will be done with a Ramsey Regression Specification Error Test. The results of the Ramsey test indicate that we reject the null hypothesis, as the P-value is very small. The model suffers from some form of misspecification. By adding interaction terms, estimating the model log-level, level-level, log-log, adding quadratic terms, removing EI from the model, and various combinations of the aforementioned methods of correcting misspecification, I could not get the model to pass the RESET test. Until I did a RESET test on the model after calculating the Cochrane Orcutt estimator on the model in log-log. It scored a P-value of .935, indicating that the model does not suffer from specification error. See table 1.1 for an example of attempting to correct for misspecification. Following the RESET testing, our selected model is now log-transformed. (II)

$$(II)\ \log(GDP) = \beta_0 + \beta_1 log(TEC) + \beta_2 log(EI) + u_i$$

While we cannot eliminate the possibility of misspecification, we do have to move on to the next issue. When our model is in log-log form, our adjusted R-Squared value rises to a value of 1, indicating a deterministic relationship between our variables. (Table 1.2) That is, all of the variation in GDP, around it's mean, is explained by the variation in EI and TEC. This indicates likely violations of classical assumptions.

The first assumption that will be checked is Classical Assumption VI. To see if the no-perfect multi-collinearity assumption is violated, we will calculate variance inflation factors. Table 1.3 shows that the VIFS for both explanatory variables are below the level of concern of 5. (7) The model does not suffer from perfect multi-collinearity.

Next, we will test for serial correlation with the Durbin-Watson test. Since our model has two slope coefficients on 59 degrees of freedom, our region of rejection is from 0 to 1.51. The area of inconclusiveness is from 1.51 to 1.65. The region of acceptance is from 1.65 to 4. (Table 1.5) Our calculated Durbin-Watson statistic is .260 which clearly falls in our region of rejection, meaning that the result of the Durbin-Watson test indicates that the model suffers from serial correlation. (Table 1.4) This is a common issue with time-series data, where our inference is undermined by the unreliability of the model's standard errors. To correct for this, we will use the Cochrane-Orcutt method. The Durbin-Watson statistic of the Cochrane-Orcutt estimator for the model (II) is 1.71, which is in the acceptance region. The Cochrane-Orcutt method has improved the reliability of our model, and thereby our inference. Furthermore, our adjusted R-Squared value has fallen from 1, which means our model is closer to what would be expected theoretically. (Table 1.6)

Before we move on to discussing what we can infer from the model, we will test for and correct for heteroskedasticity. To do this, we will run a studentized Breusch-Pagan test. To do the Breusch-Pagan test, we store the estimated models residuals in an object, and run an auxiliary regression with the squared error term as the dependent variable. If the P-Value is higher than .05, we fail to reject the null hypothesis, indicating that the model does not suffer from heteroskedasticity. The results of the B-P test indicate that our model does suffer from heteroskedasticity, as the p-value is .03553 (Table 1.7) To correct for this, we will have to estimate heteroskedastically robust Eicker-Huber-White standard errors. See table 1.9 for the comparison between robust and non-robust standard errors.

After correcting for serial correlation, and for heteroskedasticity our final model with estimated coefficients (III) is ready to be interpreted.

$$(III)\ \log(GDP) = -4.32 + (.333)log(TEC) - (.335)log(EI) + u_i$$

As mentioned previously, the signs of the beta coefficients align with what is expected in theory. Ceteris paribus, with a 1% increase in total energy consumption in billions of BTUs, we can expect a .33% increase in GDP indexed to 1985 years. This indicates what you may intuitively understand, increased energy consumption represents increased economic activity. Ceteris paribus, a 1% increase in energy intensity, the ratio between GDP indexed to 1985 years and total energy consumption indexed to 1985 years, will result in a .335% decrease in GDP. The adjusted R-squared value is .999, indicating that over 99% of the variation in GDP, around it's mean, adjusted for degrees of freedom is explained by the model.

4. Granger-Type Causality

While causality is not the primary concern of this research, it may be beneficial to our interpretation of the model to understand precedence, as we are attempting to predict a change in GDP from a change in total energy consumption. Since there is so much conflicting information in the literature on the directional causal relationship between energy and GDP, we will calculate and discuss the results found in our data on the United States. As the United States is a heavily industrialized nation with low energy capacity utilization, similar to Germany and Japan, we will expect that there is a unidirectional causal relationship from energy consumption to GDP. Firstly, we will test causality from GDP to energy consumption, and energy consumption to GDP by estimating two dynamic models with our variables of interest, and running two F-Tests. (3)(4)

$$(IV)\ \log(GDP) = \beta_0 + \beta_1 L(GDP,1) + \beta_2 L(GDP,2) + \beta_3 L(TEC,1) + u_i$$

$$(V)\ \log(TEC) = \beta_0 + \beta_1 L(TEC,1) + \beta_2 L(TEC,2) + \beta_3 L(GDP,1) + u_i$$

For Granger-type causality from GDP to Energy consumption, the F-statistic of 247 is much higher than our threshold value of 4.00. For causality from energy consumption to GDP, the F-statistic of 43 is higher than the threshold value of 4.00. The results of both of these tests in conjunction indicate bi-directional long-run Granger-type causality. This is not the outcome that was anticipated, but does not preclude the possibility that energy consumption precedes GDP. Perhaps consumption of energy occurs simultaneously with GDP. Now we can continue with modeling the coronavirus recession of 2020 with our data.

5. Modeling the Coronavirus Economic Shock

In January 2020, total energy consumption in the U.S. stood at 8.963 billion BTU. By April, it had dropped to 6.517 billion BTU. In May when the data was updated on the EIA website, could we have forecasted what 2020 Q2 GDP would have been? The drop from 8.963 to 6.517 represents a 27.3% decrease in total energy consumption. From our model, we can infer that would correspond to a 9.08% drop in GDP from Q1 to Q2. The Bureau of Economic Analysis has posted that GDP for Q1 of 2020 was 21,561 billion dollars. GDP for Q2 was 19,520 billion dollars, or a 9.47% decrease. For one of the most extreme economic shocks of our time, the model predicts within .5% accuracy. While this result demonstrates the relationship between GDP and energy consumption, there are considerations to make from here. What could be done to improve the results of the model? What other variables could we have included in our regression? What next?

6. Outstanding Issues and Improvements

The most considerable problem that stands with the specification. Since only exhaustive testing of functional forms produced a passing result, it is likely there is a variable omitted that we have not considered. With an adjusted R-Squared value of .999, we would likely have to drop the dependent variable, energy intensity of GDP, before adding a new variable to the model. Perhaps adding a variable, such as the emissions intensity of GDP, which is not directly calculated by the other two variables in the model will produce more reliable results. In regards to what we have forecasted from the model, inferring the monthly effects of energy consumption from aggregate annual modeling may not provide the precision needed for more accurate results. It may also be illuminating to test how the model performs on other recessions and economic shocks, or by testing the model on other countries during the coronavirus pandemic.

7. Conclusion

This regression provides some insight into how energy consumption, energy intensity of GDP, and GDP are related, and adds to the argument against the neutral case of directionality from energy to GDP. We found some success in using the model to “forecast” changes in GDP, and this paper can serve as some evidence of how energy data may provide leading information on changes in GDP, which could prove some use to researchers, investors, and policymakers.

8. Appendix

$$(1)\ GDP = \beta_0 + \beta_1(TEC) + \beta_2(EI) + u_i$$
RESET = 7176.1, df1 = 2, df2 = 58, p-value < 2.2e-16
$$(2)\ \log(GDP) = \beta_0 + \beta_1 log(TEC) + \beta_2 log(EI) + u_i$$
RESET = 0.067459, df1 = 2, df2 = 57, p-value = 0.9348

Table 1.1 – RESET TEST RESULTS

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==================================================
                    Dependent variable:
                ------------------------------
                          lgdp
--------------------------------------------------
Log(energy)           0.333***
                      (0.0002)

Log(ei)               -0.335***
                      (0.0003)

Constant              -4.324***
                      (0.003)

--------------------------------------------------
Observations                 63
R2                        1.000
Adjusted R2                  1.000
Residual Std. Error       0.001 (df = 60)
F Statistic        12,571,639.000*** (df = 2; 60)
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Note:              *p<0.1; **p<0.05; ***p<0.01

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Regression Output
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Table 1.2 – Equation (2) Regression Summary

Log(energy)	Log(Energy Intensity)
VIF: 3.365935	VIF: 3.365935

Table 1.3 – Variance Inflation Factors

DW = 0.2606, p-value < 2.2e-16
alternative hypothesis: true autocorrelation is greater than 0

Table 1.4 – Durbin-Watson Test Results for Model (2)

RR	IR	AR
dL=1.51		dU= 1.65
0		4

Table 1.5 – Durbin-Watson Decision Regions

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=======================================
                Dependent variable:
            ---------------------------
                      lgdp
---------------------------------------
lenergy              0.333***
                    (0.001)

lei                 -0.335***
                    (0.001)

Constant             -4.325***
                    (0.008)

---------------------------------------
Observations           63
=======================================
Note:       *p<0.1; **p<0.05; ***p<0.01

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Residual standard error: 5e-04 on 59 degrees of freedom
Multiple R-squared:  0.9999 ,  Adjusted R-squared:  0.9999
F-statistic: 459753.5 on 2 and 59 DF,  p-value: < 2.063e-124

Regression Output
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Durbin-Watson statistic
(original):    0.26060 , p-value: 3.329e-23
(transformed): 1.70570 , p-value: 8.988e-02
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Table 1.6 – Regression Output and Durbin-Watson Transformation Results – Equation (3)

Studentized Breusch-Pagan Test	BP = 6.6747, df = 2, p-value = 0.03553

Table 1.7 – Breusch-Pagan Test Results

Model 1: restricted model Model 2: lgdp ~ L(gdp, 1) + L(gdp, 2) + L(en ergy, 1) Res.Df RSS Df Sum of Sq F Pr(>F) 1 58 1.19193 2 57 0.22341 1 0.96852 247.1 < 2.2e-16 ** * ---	Model 1: restricted model Model 2: lenergy ~ L(energy, 1) + L(energy, 2) + L(gdp, 1) Res.Df RSS Df Sum of Sq F Pr(>F) 1 58 1.52725 2 57 0.86845 0.6588 43.24 1.615e-08 ***
qf(0.95, df1=1, df2=59) [1] 4.003983	qf(0.95, df1=1, df2=59) [1] 4.003983

(Table 1.8) – Granger-Type Causality Tests and F-Tests

Non-Robust Standard Error	Robust Standard Errors
Std. Error (Intercept) 0.0081063 Log(energy 0.0018444 Log(ei) 0.0017352	Std. Error (Intercept) 0.00248095 Log(energy 0.00055033 Log(ei) 0.00109145

(Table 1.9)- Eicker-Huber-White Standard Errors

9. References

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(5) Ugur Soytas, Ramazan Sari, (2003) "Energy consumption and GDP: causality relationship in G-7 countries and emerging markets" *Energy Economics, Volume 25*, Issue 1, pp. 33-37

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(8) Stacy MacIntyre, (2020) “EIA projects U.S. energy intensity to continue declining, but at a slower rate” [Link]