4. Time-series econometric pretesting and specification testing

While it may seem obvious that a relationship exists among the economic variables, it may be difficult to accurately model it. Natural gas, oil, and coal are mined, delivered, and used in different ways which makes substitution difficult to show but logically plausible since they are major energy inputs for many industries. There are five steps to test the dynamic relationship among natural gas, oil, and coal variables which are: (1) test for unit roots to determine if the data is stationary or follows a random walk; (2) use cointegration techniques to identify long run relationships; (3) test for causality among the variables using Granger causality test; (4) test for weak exogeneity to identify variables that are determined outside the system; and (5) use acyclic directed graphs to determine contemporaneous causality and in turn endogeneity or exogeneity.

4.1. Unit root testing The Augmented Dickey–Fuller (ADF) test is used to determine if a variable has a unit root or is stationary. A variable has a unit root if after a shock it does not move back to a long-run trend. Dickey and Fuller (1979) showed that the null hypothesis of their test is that the series has a unit root and is non-stationary. The test gives you the choice of including a constant, a constant and a linear time trend, or none in the regression. Including the constant and trend is the most general specification, and was the choice for this study. Also, the test allows for the specification of the number of lagged difference terms. Based on the results of the ADF, the null hypothesis of a unit root cannot be rejected for level data (Table 1). After the series has been differenced once and retested, the results indicate that the null hypothesis is rejected and that the data does not have a unit root. Thus, after differencing all of the variables and taking the second difference of total asset, federal funds rate, unemployment rate, the data stationarity has been acheived. One issue with the ADF test is that it has weak power, because it only allows for the rejection of the hypothesis that the series has a unit root rather than accepting the hypothesis that the series is stationary.

Table: Augmented Dickey–Fuller test

|  |  |  |  |
| --- | --- | --- | --- |
| Variables | ADF statistic (levels) | ADF statistic (first diff) | ADF statistic (second diff) |
| Money Supply | 2.548278 | -15.211102\*\*\* | -8.381034\*\*\* |
| Total Assets | -2.081078 | -2.732047 | -6.016185\*\*\* |
| Currency in Circulation | -3.653973\*\*\* | -5.133268\*\*\* | -6.497273\*\*\* |
| **Effective Federal Funds Rate** | -2.503304 | -1.657520 | -3.943879\*\*\* |
| **Unemployment Rate** | -2.223388 | -1.758765 | -7.922465\*\*\* |

\*\*\*1% significant

|  |  |  |  |
| --- | --- | --- | --- |
| Variables | ADF statistic (levels) | ADF statistic (first diff) | ADF statistic (second diff) |
| Money Supply | 2.548278 | -15.211102\*\*\* | - |
| Total Assets | -2.081078 | -2.732047 | -6.016185\*\*\* |
| Currency in Circulation | -3.653973\*\*\* | - | - |
| **Effective Federal Funds Rate** | -2.503304 | -1.657520 | -3.943879\*\*\* |
| **Unemployment Rate** | -2.223388 | -1.758765 | -7.922465\*\*\* |

4.2. Cointegration analysis:

The Johansen Cointegration test is used to find the number of cointegrating vectors among the variables (Johansen, 1991; Johansen and Juselius, 1994). Cointegration is a linear long-run relationship between two or more variables. All of the variables must be integrated in the same order to be cointegrated. With the results from the ADF test it can be concluded that all of the variables are integrated..

|  |  |  |
| --- | --- | --- |
| Variables | Test Statistic | P Value |
| Money Supply | 224.01 | 0.000000 |
| Total Assets | 147.03 | 0.000000 |
| Currency in Circulation | 85.81 | 0.000000 |
| **Effective Federal Funds Rate** | 41.46 | 0.000000 |
| **Unemployment Rate** | 18.09 | 0.000000 |

4.3. Granger causality test:

The Granger causality tests (Granger, 1969) can help identify if variables that are assumed endogenous can be treated as exogenous. The null hypothesis is that “X does not cause Y.”. An F-test determines if lagged values of X significantly impact Y, and if they do then X is said to Granger cause Y. The variables in the study were differenced twice and tested. The results indicate that natural gas price Granger causes the coal price, coal price Granger causes the oil price, and oil price Granger causes the natural gas price. This cyclical causal flow makes it difficult to determine a meaningful causal relationship among the variables. Given these mixed results, the weak exogeneity test is used to test for exogeneity.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **M4\_x** | **TA\_x** | **FFR\_x** | **CC\_x** | **Unemployment Rate\_x** |
| **M4\_y** | 1.0000 | 0.0000 | 0.3917 | 0.0120 | 0.0026 |
| **TA\_y** | 0.0031 | 1.0000 | 0.0080 | 0.3248 | 0.1002 |
| **FFR\_y** | 0.1405 | 0.2517 | 1.0000 | 0.0217 | 0.2008 |
| **CC\_y** | 0.0060 | 0.0103 | 0.6505 | 1.0000 | 0.0671 |
| **Unemployment Rate\_y** | 0.0567 | 0.0000 | 0.5694 | 0.2324 | 1.0000 |

Now , I wanted to see the effects of unconventional monetary policy on the M4. Here, the row are the Response (Y) and the columns are the predictor series (X). If a given p-value is < significance level (0.05), then, the corresponding X series (column) causes the Y (row). For example, p-value of 0.0031 means (column 1, row 2) represents the p-value of the Grangers Causality test for **M4 causing total asset, which is less that the significance level of 0.05. So, we can reject the null hypothesis and conclude money supply causes total asset of Fed. Here, 0.1405 means (column 1, row 3): M4 has insignificant effect on federal funds rate. However, money supply has significant effect on currency in circulation and also on the unemployment rate at 1% and 10% respectively**.

Likewise, we can see that **total asset has effects on money supply, unemployment rate, currency in circulation**. However, it has insignificant effect on federal funds rate. Moreover, **currency in circulation causes money supply and federal funds rate at 5% significance level** whereas it has very insignificant effects on total asset and unemployment rate;

Also, **federal funds rate has significant effect on total asset of Fed** but has very insignificant effects on the rest of the variables. However, **unemployment rate has significant effect on money supply and currency in circulation** but it has very insignificant effects on total assets and federal funds rate.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **M4\_x** | **TA\_x** | **FFR\_x** | **CC\_x** | **Unemployment Rate\_x** |
| **M4\_y** | 1.0000 | 0.0000 | 0.3924 | 0.0004 | 0.0108 |
| **TA\_y** | 0.0002 | 1.0000 | 0.0077 | 0.2116 | 0.1110 |
| **FFR\_y** | 0.0625 | 0.2477 | 1.0000 | 0.0156 | 0.1985 |
| **CC\_y** | 0.0019 | 0.0216 | 0.7152 | 1.0000 | 0.2312 |
| **Unemployment Rate\_y** | 0.1152 | 0.0000 | 0.5653 | 0.0048 | 1.0000 |

For example, p-value of 0.002 means (column 1, row 2) represents the p-value of the Grangers Causality test for **M4 causing total asset, which is less that the significance level of 0.05. So, we can reject the null hypothesis and conclude money supply causes total asset of Fed. Here, 0.1405 means (column 1, row 3): M4 has insignificant effect on federal funds rate. However, money supply has significant effect on currency in circulation and also on the unemployment rate at 1% and 10% respectively**.

Likewise, we can see that **total asset has effects on money supply, unemployment rate, currency in circulation**. However, it has insignificant effect on federal funds rate. Moreover, **currency in circulation causes money supply, unemployment rate and federal funds rate at 5% significance level** whereas it has very insignificant effects on total asset;

Also, **federal funds rate has significant effect on total asset of Fed** but has very insignificant effects on the rest of the variables. However, **unemployment rate has significant effect on money supply, TA, FFR** but it has very insignificant effects on CC.

4.5. Directed acyclic graphs Directed acyclic graphs are visual representations of defined causal flows between and among a set of variables. These graphs were developed in the field of artificial intelligence and computer science. DAGs use algorithms programed into a computer to illustrate causal relations from observational data (Lauritzen and Richardson, 2002). The recent applications of DAGs in applied economics have been used by Roh and Bessler (1999), Besler and Yang (2003), and Li et al. (2013), among others. Mathematically, these graphs represent conditional independence as shown by the recursive product decomposition:

pr ¼ ð Þ v1; v2; …:; vn ¼ ∏n i¼1pr vi ð Þ

where pr is the probability of the variables (v1,v2,….,vn), and πi represents the realization of some subset of the variables that cause vi in order (i= 1, 2,….,n). The character ∏ is the product operator. Due to the contributions by Pearl (1986, 1995), the independencies and direct causes implied by the above equation can be translated graphically using the d-separation criteria. Spirtes et al. (2000) was able to incorporate Pearl's work on d-separation into algorithms that build DAGs. D-separation can be explained using a three variable set X, Y, and Z. Variables are said to be d-separated if the flow of information between them is blocked. This can occur in two ways: (1) when one variable is the cause for two variables, say Y in the graph X←Y→Z, or when Y is the passthough variable in graph X→Y→Z; (2) if Y is the common effect of two variables such as in the graph X→Y←Z. There are two algorithms that this study will focus on, PC and GES. The PC algorithm starts with a complete undirected graph. An undirected graph has every variable connected to each other with a line called an edge, which does not include any directional arrows. Then the edges between the variables are removed systematically based on vanishing zero-order correlation or higher-order correlation at a predetermined significance level of the normal distribution. The remaining edges are directed according to the definition of d-separation. There are two problems with the PC algorithm when examining sample sizes of 100 or less; edge exclusion or inclusion and edge direction. This can be overcome by raising the significance level to between 20% and 30% (Spirtes et al., 2000, p 116). The GES algorithm uses a different approach to create DAGs that use Bayesian posterior over alternative scores to search DAGs. The algorithm's first step is to begin with a DAG that has no edges connecting any of the variables. Then edges are added and/or directions reversed in a search across all possible DAGs to improve the Bayesian posterior score. Once a local maximum of the Bayesian score is found, which occurs when no edges or directions can be added, then edges are deleted or directions reversed as long as such actions improve the Bayesian posterior score (Chickering, 2003). The DAGs were used as an alternative way to examine causal relationships between the variables selected for this study. The variables used for the graphs are the natural gas, oil, and coal prices and corresponding consumptions. GDP per capita was added and is constrained in both models so that it cannot be caused by any of the other variables, since it is assumed to be exogenous. The PC and the GES algorithms are embedded in the software TETRAD IV, which was used in this study. The correlation matrix for the graphs is displayed below. This matrix is the starting point for the PC algorithm which begins with a completed un-directional graph and removes lines and includes directions based on zero correlation and higher-order correlations. The correlation matrix shows that all of the variables are significantly correlated with at least one other variable so it can be expected that direct and indirect casual flows exist among the variables. The DAGs for the PC algorithm are found in Fig. 2 at the 10% and 20% significance levels. At both significant levels the graph indicates that there is a causal flow from GDP per capita to natural gas price, natural gas consumption, coal price, and coal consumption. There are direct lines from natural gas price to oil price and natural gas consumption to oil consumption. Finally, coal price has two causal flows from both GDP per capita and oil consumption. The DAG for the GES algorithm is displayed in Fig. 3. Recall that the GES algorithm begins with a graph of independence among all of the variables and no choice of significant levels. As one can see from the graph, the same exogeneity issues from the Granger causality test and the weak exogeneity test are still present. Coal consumption is the only variable that is completely endogenous in the system, affected by oil price, natural gas consumption, natural gas price, and coal price; while the graph shows that oil price is weakly exogenous being caused by oil consumption, natural gas consumption, natural gas price, and coal price. As seen in the PC graph there is a causal flow from GDP per capita to natural gas price and then to oil price. The direction of the arrow from natural gas consumption to oil consumption in the PC model is reversed in the GES model, which indicates that the demand for oil drives demand for natural gas. Also, there is again a connection between oil demand and coal price, but it is undirected which means the algorithm could not determine the causal flow given the available information. This indicates that there may be a variable missing between coal price and coal consumption. To determine the appropriateness of the DAGs generated by the PC and GES algorithms, a chi-square test is performed. The null hypothesis of the test is that, “the population covariance matrix over all the measured variables is equal to the e000

stimated covariance matrix over all the measured variables written as a function of the free model parameters.” (TETRAD IV user's manual). If one fails to reject then the causal structure estimated from the covariance matrix is expected to be valid. Both of the PC graphs had a p-value of 0, while the GES graph had a p-value of 0.3783, indicating that the GES graph fits the data better.