Determinants of Inflation in Denmark and a Panel Data analysis of Denmark and 4 other countries.

### Section I: Introduction

Inflation is defined as the sustained rise in the general price level (Blanchard, Amighini, & Giavazzi, 2021, p. 577).

Negative effects of inflation are well documented. One such cost is that inflation induces overinvestment in the financial sector: as price instability increases, arbitrage opportunities grow (*ibid*, p. 4); this transfer of resources out of the productive sector can be “as large as a few percentage points of GDP and can even be seen at relatively low or moderate rates of inflation.” (Mishkin & Posen, 1997, p. 4) Inflation also causes fiscal drag, which occurs when nominal income rises while real income and tax brackets remain frozen; as a result, income after tax decreases in real terms; Fischer (1994, p. 14) estimates that an inflation rate of 10% could put the social cost of fiscal drag at 2-3% of GNP.

Due to these problems, governments around the world have decided to target low and stable inflation as a policy objective of their monetary authorities (Mishkin & Posen, 1997). These monetary authorities must have a clear model for producing inflation forecasts (Masson, Savastano, & Sharma, 1997, p. 9) and understand the determinants of inflation. This paper will contribute to this understanding by estimating the relationship between inflation and past inflation, money supply, exchange rates, and global energy prices. Inflation determinants and targeting will be investigated first in Denmark, then also Norway, Sweden, Iceland and the UK.

### Section II: Literature Review

Among economists, there are competing explanations for the fundamental causes of inflation. Friedman provides the well-known monetarist explanation where inflation is the result of money supply rising faster than output (Leeson & Palm, 2012, p. 3). This view is popular and the relationship between money supply growth and inflation has been examined by a number of studies.

Holod (2000) uses a VEC model to investigate the relationship between price level, exchange rate and money supply in Ukraine. Holod (2000) finds that the influence of money supply on inflation is not very strong, which he explains is due to concurrent fluctuations in the money demand.

Lim & Sek (2015) explore panel data on 28 countries by estimating inflation as an ARDL model against money supply (M4) and a number of other regressors. In high inflation countries, every 1% increase in the money supply is found to induce a 0.77% increase in inflation, in the long-run. In low-inflation countries, increased money supply does not have a significant effect in the long-run and decreases inflation in the short-run in low inflation countries.

Money growth leads to inflation by increasing aggregate demand, known as demand-pull inflation. On the other hand, cost-push inflation, which follows a reduction in aggregate supply, has also been examined in the literature. Cost-push inflation is typically caused by high factor prices (Ellahi, 2017, p. 3). Global energy prices are one example of a variable which should have such an effect on factor prices, and this view is supported by existing evidence.

Jatuporn (2024) and Liang & Long (2018) both estimated the impacts of global oil price changes on CPI and PPI using ARDL and NARDL models to analyse Thailand and China, respectively. Both studies find that ARDL models do not find evidence of long-run effects of oil price shocks on inflation, however NARDL models can capture the effects at a 1% significance level. Jatuporn (2024) finds: +1% change in oil price led to +0.147% CPI change; -1% change in oil price led to -0.115% CPI change. Liang & Long (2018) did not find significant long-run effects due to a drop in oil prices, but found a +1% change in oil price led to a +0.143% CPI change.

Finally, there is also a lot of evidence examining the effects of a currency’s exchange rate on domestic prices. Movements in the exchange rate influence domestic prices through various channels, from direct effects on energy prices (discussed above) to indirect effects on import prices (Ha et al., 2019); this raises the price of inputs and thus the price of capital, reducing aggregate supply. The marginal effect of a 1% depreciation in the exchange rate on inflation is known as the exchange rate pass-through ratio (Ha et al., 2019, p. 271).

The exchange rate pass-through varies across countries and time (Ha, Kose, Ohnsorge, & Yilmazkuday, 2019, p. 284). Choudhri & Hakura (2001) estimated inflation as an ARDL model, using panel data of 71 countries. The explanatory variables were the nominal exchange rate and foreign CPI. They find that the long-run pass-through rates in Denmark, Sweden, Norway, and the UK are 0.24, 0.03, 0.13, and 0.03, respectively – Iceland did not form part of the panel. They also determine that the main reason for cross-country variation in the pass-through rate is due to the different inflationary regimes between countries.

### Section III: Timeseries variables, data and models

#### Data sources

The databases utilised are the IMF, OECD, Bank for International Statistics (BIS), and Federal Reserve Economic Data (FRED). CPI data was obtained from the IMF, money supply (M3) data from OECD, the exchange rate from BIS and global energy prices from FRED. The literature varies between using real effective exchange rates (Deniz, Tekce, & Yilmaz, 2016) and nominal effective exchange rates (Choudhri & Hakura, 2001; Campa & Goldberg, 2005) – in this paper I will use the nominal exchange rate following from Campa & Goldberg’s (2005) model where it is the nominal rate that influences decision-makers at the microlevel.

#### Presenting and transforming the data

Table I contains the summary statistics for Denmark in the studied period (2000:1-2023:4). This includes the consumer price index () in 2015=100, money supply aggregate M4 (), nominal effective exchange rate index () in 2020=100, and the global energy price index () in 2016=100. Any monthly data was converted into quarterly data by taking the value for the last month of each quarter.

Table

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Statistic | cpi | m | xr | gep |
| Mean | 94.527 | 1271726.000 | 96.050 | 153.268 |
| Median | 96.967 | 1394929.000 | 96.120 | 148.764 |
| S.D. | 10.845 | 377165.800 | 3.815 | 64.919 |
| Min | 75.429 | 507134.000 | 85.430 | 61.703 |
| Max | 117.867 | 1922206.000 | 103.240 | 350.124 |
| Obs | 96 | 96 | 96 | 96 |

Figure I represents the variables visually in the studied period (2000:1-2023:4).

Figure

|  |  |
| --- | --- |
|  |  |
|  |  |

To reduce data variability and find elastic relationships (Jatuporn, 2024), all variables have been transformed into logarithmic functions (lcpi, lm, lxr, lgep).

#### Stationarity Testing

The Augmented Dickey-Fuller (ADF) test will be used to test for stationarity.

Each variable is first estimated as:

Where:

* , is the number of lagged, differenced, dependent variables to include to eliminate serial correlation;
* is an array of variables , added if the variable is exhibiting drifting or trending behaviour;
* is a stochastic error term.

The Breusch-Godfrey (BG) test is used to find autoregressive lags to eliminate serial correlation. As all variables have non-zero means, they must have a drift/constant component. All variables – except – appear to be increasing over time, and thus will also be testing with trend components.

Table II shows results for estimated with a drift term and all other variables estimated with a trend term. BG test is included in and ADF test in .

Lags were computed using the BG test[[1]](#footnote-1) and the Mackinnon approximate p-value displays significance for the ADF test.[[2]](#footnote-2)

Table

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Lags (p) | Test statistic | 5% critical value | MacKinnon p-value |
|  | 5 | -2.131 | -3.460 | 0.529 |
|  | 0 | -1.616 | -3.455 | 0.786 |
|  | 3 | -3.271 | -3.458 | 0.0712 |
| \* | 1 | -2.743 | -1.662 | 0.0059\*\*\* |

*\*\*\* denotes the 1% significance level*

\*

We do not accept the alternate hypothesis that are trend-stationary. We accept the alternate hypothesis that stationary with drift.

, and are then re-estimated using the ADF[[3]](#footnote-3) test **with a drift constant** and tested for serial correlation[[4]](#footnote-4), shown in Table III.

Table

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Lags (p) | Test statistic | 5% critical value | MacKinnon p-value |
|  | 5 | -0.286 | -1.663 | 0.388 |
|  | 0 | -1.937 | -1.661 | 0.0279\*\* |
|  | 4 | -2.095 | -1.663 | 0.0196\*\* |

*\*\* denotes the 5% significance level*

*\*\*\* denotes the 1% significance level*

We accept the null hypothesis that is a random walk with drift, and accept the alternative hypothesis that and are drift-stationary processes due to their non-zero means.

As is non-stationary, it is differenced (=) and tested again for stationarity. Serial correlation is tested[[5]](#footnote-5) and then an ADF test is used[[6]](#footnote-6). As has a non-zero mean, tests are conducted using a **drift constant**. Results are shown in Table IV.

Table

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Lags (p) | Test statistic | 5% critical value | MacKinnon p-value |
|  | 4 | -4.114 | -1.663 | 0.0000\*\*\* |

*\*\*\* denotes the 1% significance level*

We accept the alternate hypothesis that is drift-stationary.

All stationary variables are displayed in Figure II.

Figure

|  |  |
| --- | --- |
|  |  |
|  |  |

#### Inflation as an ARMA model

##### Estimation

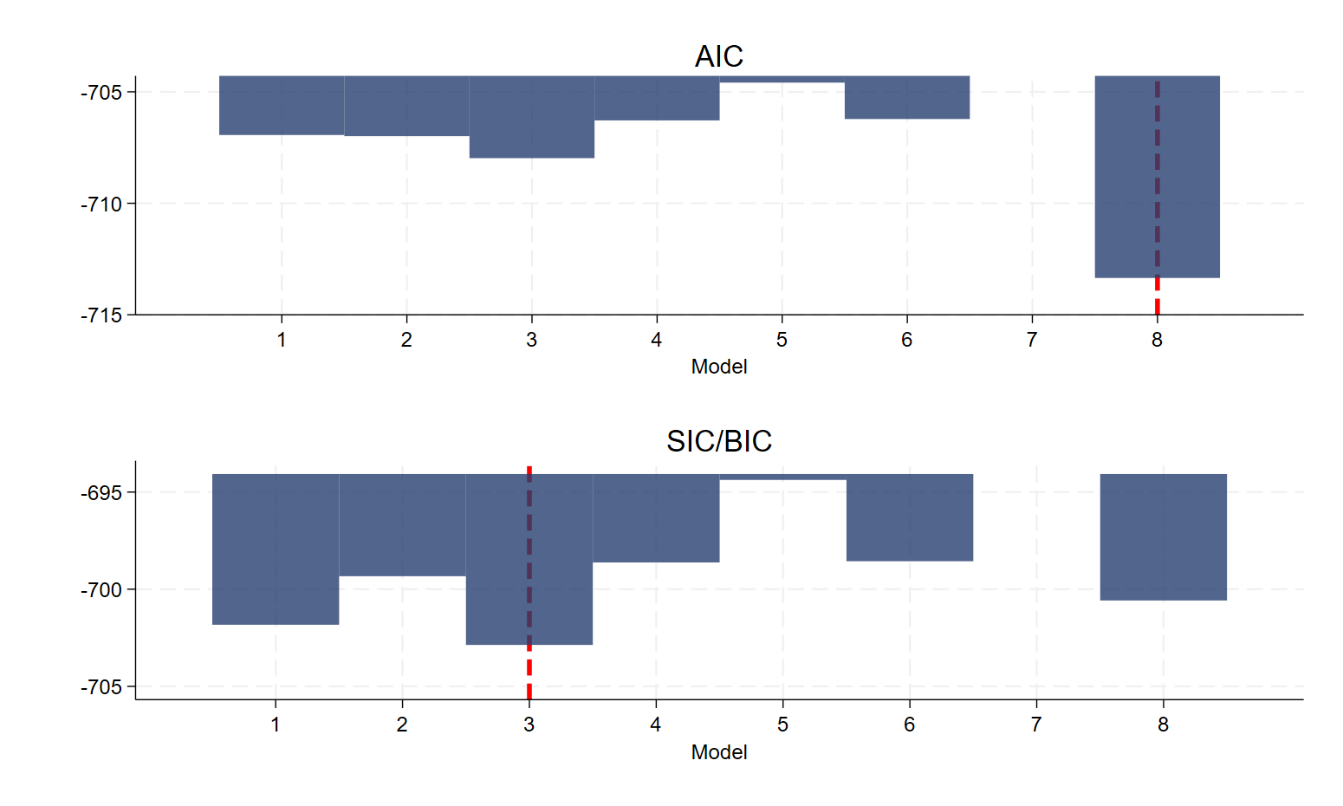
will be estimated as an ARMA(p,q) model:

To select lags (*p* and *q*), I will be using the AIC and BIC up to a maximum of .

Table

|  |  |  |  |
| --- | --- | --- | --- |
| Model | ARMA Specification | AIC | BIC |
| 1 | (0,1) | -706.9376 | -701.8299 |
| 2 | (0,2) | -706.9988 | -699.3292 |
| 3 | (1,0) | -707.9764 | **-702.8686** |
| 4 | (1,1) | -706.2838 | -698.6222 |
| 5 | (1,2) | -704.5892 | -694.3737 |
| 6 | (2,0) | -706.2211 | -698.5594 |
| 7 | (2,1) | -704.2863 | -694.0708 |
| 8 | (2,2) | **-713.3489** | -700.5795 |

Figure



Shown in Figure III and Table V, AIC selects model 8, ARMA(2,2), whereas SIC/BIC selects model 3, ARMA(1,0), i.e., a pure AR(1) model[[7]](#footnote-7).

*Model 3:[[8]](#footnote-8)*

|  |  |  |
| --- | --- | --- |
| Variable | Coefficient  (Robust Std. Err) | p-value |
|  | 0.380355  (0.1405789) | 0.000\*\*\* |

*\*\*\* denotes the 1% significance level*

*Model 8:[[9]](#footnote-9)*

|  |  |  |
| --- | --- | --- |
| Variable | Coefficient  (Robust Std. Err) | p-value |
|  | -0.899534  (0.2194136) | 0.000\*\*\* |
|  | 0.076611  (0.221312) | 0.688 |
|  | 1.427597  (0.1399993) | 0.000\*\*\* |
|  | 0.5024687  (0.1556634) | 0.006\*\*\* |

*\*\*\* denotes the 1% significance level*

Model 8 is chosen because the extra parameters which it adds are mostly very significant and make theoretical sense and, while the extra autoregressive term is insignificant, it decreases overall autocorrelation – this can be seen when estimating the correlogram for each model:

|  |  |
| --- | --- |
|  |  |

However, model 8 suffers from serial correlation – further error terms are added to reduce this until there is no serial correlation; this process is shown in Figure IV.

Figure

|  |  |
| --- | --- |
|  |  |

ARMA(4,2) is preferred to eliminate serial correlation, but its coefficients are mostly insignificant,[[10]](#footnote-10) whereas ARMA(3,2) contains significant results while exhibiting very small signs of autocorrelation and so is preferred. Regression results are shown in Table VI.[[11]](#footnote-11)

Table

|  |  |  |
| --- | --- | --- |
| Variable | Coefficient  (Robust Std. Err) | p-value |
|  | 0.606  (0.125) | 0.000\*\*\* |
|  | -1.009  (0.0223) | 0.000\*\*\* |
|  | 0.558  (0.131) | 0.000\*\*\* |
|  | -0.163  (0.0830) | 0.050\* |
|  | 1.000  () | 0.000\*\*\* |

*\* denotes the 10% significance level*

*\*\*\* denotes the 1% significance level*

##### Analysis

Regressing on finds effects on a *unit change in the percentage change of CPI*, i.e., a percentage point change in period-on-period inflation. For example, a 1pp increase in inflation from quarters to will, on average, cause a 0.606pp increase in inflation from quarters to .

The autoregressive coefficients tell us that inflation in past periods has varying effects on the present period; an increase in inflation by 1pp two periods ago will decrease present inflation by 1.009pp today. However, by summing past period coefficients we know that in general, a homogenous increase in past inflation (i.e., +1pp in all past periods) will still increase inflation by 0.155pp today.

The moving average coefficients indicate the impulse response due to an exogenous shock. The effects of a shock two periods ago are fully passed on to the current period; an inflation shock in the previous period is very close to conventional statistical significance and will cause an opposing change in inflation in the present period. This sign variation indicates that shocks will eventually dissipate as its effects will not be fully passed on.

#### Estimating inflation as an ARDL model

##### Estimation

will be estimated as an ARDL model:

Specification selection, i.e., choosing , will be done on the basis of AIC/BIC testing and prevalence of autocorrelation. All 54 possible specification combinations will be checked and the entire table of results is available in Appendix 10.

Figure

Figure

Model 11 is selected by both AIC and BIC, shown in Figure IV and Figure V.

This model does suffer from autocorrelation which can be eliminated by adjusting the model to ARDL(5,1,0,1).[[12]](#footnote-12)

*ARDL(5,1,0,1):*

Table

|  |  |  |
| --- | --- | --- |
| Variable | Coefficient  (Robust Std. Err) | p-value |
|  | 0.394  (0.139) | 0.006\*\*\* |
|  | -0.00215  (0.0895) | 0.981 |
|  | 0.00469  (0.0983) | 0.962 |
|  | 0.473  (0.104) | 0.000\*\*\* |
|  | -0.401  (0.137) | 0.004\*\*\* |
|  | 0.0160  (0.0104) | 0.129 |
|  | -0.0159  (0.0103) | 0.127 |
|  | -0.0164  (0.0155) | 0.294 |
|  | 0.0197  (0.00311) | 0.000\*\*\* |
|  | -0.0171  (0.00304) | 0.000\*\*\* |

*\*\* denotes the 5% significance level*

*\*\*\* denotes the 1% significance level*

##### Analysis

As in the ARMA model, regressing on finds a percentage point change in period-on-period inflation.

Most coefficients are insignificant, with only autoregressive and global energy prices being anywhere near a conventional significance level, indicating that changes in the money supply or nominal exchange rate have no measurable effect on inflation. The effects of energy prices vary; a 1% increase in current global energy prices increases inflation by 0.0197pp, but decreases inflation by 0.0171pp in the next period.

The autoregressive terms also vary; in general, past increases in inflation increase current inflation: a 1pp increase in all past levels of inflation will increase current inflation by 0.466pp.

### Section IV: Panel Data Estimation

Inflation will be modelled using the Fixed Effect, Random Effect, and Pooled OLS Models (FEM, REM, POLS). Each model is tested against the others to calculate which provides the most consistent, efficient and unbiased estimators. The units and their corresponding time periods are shown in Table VII.

Table

|  |  |
| --- | --- |
| Unit | Time Period |
| Denmark | 2000Q1-2023Q4 [no omissions] |
| Sweden | 2000Q1-2023Q4 [no omissions] |
| Norway | 2000Q1-2023Q4 [no omissions] |
| Iceland | 2000Q1-2023Q4 [no omissions] |
| United Kingdom | 2000Q1-2023Q4 [no omissions] |

#### Defining and testing each model

In the POLS, inflation is modelled as:

In the FEM, inflation is modelled as:

Where , i.e., the variable has been de-meaned. It can also be modelled as:

Where is the total number of units.

In the REM, inflation is modelled as:

Where and , i.e., the variable has been de-meaned to a certain degree .

##### FEM and POLS (F-test)

The F-test for FEM and POLS tests to see if the coefficients of the fixed effect dummies in the FEM are jointly statistically significant.

The null hypothesis is rejected at the 1% significance level: .[[13]](#footnote-13) The FEM is preferred to the POLS.

##### REM and POLS (Breusch-Pagan test)

The Breusch-Pagan test for REM and POLS tests for heterogeneity between units. If there is no heterogeneity, i.e., if , then and the REM is the same as POLS.

The null hypothesis is rejected at the 1% significance level: .[[14]](#footnote-14) The REM is preferred to the POLS.

##### FEM and REM (Hausman test)

The Hausman test for FEM and REM tests if . If there is covariance, the variables must be fully de-meaned to preserve consistency and the FEM would be preferred.

The null hypothesis is not rejected at any conventionally significance level: .[[15]](#footnote-15) The REM is preferred to the FEM.

#### Results of the REM

##### Estimation

After tests have concluded the model is re-estimated with cluster-robust standard errors.[[16]](#footnote-16)

|  |  |  |
| --- | --- | --- |
| Variable | Coefficient  (Robust Std. Error) | p-value |
|  | -0.00124  (0.00124) | 0.318 |
|  | -0.00317  (0.00416) | 0.446 |
|  | 0.00567  (0.00125) | 0.000\*\*\* |

*\*\*\* denotes the 1% significance level*

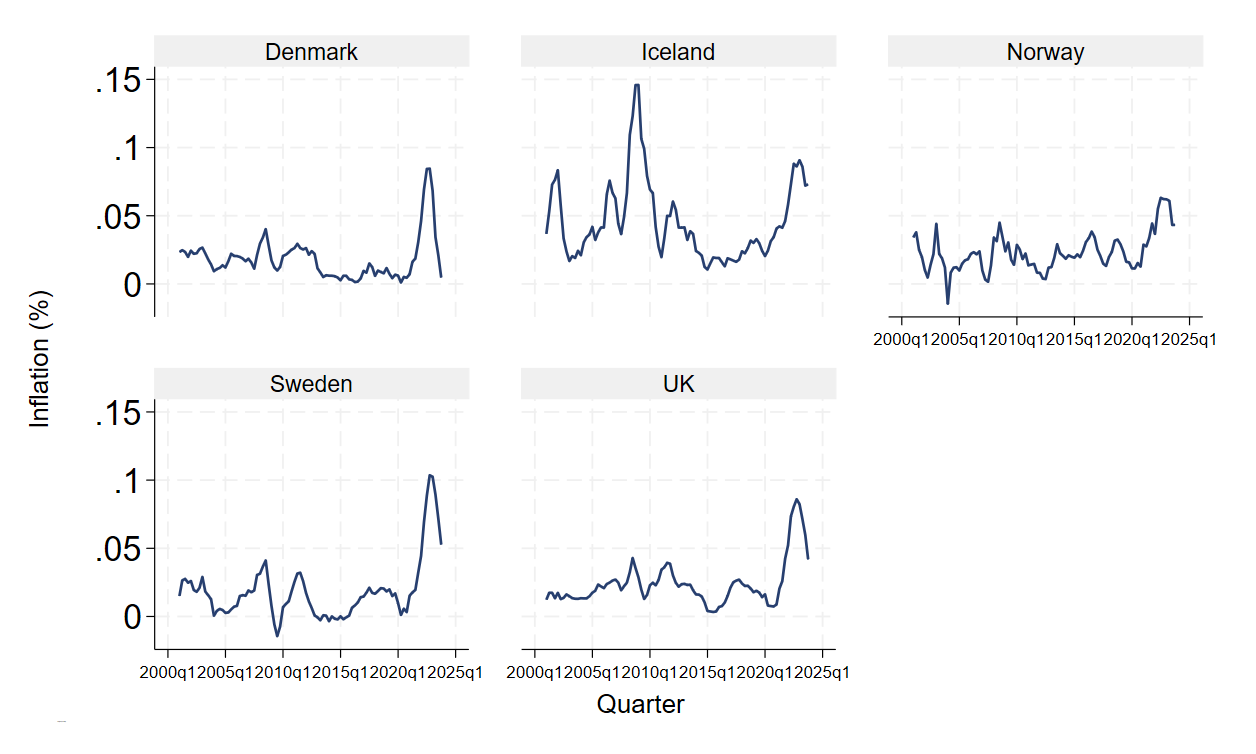
##### Analysis

All variables are not significant at any conventional level except global energy prices. It is estimated that a 1% increase in global energy prices will increase inflation by 0.00567pp. This supports our prior ARDL analysis that money supply and the exchange rate have no measurable effect on inflation.

### Section V: Inflation Targeting Logit Estimation

Previous inflation regressions estimated inflation as period-on-period inflation. However, inflation targeting in industrialised countries typically attempts to control for year-on-year (YoY) inflation (Hammond, 2012, p. 8). Consequently, YoY inflation will be for assessing inflation targeting success; the YoY inflation for each country is shown in Figure VII and the equation is shown below.

Figure



I will be using a logistic model to fit the data as this model is present in the literature when estimating inflation targeting (Milas, Dergaides, Panagiotidis, & Papapanagiotou, 2024).

The model I will be using is:

Where is the probability a country is under 2% inflation and is an array of variables ; an LR test is applied to examine whether the variables should be included as the model is primarily meant to examine the impact of global energy prices – the results are that the array is significant: , .[[17]](#footnote-17) Consequently, the model is:

Table VIII shows that the model correctly classified 61.88% of estimates, indicating the model is a good fit.[[18]](#footnote-18)

Table

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Logistic Model Estimation | | | | | | | |
| Prediction | Truly 1 | |  | | Truly 0 | Total | |
|  |  | |  | |  |  | |
|  |  | |  | |  |  | |
| Total |  | |  | |  |  | |
| Sensitivity |  |  | |  | | |
| Specificity |  |  | |  | | |
| Correctly Classified |  |  | |  | | |

Table IX and Table X present the marginal effects at average (MEA) and average marginal effects (AME), respectively.

Table

|  |  |  |
| --- | --- | --- |
| Variable | MEA  (Delta-method Std. Error) | p-value |
|  | -0.426  (0.0678) | 0.000\*\*\* |
|  | 0.0713  (0.169) | 0.673 |
|  | 0.282  (0.0598) | 0.000\*\*\* |

Table

|  |  |  |
| --- | --- | --- |
| Variable | AME  (Delta-method Std. Error) | p-value |
|  | -0.385  (0.0510) | 0.000\*\*\* |
|  | 0.0644  (0.153) | 0.673 |
|  | 0.255  (0.0491) | 0.000\*\*\* |

# Appendix

## Appendix

Estimated using a foreach loop in Stata. The name of the variable, e.g., , is at the top of each section followed by the results of the BG test looking at 4 lags of the error term, up to a maximum of 5 lags in the ADF test. Each variable section is then followed by a dashed line to indicate the next variable’s estimation has begun. Output has been split into two columns to reduce pagination. The ADF test includes a **trend term**.

. foreach v of varlist lcpi lm lxr lgep {

2. display "`v'"

3. display "Lags: 0"

4. quietly regress D.`v' L.`v' trend

5. estat bgodfrey, lags(1/4) nomiss0

6. forvalues lags = 1/5 {

7. display "Lags: `lags'"

8. quietly regress D.`v' L(1/`lags')D.`v' L.`v' trend

9. estat bgodfrey, lags(1/4) nomiss0

10. }

11. display "\*-----------------\*"

12. }

lcpi

Lags: 0

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 15.522 1 0.0001

2 | 16.469 2 0.0003

3 | 18.263 3 0.0004

4 | 28.871 4 0.0000

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 1

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.112 1 0.7378

2 | 2.358 2 0.3076

3 | 15.398 3 0.0015

4 | 22.773 4 0.0001

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 2

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 2.284 1 0.1307

2 | 15.294 2 0.0005

3 | 14.431 3 0.0024

4 | 21.716 4 0.0002

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 3

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 13.099 1 0.0003

2 | 20.590 2 0.0000

3 | 19.580 3 0.0002

4 | 19.510 4 0.0006

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 4

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 10.241 1 0.0014

2 | 9.600 2 0.0082

3 | 9.516 3 0.0232

4 | 13.602 4 0.0087

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 5

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.712 1 0.3989

2 | 0.758 2 0.6844

3 | 4.798 3 0.1872

4 | 5.159 4 0.2714

---------------------------------------------------------------------------

H0: no serial correlation

\*-----------------\*

lm

Lags: 0

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 2.513 1 0.1129

2 | 3.532 2 0.1710

3 | 3.916 3 0.2707

4 | 4.498 4 0.3428

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 1

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 1.045 1 0.3065

2 | 1.908 2 0.3851

3 | 2.318 3 0.5091

4 | 2.432 4 0.6568

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 2

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.487 1 0.4852

2 | 0.954 2 0.6205

3 | 1.118 3 0.7728

4 | 1.954 4 0.7442

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 3

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.674 1 0.4115

2 | 0.680 2 0.7117

3 | 1.444 3 0.6953

4 | 2.043 4 0.7278

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 4

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.048 1 0.8259

2 | 0.884 2 0.6429

3 | 2.181 3 0.5358

4 | 7.039 4 0.1338

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 5

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.815 1 0.3668

2 | 1.882 2 0.3903

3 | 6.664 3 0.0834

4 | 7.755 4 0.1010

---------------------------------------------------------------------------

H0: no serial correlation

\*-----------------\*

lxr

Lags: 0

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.349 1 0.5548

2 | 1.141 2 0.5654

3 | 7.332 3 0.0620

4 | 10.069 4 0.0393

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 1

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.524 1 0.4692

2 | 6.704 2 0.0350

3 | 9.631 3 0.0220

4 | 8.957 4 0.0622

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 2

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 6.436 1 0.0112

2 | 9.533 2 0.0085

3 | 10.641 3 0.0138

4 | 10.119 4 0.0385

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 3

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 3.419 1 0.0644

2 | 6.294 2 0.0430

3 | 6.598 3 0.0859

4 | 9.300 4 0.0540

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 4

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 3.080 1 0.0792

2 | 3.800 2 0.1496

3 | 7.488 3 0.0579

4 | 8.155 4 0.0861

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 5

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 1.058 1 0.3036

2 | 3.835 2 0.1470

3 | 4.354 3 0.2257

4 | 4.601 4 0.3308

---------------------------------------------------------------------------

H0: no serial correlation

\*-----------------\*

lgep

Lags: 0

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 14.588 1 0.0001

2 | 14.576 2 0.0007

3 | 14.406 3 0.0024

4 | 14.619 4 0.0056

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 1

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.261 1 0.6093

2 | 0.293 2 0.8636

3 | 0.235 3 0.9718

4 | 0.340 4 0.9871

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 2

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.039 1 0.8443

2 | 0.099 2 0.9517

3 | 0.266 3 0.9664

4 | 0.548 4 0.9687

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 3

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.050 1 0.8237

2 | 0.200 2 0.9049

3 | 0.441 3 0.9316

4 | 1.328 4 0.8566

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 4

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.104 1 0.7469

2 | 0.271 2 0.8732

3 | 0.899 3 0.8257

4 | 0.923 4 0.9213

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 5

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.123 1 0.7254

2 | 0.876 2 0.6452

3 | 1.435 3 0.6974

4 | 2.940 4 0.5679

---------------------------------------------------------------------------

H0: no serial correlation

\*-----------------\*

## 

## Appendix

ADF test using trend term for and drift term for . Horizontal lines added to split output into variable sections.

. dfuller lcpi, lags(5) trend

Augmented Dickey–Fuller test for unit root

Variable: lcpi Number of obs = 90

Number of lags = 5

H0: Random walk with or without drift

Dickey–Fuller

Test -------- critical value ---------

statistic 1% 5% 10%

--------------------------------------------------------------

Z(t) -2.131 -4.062 -3.460 -3.156

--------------------------------------------------------------

MacKinnon approximate p-value for Z(t) = 0.5289

. dfuller lm, trend

Dickey–Fuller test for unit root Number of obs = 95

Variable: lm Number of lags = 0

H0: Random walk with or without drift

Dickey–Fuller

Test -------- critical value ---------

statistic 1% 5% 10%

--------------------------------------------------------------

Z(t) -1.616 -4.051 -3.455 -3.153

--------------------------------------------------------------

MacKinnon approximate p-value for Z(t) = 0.7861.

. dfuller lxr, lags(3) trend

Augmented Dickey–Fuller test for unit root

Variable: lxr Number of obs = 92

Number of lags = 3

H0: Random walk with or without drift

Dickey–Fuller

Test -------- critical value ---------

statistic 1% 5% 10%

--------------------------------------------------------------

Z(t) -3.271 -4.058 -3.458 -3.155

--------------------------------------------------------------

MacKinnon approximate p-value for Z(t) = 0.0712.

. dfuller lgep, lags(1) drift

Augmented Dickey–Fuller test for unit root

Variable: lgep Number of obs = 94

Number of lags = 1

H0: Random walk with drift, d = 0

t-distribution

Test -------- critical value ---------

statistic 1% 5% 10%

--------------------------------------------------------------

Z(t) -2.568 -2.368 -1.662 -1.291

--------------------------------------------------------------

p-value for Z(t) = 0.0059

## Appendix

Estimated using a foreach loop in Stata. The name of the variable, e.g., , is at the top of each section followed by the results of the BG test looking at 4 lags of the error term, up to a maximum of 5 lags in the ADF test. Each variable section is then followed by a dashed line to indicate the next variable’s estimation has begun. Output has been columnated to reduce pagination. The ADF test includes a **drift term**

. foreach v of varlist lcpi lm lxr lgep {

2. display "`v'"

3. display "Lags: 0"

4. quietly regress D.`v' L.`v'

5. estat bgodfrey, lags(1/4) nomiss0

6. forvalues lags = 1/5 {

7. display "Lags: `lags'"

8. quietly regress D.`v' L(1/`lags')D.`v' L.`v'

9. estat bgodfrey, lags(1/4) nomiss0

10. }

11. display "\*-----------------\*"

12. }

lcpi

Lags: 0

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 13.451 1 0.0002

2 | 14.315 2 0.0008

3 | 15.226 3 0.0016

4 | 21.778 4 0.0002

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 1

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.300 1 0.5839

2 | 1.331 2 0.5139

3 | 9.225 3 0.0264

4 | 22.072 4 0.0002

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 2

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.992 1 0.3193

2 | 8.887 2 0.0118

3 | 21.834 3 0.0001

4 | 21.661 4 0.0002

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 3

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 7.893 1 0.0050

2 | 20.768 2 0.0000

3 | 20.442 3 0.0001

4 | 20.547 4 0.0004

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 4

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 15.204 1 0.0001

2 | 15.393 2 0.0005

3 | 15.608 3 0.0014

4 | 18.000 4 0.0012

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 5

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 1.482 1 0.2235

2 | 1.910 2 0.3847

3 | 4.187 3 0.2420

4 | 5.560 4 0.2345

---------------------------------------------------------------------------

H0: no serial correlation

\*-----------------\*

lm

Lags: 0

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 2.122 1 0.1452

2 | 2.793 2 0.2474

3 | 3.303 3 0.3472

4 | 3.642 4 0.4566

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 1

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.715 1 0.3977

2 | 1.701 2 0.4272

3 | 1.824 3 0.6096

4 | 2.000 4 0.7357

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 2

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.674 1 0.4118

2 | 0.850 2 0.6538

3 | 1.059 3 0.7870

4 | 2.289 4 0.6827

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 3

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.398 1 0.5281

2 | 0.463 2 0.7934

3 | 1.657 3 0.6464

4 | 2.587 4 0.6292

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 4

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.115 1 0.7350

2 | 1.354 2 0.5082

3 | 2.863 3 0.4132

4 | 6.626 4 0.1570

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 5

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 1.232 1 0.2671

2 | 2.450 2 0.2938

3 | 6.109 3 0.1064

4 | 9.148 4 0.0575

---------------------------------------------------------------------------

H0: no serial correlation

\*-----------------\*

lxr

Lags: 0

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.143 1 0.7049

2 | 0.873 2 0.6464

3 | 5.573 3 0.1343

4 | 9.625 4 0.0472

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 1

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.484 1 0.4866

2 | 5.191 2 0.0746

3 | 9.390 3 0.0245

4 | 8.767 4 0.0672

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 2

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 4.962 1 0.0259

2 | 9.383 2 0.0092

3 | 11.411 3 0.0097

4 | 10.156 4 0.0379

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 3

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 4.735 1 0.0296

2 | 8.342 2 0.0154

3 | 8.134 3 0.0433

4 | 10.126 4 0.0384

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 4

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 3.883 1 0.0488

2 | 4.222 2 0.1211

3 | 7.269 3 0.0638

4 | 7.522 4 0.1107

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 5

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.713 1 0.3984

2 | 2.754 2 0.2523

3 | 2.880 3 0.4105

4 | 3.511 4 0.4762

---------------------------------------------------------------------------

H0: no serial correlation

\*-----------------\*

lgep

Lags: 0

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 13.833 1 0.0002

2 | 13.977 2 0.0009

3 | 13.824 3 0.0032

4 | 14.161 4 0.0068

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 1

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.466 1 0.4950

2 | 0.453 2 0.7972

3 | 0.350 3 0.9503

4 | 0.449 4 0.9783

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 2

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.004 1 0.9503

2 | 0.076 2 0.9625

3 | 0.277 3 0.9642

4 | 0.451 4 0.9781

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 3

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.058 1 0.8101

2 | 0.249 2 0.8831

3 | 0.401 3 0.9400

4 | 1.012 4 0.9080

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 4

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.153 1 0.6956

2 | 0.275 2 0.8714

3 | 0.972 3 0.8080

4 | 1.621 4 0.8051

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 5

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.096 1 0.7564

2 | 0.839 2 0.6572

3 | 1.488 3 0.6850

4 | 3.106 4 0.5402

---------------------------------------------------------------------------

H0: no serial correlation

\*-----------------\*

## Appendix

ADF test using drift term for . Horizontal lines added to split output into variable sections.

. dfuller lcpi, lags(5) drift

Augmented Dickey–Fuller test for unit root

Variable: lcpi Number of obs = 90

Number of lags = 5

H0: Random walk with drift, d = 0

t-distribution

Test -------- critical value ---------

statistic 1% 5% 10%

--------------------------------------------------------------

Z(t) -0.286 -2.372 -1.663 -1.292

--------------------------------------------------------------

p-value for Z(t) = 0.3879

. dfuller lm, drift

Dickey–Fuller test for unit root Number of obs = 95

Variable: lm Number of lags = 0

H0: Random walk with drift, d = 0

t-distribution

Test -------- critical value ---------

statistic 1% 5% 10%

--------------------------------------------------------------

Z(t) -1.937 -2.367 -1.661 -1.291

--------------------------------------------------------------

p-value for Z(t) = 0.0279

. dfuller lxr, lags(4) drift

Augmented Dickey–Fuller test for unit root

Variable: lxr Number of obs = 91

Number of lags = 4

H0: Random walk with drift, d = 0

t-distribution

Test -------- critical value ---------

statistic 1% 5% 10%

--------------------------------------------------------------

Z(t) -2.095 -2.371 -1.663 -1.292

--------------------------------------------------------------

p-value for Z(t) = 0.0196

## Appendix

Estimated using a foreach loop in Stata. The ADF test includes a **drift term**

. foreach v of varlist D.lcpi {

2. display "`v'"

3. display "Lags: 0"

4. quietly regress D.`v' L.`v'

5. estat bgodfrey, lags(1/4) nomiss0

6. forvalues lags = 1/5 {

7. display "Lags: `lags'"

8. quietly regress D.`v' L(1/`lags')D.`v' L.`v'

9. estat bgodfrey, lags(1/4) nomiss0

10. }

11. display "\*-----------------\*"

12. }

D.lcpi

Lags: 0

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.261 1 0.6092

2 | 1.283 2 0.5265

3 | 8.876 3 0.0310

4 | 22.001 4 0.0002

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 1

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.920 1 0.3374

2 | 8.535 2 0.0140

3 | 21.670 3 0.0001

4 | 21.553 4 0.0002

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 2

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 7.627 1 0.0058

2 | 20.688 2 0.0000

3 | 20.412 3 0.0001

4 | 20.398 4 0.0004

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 3

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 15.287 1 0.0001

2 | 15.647 2 0.0004

3 | 15.757 3 0.0013

4 | 18.242 4 0.0011

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 4

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 1.411 1 0.2348

2 | 1.737 2 0.4197

3 | 4.249 3 0.2358

4 | 5.497 4 0.2400

---------------------------------------------------------------------------

H0: no serial correlation

Lags: 5

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.349 1 0.5547

2 | 3.125 2 0.2096

3 | 4.429 3 0.2187

4 | 5.378 4 0.2507

---------------------------------------------------------------------------

H0: no serial correlation

## Appendix

ADF test using drift term for .

. dfuller d.lcpi, lags(4) drift

Augmented Dickey–Fuller test for unit root

Variable: D.lcpi Number of obs = 90

Number of lags = 4

H0: Random walk with drift, d = 0

t-distribution

Test -------- critical value ---------

statistic 1% 5% 10%

--------------------------------------------------------------

Z(t) -4.114 -2.372 -1.663 -1.292

--------------------------------------------------------------

p-value for Z(t) = 0.0000

## Appendix

. eststo ARMA: arimasel d.lcpi, ar(2) ma(2)

Model1: AR(0) MA(1)

Model2: AR(0) MA(2)

Model3: AR(1) MA(0)

Model4: AR(1) MA(1)

Model5: AR(1) MA(2)

Model6: AR(2) MA(0)

Model7: AR(2) MA(1)

Model8: AR(2) MA(2)

| AR MA Nparm LLF AIC SIC

-------------+-----------------------------------------------------------------

Model1 | 0 1 2 355.4688 -706.9376 -701.8299

Model2 | 0 2 3 356.4954 -706.9908 -699.3292

Model3 | 1 0 2 355.9882 -707.9764 -702.8686

Model4 | 1 1 3 356.1419 -706.2838 -698.6222

Model5 | 1 2 4 356.2946 -704.5892 -694.3737

Model6 | 2 0 3 356.1105 -706.2211 -698.5594

Model7 | 2 1 4 356.1431 -704.2863 -694.0708

Model8 | 2 2 5 361.6745 -713.3489 -700.5795

## Appendix

. arima dlcpi, ar(1) robust

(setting optimization to BHHH)

Iteration 0: Log pseudolikelihood = 355.98779

Iteration 1: Log pseudolikelihood = 355.98812

Iteration 2: Log pseudolikelihood = 355.98816

Iteration 3: Log pseudolikelihood = 355.98817

Iteration 4: Log pseudolikelihood = 355.98818

ARIMA regression

Sample: 2000q2 thru 2023q4 Number of obs = 95

Wald chi2(1) = 7.32

Log pseudolikelihood = 355.9882 Prob > chi2 = 0.0068

------------------------------------------------------------------------------

| Semirobust

dlcpi | Coefficient std. err. z P>|z| [95% conf. interval]

-------------+----------------------------------------------------------------

dlcpi |

\_cons | .0046215 .0009386 4.92 0.000 .0027819 .0064611

-------------+----------------------------------------------------------------

ARMA |

ar |

L1. | .380355 .1405789 2.71 0.007 .1048253 .6558846

-------------+----------------------------------------------------------------

/sigma | .0057014 .0005091 11.20 0.000 .0047036 .0066993

------------------------------------------------------------------------------

Note: The test of the variance against zero is one sided, and the two-sided

confidence interval is truncated at zero.

## Appendix

. arima dlcpi, ar(1/2) ma(1/2) robust

(setting optimization to BHHH)

Iteration 0: Log pseudolikelihood = 347.23067

Iteration 1: Log pseudolikelihood = 352.68152

Iteration 2: Log pseudolikelihood = 353.68017

Iteration 3: Log pseudolikelihood = 355.04277

Iteration 4: Log pseudolikelihood = 359.79432

(switching optimization to BFGS)

Iteration 5: Log pseudolikelihood = 361.0122

Iteration 6: Log pseudolikelihood = 361.10737

Iteration 7: Log pseudolikelihood = 361.39219

Iteration 8: Log pseudolikelihood = 361.61468

Iteration 9: Log pseudolikelihood = 361.65691

Iteration 10: Log pseudolikelihood = 361.65801

Iteration 11: Log pseudolikelihood = 361.67069

Iteration 12: Log pseudolikelihood = 361.67379

Iteration 13: Log pseudolikelihood = 361.67444

Iteration 14: Log pseudolikelihood = 361.67445

ARIMA regression

Sample: 2000q2 thru 2023q4 Number of obs = 95

Wald chi2(4) = 680.78

Log pseudolikelihood = 361.6745 Prob > chi2 = 0.0000

------------------------------------------------------------------------------

| Semirobust

dlcpi | Coefficient std. err. z P>|z| [95% conf. interval]

-------------+----------------------------------------------------------------

dlcpi |

\_cons | .0045876 .0008768 5.23 0.000 .0028691 .0063061

-------------+----------------------------------------------------------------

ARMA |

ar |

L1. | -.8995348 .2194136 -4.10 0.000 -1.329578 -.4694921

L2. | .076611 .221312 0.35 0.729 -.3571526 .5103746

|

ma |

L1. | 1.427597 .1399993 10.20 0.000 1.153203 1.701991

L2. | .5024687 .1556634 3.23 0.001 .197374 .8075633

-------------+----------------------------------------------------------------

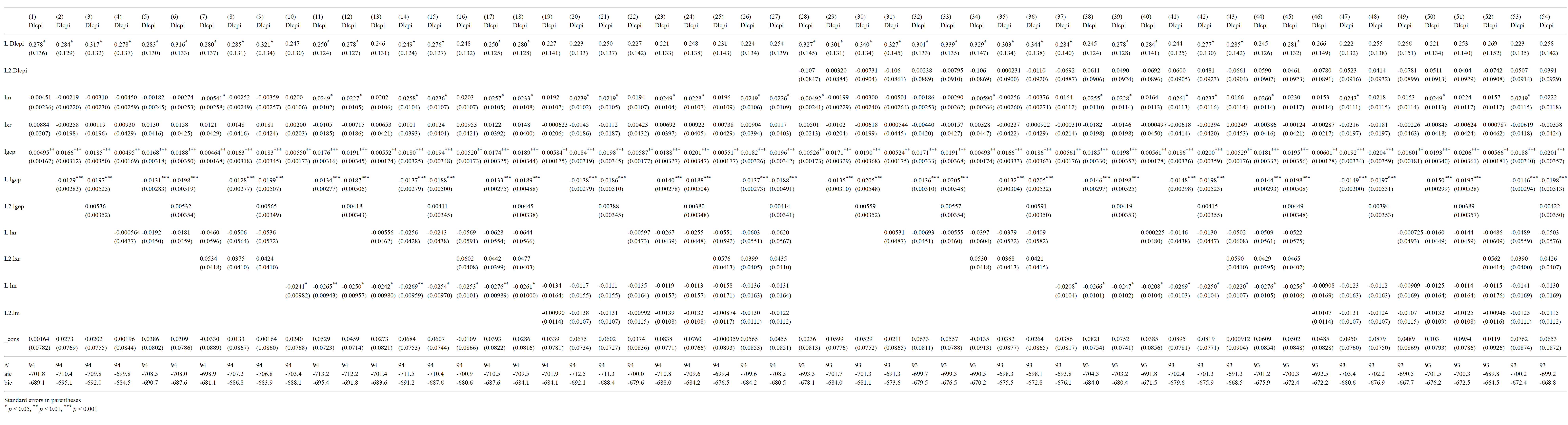
/sigma | .0053414 .0005515 9.68 0.000 .0042605 .0064224

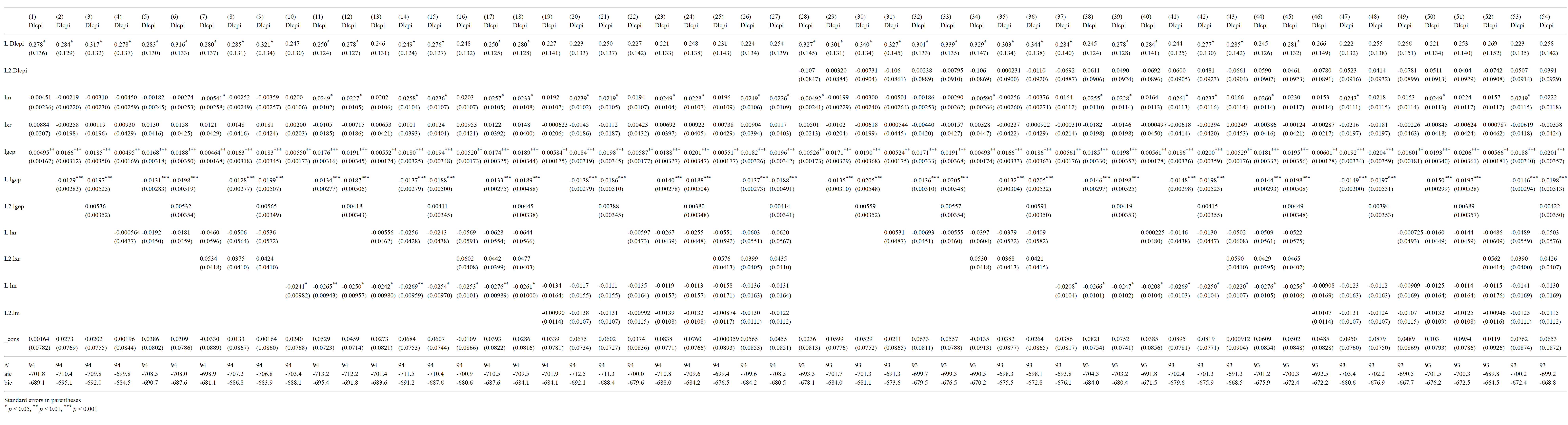
------------------------------------------------------------------------------

Note: The test of the variance against zero is one sided, and the two-sided

confidence interval is truncated at zero.

## Appendix





## Appendix

. xtreg dlcpi lm lxr lgep, fe

Fixed-effects (within) regression Number of obs = 475

Group variable: countryID Number of groups = 5

R-squared: Obs per group:

Within = 0.0915 min = 95

Between = 0.0248 avg = 95.0

Overall = 0.0718 max = 95

F(3, 467) = 15.68

corr(u\_i, Xb) = -0.0684 Prob > F = 0.0000

------------------------------------------------------------------------------

dlcpi | Coefficient Std. err. t P>|t| [95% conf. interval]

-------------+----------------------------------------------------------------

lm | -.0012838 .0011473 -1.12 0.264 -.0035382 .0009707

lxr | -.004254 .0031981 -1.33 0.184 -.0105385 .0020305

lgep | .0056259 .0009738 5.78 0.000 .0037124 .0075394

\_cons | .0172206 .0264191 0.65 0.515 -.0346944 .0691355

-------------+----------------------------------------------------------------

sigma\_u | .00311715

sigma\_e | .00727819

rho | .15499753 (fraction of variance due to u\_i)

------------------------------------------------------------------------------

F test that all u\_i=0: F(4, 467) = 14.31 Prob > F = 0.0000

## Appendix

. reg dlcpi lm lxr lgep

Source | SS df MS Number of obs = 475

-------------+---------------------------------- F(3, 471) = 16.06

Model | .002840985 3 .000946995 Prob > F = 0.0000

Residual | .027770526 471 .000058961 R-squared = 0.0928

-------------+---------------------------------- Adj R-squared = 0.0870

Total | .03061151 474 .000064581 Root MSE = .00768

------------------------------------------------------------------------------

dlcpi | Coefficient Std. err. t P>|t| [95% conf. interval]

-------------+----------------------------------------------------------------

lm | -.001447 .0008487 -1.70 0.089 -.0031148 .0002207

lxr | .0029066 .0024725 1.18 0.240 -.0019518 .0077651

lgep | .0061984 .0009348 6.63 0.000 .0043616 .0080353

\_cons | -.0169459 .0191463 -0.89 0.377 -.0545686 .0206768

------------------------------------------------------------------------------

. xtreg dlcpi lm lxr lgep, re

Random-effects GLS regression Number of obs = 475

Group variable: countryID Number of groups = 5

R-squared: Obs per group:

Within = 0.0912 min = 95

Between = 0.0021 avg = 95.0

Overall = 0.0769 max = 95

Wald chi2(3) = 46.33

corr(u\_i, X) = 0 (assumed) Prob > chi2 = 0.0000

------------------------------------------------------------------------------

dlcpi | Coefficient Std. err. z P>|z| [95% conf. interval]

-------------+----------------------------------------------------------------

lm | -.0012355 .0010923 -1.13 0.258 -.0033764 .0009053

lxr | -.0031661 .003064 -1.03 0.301 -.0091715 .0028393

lgep | .005667 .000961 5.90 0.000 .0037835 .0075505

\_cons | .0112128 .0250962 0.45 0.655 -.0379748 .0604005

-------------+----------------------------------------------------------------

sigma\_u | .00222592

sigma\_e | .00727819

rho | .08553384 (fraction of variance due to u\_i)

------------------------------------------------------------------------------

. xttest0

Breusch and Pagan Lagrangian multiplier test for random effects

dlcpi[countryID,t] = Xb + u[countryID] + e[countryID,t]

Estimated results:

| Var SD = sqrt(Var)

---------+-----------------------------

dlcpi | .0000646 .0080362

e | .000053 .0072782

u | 4.95e-06 .0022259

Test: Var(u) = 0

chibar2(01) = 151.19

Prob > chibar2 = 0.0000

## Appendix

. eststo fixed: qui xtreg dlcpi lm lxr lgep, fe

. xtreg dlcpi lm lxr lgep, re

Random-effects GLS regression Number of obs = 475

Group variable: countryID Number of groups = 5

R-squared: Obs per group:

Within = 0.0912 min = 95

Between = 0.0021 avg = 95.0

Overall = 0.0769 max = 95

Wald chi2(3) = 46.33

corr(u\_i, X) = 0 (assumed) Prob > chi2 = 0.0000

------------------------------------------------------------------------------

dlcpi | Coefficient Std. err. z P>|z| [95% conf. interval]

-------------+----------------------------------------------------------------

lm | -.0012355 .0010923 -1.13 0.258 -.0033764 .0009053

lxr | -.0031661 .003064 -1.03 0.301 -.0091715 .0028393

lgep | .005667 .000961 5.90 0.000 .0037835 .0075505

\_cons | .0112128 .0250962 0.45 0.655 -.0379748 .0604005

-------------+----------------------------------------------------------------

sigma\_u | .00222592

sigma\_e | .00727819

rho | .08553384 (fraction of variance due to u\_i)

------------------------------------------------------------------------------

. hausman fixed

---- Coefficients ----

| (b) (B) (b-B) sqrt(diag(V\_b-V\_B))

| fixed . Difference Std. err.

-------------+----------------------------------------------------------------

lm | -.0012838 -.0012355 -.0000482 .0003508

lxr | -.004254 -.0031661 -.0010879 .0009165

lgep | .0056259 .005667 -.0000411 .0001573

------------------------------------------------------------------------------

b = Consistent under H0 and Ha; obtained from xtreg.

B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

chi2(3) = (b-B)'[(V\_b-V\_B)^(-1)](b-B)

= 6.07

Prob > chi2 = 0.1085

(V\_b-V\_B is not positive definite)

## Appendix

. xtreg dlcpi lm lxr lgep, re robust

Random-effects GLS regression Number of obs = 475

Group variable: countryID Number of groups = 5

R-squared: Obs per group:

Within = 0.0912 min = 95

Between = 0.0021 avg = 95.0

Overall = 0.0769 max = 95

Wald chi2(3) = 1290.99

corr(u\_i, X) = 0 (assumed) Prob > chi2 = 0.0000

(Std. err. adjusted for 5 clusters in countryID)

------------------------------------------------------------------------------

| Robust

dlcpi | Coefficient std. err. z P>|z| [95% conf. interval]

-------------+----------------------------------------------------------------

lm | -.0012355 .0012365 -1.00 0.318 -.003659 .0011879

lxr | -.0031661 .0041577 -0.76 0.446 -.011315 .0049828

lgep | .005667 .0012543 4.52 0.000 .0032086 .0081255

\_cons | .0112128 .0200629 0.56 0.576 -.0281097 .0505354

-------------+----------------------------------------------------------------

sigma\_u | .00222592

sigma\_e | .00727819

rho | .08553384 (fraction of variance due to u\_i)

------------------------------------------------------------------------------

## Appendix

. logistic it lgep

Logistic regression Number of obs = 480

LR chi2(1) = 20.34

Prob > chi2 = 0.0000

Log likelihood = -321.47399 Pseudo R2 = 0.0307

------------------------------------------------------------------------------

it | Odds ratio Std. err. z P>|z| [95% conf. interval]

-------------+----------------------------------------------------------------

lgep | .3874224 .083324 -4.41 0.000 .2541642 .5905479

\_cons | 94.15234 100.2411 4.27 0.000 11.68377 758.7161

------------------------------------------------------------------------------

Note: \_cons estimates baseline odds.

. estimates store restricted

. logistic it lgep lm lxr

Logistic regression Number of obs = 480

LR chi2(3) = 48.28

Prob > chi2 = 0.0000

Log likelihood = -307.50326 Pseudo R2 = 0.0728

------------------------------------------------------------------------------

it | Odds ratio Std. err. z P>|z| [95% conf. interval]

-------------+----------------------------------------------------------------

lgep | .1803496 .0491709 -6.28 0.000 .1056918 .3077434

lm | 3.109738 .7472943 4.72 0.000 1.941661 4.980514

lxr | 1.331985 .9045517 0.42 0.673 .3519231 5.041395

\_cons | .0000972 .0005092 -1.76 0.078 3.38e-09 2.797531

------------------------------------------------------------------------------

Note: \_cons estimates baseline odds.

. estimates store full

. lrtest full restricted

Likelihood-ratio test

Assumption: restricted nested within full

LR chi2(2) = 27.94

Prob > chi2 = 0.0000

## Appendix

. logistic it lgep lxr lm

Logistic regression Number of obs = 480

LR chi2(3) = 48.28

Prob > chi2 = 0.0000

Log likelihood = -307.50326 Pseudo R2 = 0.0728

------------------------------------------------------------------------------

it | Odds ratio Std. err. z P>|z| [95% conf. interval]

-------------+----------------------------------------------------------------

lgep | .1803496 .0491709 -6.28 0.000 .1056918 .3077434

lxr | 1.331985 .9045517 0.42 0.673 .3519231 5.041395

lm | 3.109738 .7472943 4.72 0.000 1.941661 4.980514

\_cons | .0000972 .0005092 -1.76 0.078 3.38e-09 2.797531

------------------------------------------------------------------------------

Note: \_cons estimates baseline odds.

. estat class

Logistic model for it

-------- True --------

Classified | D ~D | Total

-----------+--------------------------+-----------

+ | 120 79 | 199

- | 104 177 | 281

-----------+--------------------------+-----------

Total | 224 256 | 480

Classified + if predicted Pr(D) >= .5

True D defined as it != 0

--------------------------------------------------

Sensitivity Pr( +| D) 53.57%

Specificity Pr( -|~D) 69.14%

Positive predictive value Pr( D| +) 60.30%

Negative predictive value Pr(~D| -) 62.99%

--------------------------------------------------

False + rate for true ~D Pr( +|~D) 30.86%

False - rate for true D Pr( -| D) 46.43%

False + rate for classified + Pr(~D| +) 39.70%

False - rate for classified - Pr( D| -) 37.01%

--------------------------------------------------

Correctly classified 61.88%

--------------------------------------------------

## Appendix

. forvalues lags = 1/5 {

2. display "AR lags: `lags'"

3. eststo: quietly regress Dlcpi L(1/`lags').Dlcpi L(0/1).lm lxr L(0/1).lxr

4. estat bgodfrey, lags(1/5)

5. }

AR lags: 1

(est1 stored)

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.096 1 0.7572

2 | 0.251 2 0.8818

3 | 0.448 3 0.9303

4 | 16.222 4 0.0027

5 | 19.089 5 0.0018

---------------------------------------------------------------------------

H0: no serial correlation

AR lags: 2

(est2 stored)

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 0.056 1 0.8123

2 | 0.082 2 0.9597

3 | 0.763 3 0.8583

4 | 15.805 4 0.0033

5 | 18.239 5 0.0027

---------------------------------------------------------------------------

H0: no serial correlation

AR lags: 3

(est3 stored)

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 3.479 1 0.0621

2 | 7.552 2 0.0229

3 | 7.891 3 0.0483

4 | 19.931 4 0.0005

5 | 20.996 5 0.0008

---------------------------------------------------------------------------

H0: no serial correlation

AR lags: 4

(est4 stored)

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 11.177 1 0.0008

2 | 14.189 2 0.0008

3 | 15.179 3 0.0017

4 | 15.275 4 0.0042

5 | 18.148 5 0.0028

---------------------------------------------------------------------------

H0: no serial correlation

AR lags: 5

(est5 stored)

Breusch–Godfrey LM test for autocorrelation

---------------------------------------------------------------------------

lags(p) | chi2 df Prob > chi2

-------------+-------------------------------------------------------------

1 | 1.819 1 0.1774

2 | 1.982 2 0.3712

3 | 3.104 3 0.3758

4 | 7.086 4 0.1314

5 | 10.393 5 0.0648

---------------------------------------------------------------------------

H0: no serial correlation

Appendix

arima Dlcpi, ar(1/4) ma(1/2) robust

(setting optimization to BHHH)

Iteration 0: Log pseudolikelihood = 353.88446

Iteration 1: Log pseudolikelihood = 354.30768

Iteration 2: Log pseudolikelihood = 354.67405

Iteration 3: Log pseudolikelihood = 356.86616

Iteration 4: Log pseudolikelihood = 362.36155

(switching optimization to BFGS)

Iteration 5: Log pseudolikelihood = 364.40223

Iteration 6: Log pseudolikelihood = 365.41376

Iteration 7: Log pseudolikelihood = 365.48237

Iteration 8: Log pseudolikelihood = 365.61532

Iteration 9: Log pseudolikelihood = 365.62791

Iteration 10: Log pseudolikelihood = 365.6486

Iteration 11: Log pseudolikelihood = 365.66494

Iteration 12: Log pseudolikelihood = 365.67431

Iteration 13: Log pseudolikelihood = 365.67676

Iteration 14: Log pseudolikelihood = 365.67715

(switching optimization to BHHH)

Iteration 15: Log pseudolikelihood = 365.67716

ARIMA regression

Sample: 2000q2 thru 2023q4 Number of obs = 95

Wald chi2(6) = 60.95

Log pseudolikelihood = 365.6772 Prob > chi2 = 0.0000

------------------------------------------------------------------------------

| Semirobust

Dlcpi | Coefficient std. err. z P>|z| [95% conf. interval]

-------------+----------------------------------------------------------------

Dlcpi |

\_cons | .0045145 .001155 3.91 0.000 .0022507 .0067783

-------------+----------------------------------------------------------------

ARMA |

ar |

L1. | -.1539197 .6606914 -0.23 0.816 -1.448851 1.141012

L2. | -.0302372 .6519198 -0.05 0.963 -1.307976 1.247502

L3. | -.0397128 .2581571 -0.15 0.878 -.5456914 .4662658

L4. | .4167652 .1567917 2.66 0.008 .1094591 .7240713

|

ma |

L1. | .6194411 .8487993 0.73 0.466 -1.044175 2.283057

L2. | .2506852 .4961058 0.51 0.613 -.7216644 1.223035

-------------+----------------------------------------------------------------

/sigma | .0051211 .0005147 9.95 0.000 .0041124 .0061298

------------------------------------------------------------------------------

Note: The test of the variance against zero is one sided, and the two-sided

confidence interval is truncated at zero.

Appendix

. arima Dlcpi, ar(1/3) ma(1/2) robust

(setting optimization to BHHH)

Iteration 0: Log pseudolikelihood = 352.89905

Iteration 1: Log pseudolikelihood = 354.1232

Iteration 2: Log pseudolikelihood = 354.82793

Iteration 3: Log pseudolikelihood = 361.49586

Iteration 4: Log pseudolikelihood = 367.28448

(switching optimization to BFGS)

Iteration 5: Log pseudolikelihood = 370.8931

Iteration 6: Log pseudolikelihood = 371.30418

Iteration 7: Log pseudolikelihood = 371.63834

Iteration 8: Log pseudolikelihood = 371.78118

Iteration 9: Log pseudolikelihood = 371.84392

Iteration 10: Log pseudolikelihood = 371.98394

Iteration 11: Log pseudolikelihood = 372.04511

Iteration 12: Log pseudolikelihood = 372.05825

Iteration 13: Log pseudolikelihood = 372.06114

Iteration 14: Log pseudolikelihood = 372.06122

(switching optimization to BHHH)

Iteration 15: Log pseudolikelihood = 372.06123

Iteration 16: Log pseudolikelihood = 372.06123 (backed up)

Iteration 17: Log pseudolikelihood = 372.06123 (backed up)

Iteration 18: Log pseudolikelihood = 372.06123 (not concave)

Iteration 19: Log pseudolikelihood = 372.06123

(switching optimization to BFGS)

Iteration 20: Log pseudolikelihood = 372.06123 (backed up)

Iteration 21: Log pseudolikelihood = 372.06123

ARIMA regression

Sample: 2000q2 thru 2023q4 Number of obs = 95

Wald chi2(5) = 9.15e+12

Log pseudolikelihood = 372.0612 Prob > chi2 = 0.0000

------------------------------------------------------------------------------

| Semirobust

Dlcpi | Coefficient std. err. z P>|z| [95% conf. interval]

-------------+----------------------------------------------------------------

Dlcpi |

\_cons | .0046486 .0010271 4.53 0.000 .0026354 .0066617

-------------+----------------------------------------------------------------

ARMA |

ar |

L1. | .605816 .1250264 4.85 0.000 .3607687 .8508632

L2. | -1.008781 .0223089 -45.22 0.000 -1.052506 -.9650567

L3. | .5582308 .1307205 4.27 0.000 .3020234 .8144382

|

ma |

L1. | -.1625848 .0830045 -1.96 0.050 -.3252705 .000101

L2. | 1 1.92e-06 5.2e+05 0.000 .9999962 1.000004

-------------+----------------------------------------------------------------

/sigma | .0046467 .0004254 10.92 0.000 .0038129 .0054806

------------------------------------------------------------------------------

Note: The test of the variance against zero is one sided, and the two-sided

confidence interval is truncated at zero.

1. # Appendix 1

   [↑](#footnote-ref-1)
2. Appendix 2 [↑](#footnote-ref-2)
3. Appendix 4 [↑](#footnote-ref-3)
4. Appendix 3 [↑](#footnote-ref-4)
5. Appendix 5 [↑](#footnote-ref-5)
6. Appendix 6 [↑](#footnote-ref-6)
7. Appendix 7 [↑](#footnote-ref-7)
8. Appendix 8 [↑](#footnote-ref-8)
9. Appendix 9 [↑](#footnote-ref-9)
10. Appendix 18 [↑](#footnote-ref-10)
11. Appendix 19 [↑](#footnote-ref-11)
12. Appendix 17 [↑](#footnote-ref-12)
13. Appendix 11 [↑](#footnote-ref-13)
14. Appendix 12 [↑](#footnote-ref-14)
15. Appendix 13 [↑](#footnote-ref-15)
16. Appendix 14 [↑](#footnote-ref-16)
17. Appendix 15 [↑](#footnote-ref-17)
18. Appendix 16 [↑](#footnote-ref-18)