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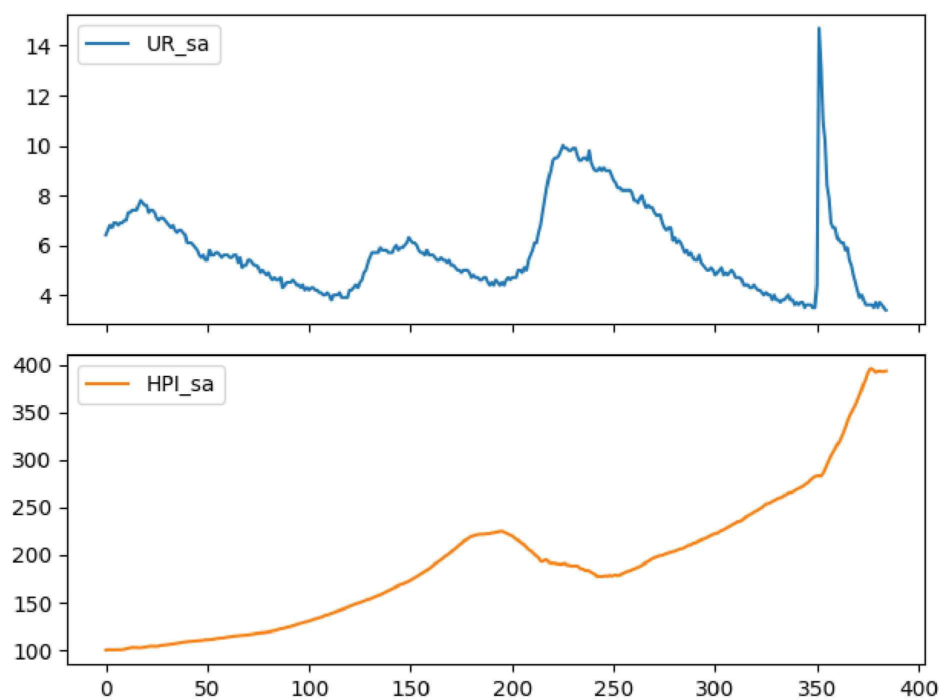
Unraveling the Dynamic Relationship Between Housing Prices and Unemployment: A Time Series Analysis

1 Introduction

This report will analyze the causal effects of the unemployment rate (x_t) on housing prices (y_t) in the United States. We use an ARDL model with 2 dependent lag variables and 4 exogenous variables. Next, we use an AR(6) model to forecast the unemployment rate. Finally, we forecast the housing price index using the ARDL(2,4) and the unemployment rate forecast.

Data

The data gathered in this report comes from the Federal Reserve Economic Data for the unemployment rates and from the Federal Housing Finance Agency for the housing price indices. Both datasets are periodized monthly and are seasonally adjusted. The data covers a period from January 1991 to January 2023. The rationale behind choosing these variables is that a higher unemployment rate may lead to decreased demand for housing, resulting in lower housing prices. This report will contribute to the academic discussion surrounding the labor market's impact on the housing market. In this report, our dependent variable y_t is the housing price index (referred to in our dataset as HPI_sa), while our exogenous variable x_t is the unemployment rate (referred to in our dataset as UR_sa).



2 ARDL model

The ARDL (2,4) model includes two lags of the dependent variable (HPI_sa) and four lags of the independent variable (UR_sa). This means that the current value of HPI_sa is influenced by its own values from two periods ago, and the current value of HPI_sa is influenced by the unemployment rate from four periods ago.

The coefficient for HPI_sa.L1 is 1.8350, indicating that a one-unit increase in the housing price index in the previous period results in a 1.8350-unit increase in the housing price index in the current period. This is statistically significant with a p-value of less than 0.05. The coefficient for HPI_sa.L2 is -0.8338, indicating that a one-unit increase in the housing price index two periods ago results in a -0.8338-unit decrease in the housing price index in the current period. This is also statistically significant with a p-value of less than 0.05.

The coefficient for UR_sa.L1 is -0.1917, indicating that a one-unit increase in the unemployment rate in the previous period results in a -0.1917-unit decrease in the housing price index in the current period. This is statistically significant with a p-value of less than 0.05. The coefficient for UR_sa.L2 is 0.3950, indicating that a one-unit increase in the unemployment rate two periods ago results in a 0.3950-unit increase in the housing price index in the current period. This is also statistically significant with a p-value of less than 0.05.

The coefficient for UR_sa.L3 is -0.1562, indicating that a one-unit increase in the unemployment rate three periods ago results in a -0.1562-unit decrease in the housing price index in the current period. However, this coefficient is not statistically significant at the 0.05 level with a p-value of 0.072. The coefficient for UR_sa.L4 is -0.0281, indicating that a one-unit increase in the unemployment rate four periods ago results in a -0.0281-unit decrease in the housing price index in the current period. This coefficient is also not statistically significant at the 0.05 level with a p-value of 0.648.

In conclusion, the ARDL model results suggest that the housing price index is positively influenced by its own lagged values and negatively influenced by the unemployment rate from the previous period. The model also suggests that the housing price index is influenced by the unemployment rate from two periods ago, but the effect is weaker and less significant than the previous period's unemployment rate. The unemployment rate from three and four periods ago does not have a statistically significant effect on the housing price index.

```python
# ARDL Model
hpi = df['HPI_sa']
ur = df['UR_sa']

exog = df[['UR_sa']]
ardl_model = ARDL(hpi, 2, exog, 4, causal=True)
ardl_results = ardl_model.fit()
print(ardl_results.summary())
```

✓ 0.1s

```
                              ARDL Model Results
==============================================================================
Dep. Variable:                 HPI_sa   No. Observations:                  385
Model:                     ARDL(2, 4)   Log Likelihood                -391.105
Method:               Conditional MLE   S.D. of innovations              0.672
Date:                Mon, 08 May 2023   AIC                            798.210
Time:                        05:21:24   BIC                            829.795
Sample:                             4   HQIC                           810.739
                                  385
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.2160      0.178     -1.216      0.225      -0.565       0.133
HPI_sa.L1      1.8350      0.031     59.963      0.000       1.775       1.895
HPI_sa.L2     -0.8338      0.031    -27.005      0.000      -0.895      -0.773
UR_sa.L1      -0.1917      0.062     -3.090      0.002      -0.314      -0.070
UR_sa.L2       0.3950      0.086      4.576      0.000       0.225       0.565
UR_sa.L3      -0.1562      0.087     -1.805      0.072      -0.326       0.014
UR_sa.L4      -0.0281      0.061     -0.457      0.648      -0.149       0.093
==============================================================================
```

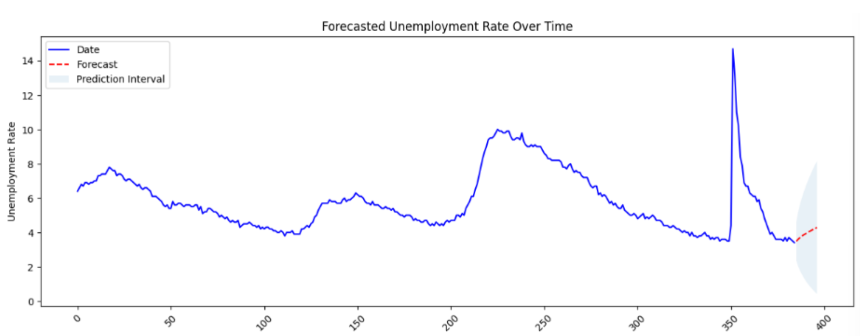
3 Forecasting x_t

The AR(6) model was used to forecast the independent variable, UR_sa, 12 months beyond the last observation which was on 1/1/2023, 384 months after the start of our time series beginning on 1/1/1991.

The coefficients of the model indicate the strength of the relationship between the variable and its past values (lags). The constant term is positive, which means that the value of UR_sa is expected to increase over time on average, even without the influence of its past values. However, the coefficients of the lagged values of UR_sa are all positive, which indicates that past values of the variable have a strong positive effect on its future values. Specifically, the first lagged value of UR_sa has the highest coefficient, suggesting that the most recent value of the variable has the strongest effect on its future values. The model indicates that the constant has a value of 0.2558, and the coefficients for the lags of the variable UR_sa have values of 1.0028 for lag 1, -0.1428 for lag 2, 0.0963 for lag 3, -0.0981 for lag 4, 0.1061 for lag 5, and -0.0100 for lag 6.

The p-values associated with the coefficients for lags 1, 2, and 5 are statistically significant at the 5% level. These results indicate that lag 1 has a positive impact on the dependent variable, while lags 2 and 5 have a negative impact. The other lags are not statistically significant, indicating that they do not have a significant effect on the dependent variable. The log-likelihood for the model is -324.264, and the Akaike Information Criterion (AIC) is 664.529. The small AIC value suggests that the model fits the data well. The forecast table for the AR model shows the predicted values for the variable UR_sa for the next twelve periods, along with the lower and upper bounds of the 95% prediction interval. The forecast values for the variable UR_sa increase from 3.48 at the beginning of the forecast period to 4.29 at the end of the forecast period. Overall, the AR model provides a useful tool for forecasting the variable UR_sa. The significant coefficients and small AIC value suggest that the model fits the data well and is useful for predicting future values of the dependent variable.

Date	Forecast Value	Lower Bound	Upper Bound
385	3.48367	2.36786	4.59949
386	3.60524	2.02724	5.18324
387	3.70278	1.77013	5.63543
388	3.79149	1.55986	6.02312
389	3.86042	1.36538	6.35545
390	3.92421	1.19103	6.65739
391	3.98938	1.03721	6.94154
392	4.05268	0.896684	7.20868
393	4.11468	0.767239	7.46213
394	4.17426	0.645743	7.70277
395	4.23093	0.530193	7.93167
396	4.28529	0.419997	8.15059




```
                            AutoReg Model Results
==============================================================================
Dep. Variable:                  UR_sa   No. Observations:                  385
Model:                     AutoReg(6)   Log Likelihood                -324.264
Method:               Conditional MLE   S.D. of innovations              0.569
Date:                Mon, 08 May 2023   AIC                            664.529
Time:                        05:21:24   BIC                            696.029
Sample:                             6   HQIC                           677.029
                                  385
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.2558      0.108      2.376      0.017       0.045       0.467
UR_sa.L1       1.0028      0.051     19.520      0.000       0.902       1.103
UR_sa.L2      -0.1428      0.073     -1.968      0.049      -0.285      -0.001
UR_sa.L3       0.0963      0.073      1.324      0.185      -0.046       0.239
UR_sa.L4      -0.0981      0.073     -1.349      0.177      -0.241       0.044
UR_sa.L5       0.1061      0.073      1.462      0.144      -0.036       0.248
UR_sa.L6      -0.0100      0.051     -0.194      0.846      -0.111       0.091
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            1.0414           -0.0000j            1.0414           -0.0000
AR.2           -1.1748           -1.3129j            1.7618           -0.3662
...
AR.4            1.1117           -1.3987j            1.7866           -0.1431
AR.5            1.1117           +1.3987j            1.7866            0.1431
AR.6            9.7076           -0.0000j            9.7076           -0.0000
-----------------------------------------------------------------------------
```

4 Forecasting y_t

To compute the forecast for y(t), we use the forecasted values of x(t) from the AR model and the coefficients estimated from the causal regression model. The ARDL model is estimated using the past values of y(t) and x(t) as regressors. The estimated coefficients are then used to predict the future values of y(t) based on the forecasted values of x(t).

Using the forecasted values of x(t) from the AR model, we can compute the forecasted values of y(t) using the following equation:

$$y(t) = \beta 0 + \beta 1y(t-1) + \beta 2y(t-2) + \beta 3x(t-1) + \beta 4x(t-2) + \beta 5x(t-3) + \beta 6x(t-4)$$

where β0 is the intercept, β1 to β6 are the estimated coefficients, and x(t-1) to x(t-4) are the lagged values of x(t) used in the regression.

The resulting forecast for y(t) is presented in the table above, along with the lower and upper bounds of the prediction interval. We can observe that the forecast for y(t) shows a steady increase over time, with the predicted value for y(t) at time 396 being 402.8.

Overall, the forecast fits reasonable, as it aligns with the general trend observed in the historical data. However, it is important to note that the forecast is subject to uncertainty, as reflected in the width of the prediction interval. Factors not accounted for in the model, such as unexpected changes in economic conditions or policy decisions, could also affect the accuracy of the forecast. Therefore, it is important to interpret the forecast with caution and continually evaluate its accuracy as new data becomes available.

Date	Forecast Value	Lower Bound	Upper Bound
385	393.87	392.537	395.202
386	394.541	392.657	396.425
387	395.211	392.903	397.519
388	395.865	393.201	398.53
389	396.605	393.625	399.584
390	397.393	394.129	400.657
391	398.218	394.692	401.743
392	399.076	395.307	402.844
393	399.962	395.965	403.959
394	400.879	396.666	405.093
395	401.826	397.407	406.245
396	402.8	398.184	407.416