The Causal Effects of Climate Change on Housing Prices

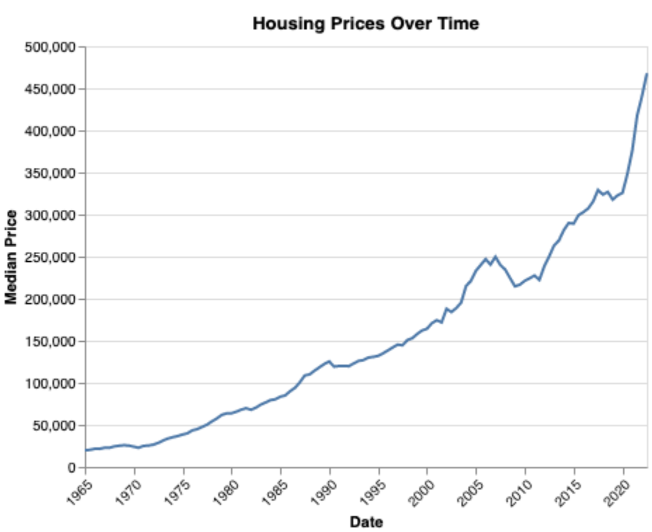
Dr. Lastrapes | ECON 6760 | Spring 2023 9:10 AM

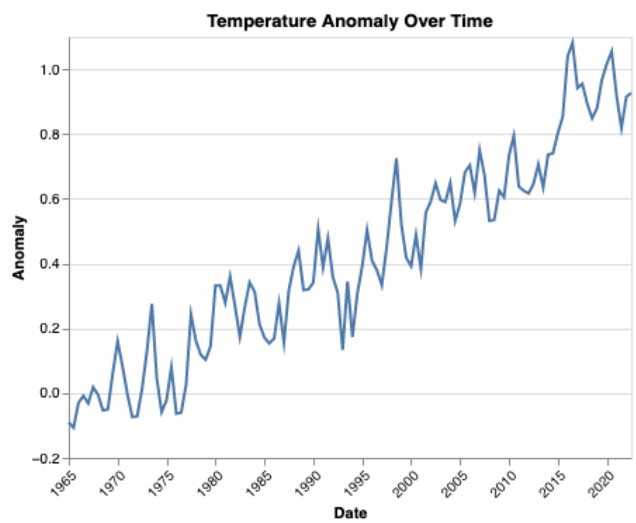
By Daniel Saul | May 8th, 2023

Over the years, climate change has become a serious global issue that has significant effects on our lives and has the potential to threaten future human life. This phenomenon is known to drastically increase temperatures, severe weather occurrences, sea levels, and biodiversity issues. One of the lesser-known factors climate change may affect is the property value of homes, and in turn, housing prices in the geographically diverse country of the United States. First, higher temperatures can cause certain building materials, such as asphalt shingles, to deteriorate, requiring more costly maintenance. The demand for other materials such as air conditioning units increase with temperature increases, driving up home value. Additionally, more natural disasters like wildfires can destroy lumber supply, increasing the price of building homes. Second, climate change may affect housing prices based on the desirability of certain locations. People may leave certain areas to escape natural weather disasters or high or low temperatures.

The purpose of this project is to analyze the causal effects that global rising temperatures have on median housing prices in the United States and forecast what housing prices may look like in the future due to climate change. I was motivated to select this topic to help me make a decision, when the time comes, to purchase or build a house which is a long-term goal of mine. Furthermore, I am curious of the effect global warming has on housing in both the present and the past.

The data used in this project includes 116 observations and 3 columns. The first column represents the date in year-month format increasing semi-annually from 1965 to 2022. The dependent variable is the median sales price in U.S. dollars of homes sold in the United States (MSPUS), sourced from the FRED database. The explanatory variable is the global temperature anomaly in degrees Celsius, sourced from the National Centers for Environmental Information (NCEI) within the National Oceanic and Atmospheric Administration (NOAA). The global temperature anomaly is defined as the difference between the average surface temperature of the Earth for a given period and a reference period and is calculated by taking the difference between the average temperature for a specific period, such as a year or a decade, and the average temperature for the reference period.





Autoregressive Distributed Lag (ARDL) Model

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                              ARDL Model Results
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Dep. Variable:      ln(Median Price)   No. Observations:                  116
Model:                    ARDL(0, 2)   Log Likelihood                 -28.180
Method:              Conditional MLE   S.D. of innovations              0.309
Date:               Mon, 24 Apr 2023   AIC                             64.361
Time:                       20:03:34   BIC                             75.375
Sample:                   01-01-1966   HQIC                            68.832
                        - 07-01-2022
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         10.5789      0.049    213.793      0.000      10.481      10.677
Anomaly.L1     1.3131      0.309      4.249      0.000       0.701       1.925
Anomaly.L2     1.2849      0.309      4.156      0.000       0.672       1.897
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Above are the results of the Autoregressive Distributed Lag (ARDL) model examining the causal effect of global temperature anomalies on median house prices in the United States over time. The ARDL model is an ordinary least square based model, applicable to non-stationary data, with its purpose being to investigate how changes in the past affect the current value of our dependent variable. Calculations were made with the 'statsmodels' package's ARDL class in the Python programming language. A natural log transformation was applied to the Median Price variable to reduce effects of outliers, stabilize variance, increase linearity, and interpretability as a relative change or rate. The ARDL(0, 2) model does not use dependent variable lags, but includes two lags for the exogenous variable—temperature anomalies. Each lagged variable's p-value is less than an alpha of 0.05, indicating more statistical significance and helping select the optimal number of lags. Based on the positive coefficients, there must be a positive and persistent relationship between temperature anomalies and log median house prices.

$$ln(price)_t = 10.5789 + \ 1.3131 anomaly_{t-1} + 1.2849 anomaly_{t-2} + \epsilon_t$$

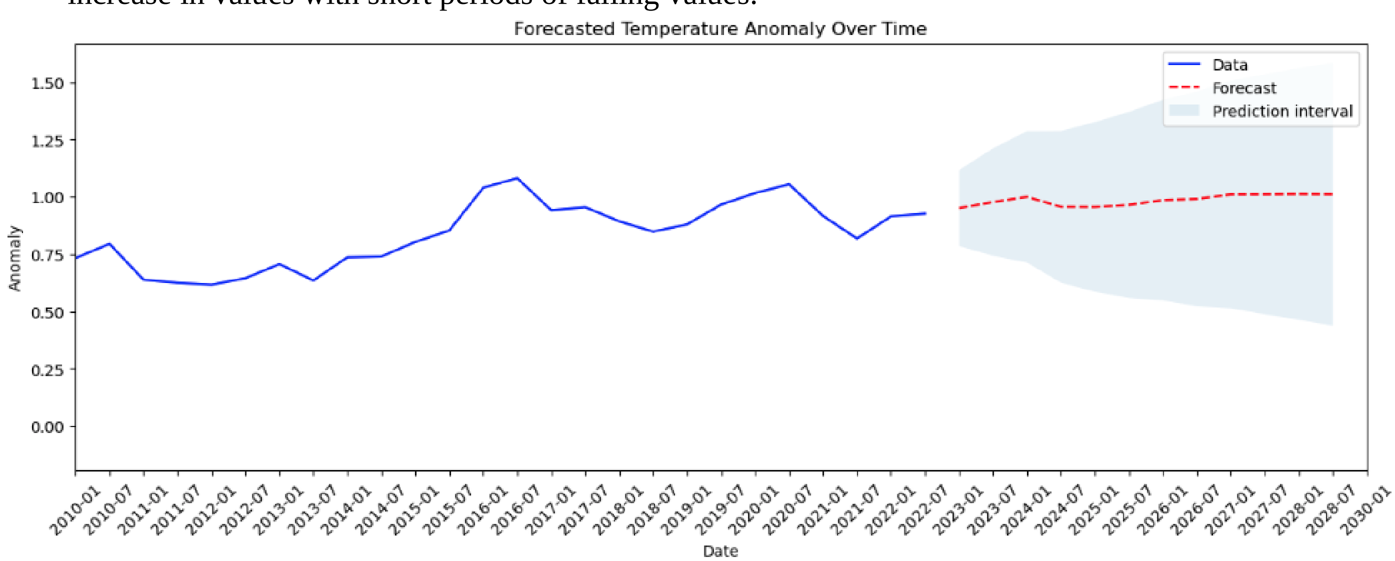
For the first lagged variable, holding all other variables constant, a 1-degree increase in the temperature anomaly for a given period leads to an increase in median house prices by 131%. For the second lagged variable, holding all other variables constant, a 1-degree increase in the temperature anomaly for a given period leads to an increase in median house prices by 128%. Regarding measures of model goodness of fit, the AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), and HQIC (Hannan-Quinn Information Criterion) values equal 64.361, 75.375, and 68.832, respectively. The lower values of these measures indicate a reasonably good fit between the data and model. The HQIC (Hannan-Quinn Information Criterion) is another goodness-of-fit measure, and its value is 68.832. The log likelihood of the model is -28.180, the standard deviation is 0.309, and the value of the constant is 10.58.

Forecasting Global Temperature Anomaly (x_t)

Date	Forecast Value	Lower Bound	Upper Bound
2023-01	0.95111	0.785585	1.11663
2023-07	0.977485	0.743397	1.21157
2024-01	1.00019	0.713495	1.28689
2024-07	0.956732	0.625682	1.28778
2025-01	0.955976	0.585851	1.3261
2025-07	0.965176	0.559724	1.37063
2026-01	0.985914	0.547977	1.42385
2026-07	0.991242	0.523067	1.45942
2027-01	1.01076	0.514182	1.50733
2027-07	1.01122	0.487787	1.53466
2028-01	1.01251	0.463529	1.5615
2028-07	1.01136	0.437967	1.58476

The results on this page display the point and interval forecasts of the independent variable, global temperature anomaly, using an Autoregression (AR) model. Calculations were made with the 'statsmodels' package's AutoReg class in the Python programming language. Although the model summary is not pictured, a description of certain aspects follows. The model uses 6 lags, specifically a AR(6) model, as the lag parameter, with most of the coefficient p-values being less than an alpha of 0.05. The goodness-of-fit indicators AIC, BIC, and HQIC are all very low numbers indicating a good fit. The log likelihood is 115.790 and the standard deviation is 0.084. The lagged anomaly coefficients include both positive and negative values; therefore, it can be determined that the relationship between time and temperature anomalies can vary in a positive or negative sense.

Above are the twelve forecasted values along with their 95% confidence interval upper and lower bounds. In other words, we are 95% confident that the forecast value will be within the lower and upper bounds. The model extends the current data's timeframe to a range from the years of 2023 to 2028, showing a pattern of small variability. Below, the line graph shows the original data points in blue, zoomed in starting at 2010, with the forecasted values in red and prediction interval of those values in light blue added to the dataset. The forecast shows a steady increase in values with short periods of falling values.



Forecasting Median House Prices (y_t)

Date	Forecast Value	Lower Bound	Upper Bound
2023-01	12.9714	12.3668	13.5761
2023-07	13.0185	12.4139	13.6232
2024-01	13.0846	12.4799	13.6892
2024-07	13.1483	12.5436	13.7529
2025-01	13.1204	12.5157	13.7251
2025-07	13.0635	12.4589	13.6682
2026-01	13.0747	12.47	13.6793
2026-07	13.1137	12.509	13.7184
2027-01	13.1474	12.5427	13.752
2027-07	13.1798	12.5752	13.7845
2028-01	13.2055	12.6008	13.8102
2028-07	13.2078	12.6031	13.8125

The results on this page display 12 future-period point and interval forecasts of the dependent variable, log median housing prices, using the previous ARDL(0, 2) causal model along with the forecasted temperature anomaly values from the AR(6) model. Calculations were made with the ‘statsmodels’ package’s ARDL class in the Python programming language. Above are the twelve forecasted values along with their 95% confidence interval upper and lower bounds. The model extends the current data’s timeframe to a range from the years of 2023 to 2028, showing a pattern of small variability, slightly increasing. Below, the line graph shows the original data points in blue, zoomed in starting at 2010, with the forecasted values in red and prediction intervals of those values in light blue added to the dataset. Using a shorter date range for the time axis and natural log of the price, the visual makes the median price data line appear more linear than data with visible shocks would. The forecast shows a steady increase in values with short periods of falling values.