The Effects of Interest Rates, GDP, and Employment Rates on House Prices

Joe Thomas

Abstract

House prices play a vital role in the health of an economy. An increase in house prices can lead to homeowners feeling more confident to spend money and consume. This paper analyses what drives fluctuations in house prices. Independent variables are gradually introduced as regressors, which are expected to have an effect on house prices. Finally, lagged independent variables and lagged dependent variables are then used in a multivariate regression.

Introduction

In February 2024 there were an estimated 82,940 (seasonally adjusted) residential transactions that took place in the United Kingdom (gov.uk, 2024). In January 2024 the average property in the UK was valued at £282,000 (gov.uk, 2024).

Although the revenue derived from existing residential properties doesn't contribute directly to GDP, house prices play a vital part in the health and confidence of an economy. If prices increase, homeowners feel more confident to spend, and may potentially borrow more money (to facilitate more spending) against the increased value of their home. If prices decrease, homeowners feel worse off, and fears of negative equity may disincentive consumer spending.

House prices rising sharply also has a disproportionately negative impact on first time homebuyers, and to a lesser extent, existing home buyers wanting to upsize (because they are paying more for the marginal increase in property size).

Given that the change in residential house prices has such a vital impact on the wider economy, what causes these changes is an important question, which deserves deeper analysis. This paper aims to answer the question of what drives changes in residential house prices within the United Kingdom.

Yearly United Kingdom time series data has been chosen as the level of granularity for this paper. A yearly cadence has been chosen for two reasons: (1) Changes in the independent variables won't see instantaneous effects on house prices. Changes will often take longer to take effect in the economy, meaning a quarterly or monthly cadence isn't necessary; (2) Many of the variables used only have data available at a yearly cadence.

The paper will first give background information on the data used, and the particular metrics that have been chosen from this data. It will then move on to more specific information about the definitions and source of the data (as well as discussing key summary statistics and abnormalities around the data). This will be followed by the analysis section. This will form the main body of the paper, discussing various linear regression models that were run, whilst analysing their outputs. Finally the paper will be concluded with a summary of the key findings reached through the analysis, along with an appraisal of whether the analysis gave significant indicators of causality.

Background

Residential House Prices

Average residential house prices within the United Kingdom will be used as our dependent variable across this paper. House prices in the UK have grown relatively consistently since 1975 (see figure 1). There have been a few years of negative house price growth which can be seen in (see figure 2). These are 1990 - 1993, 2008 - 2009 and 2011.

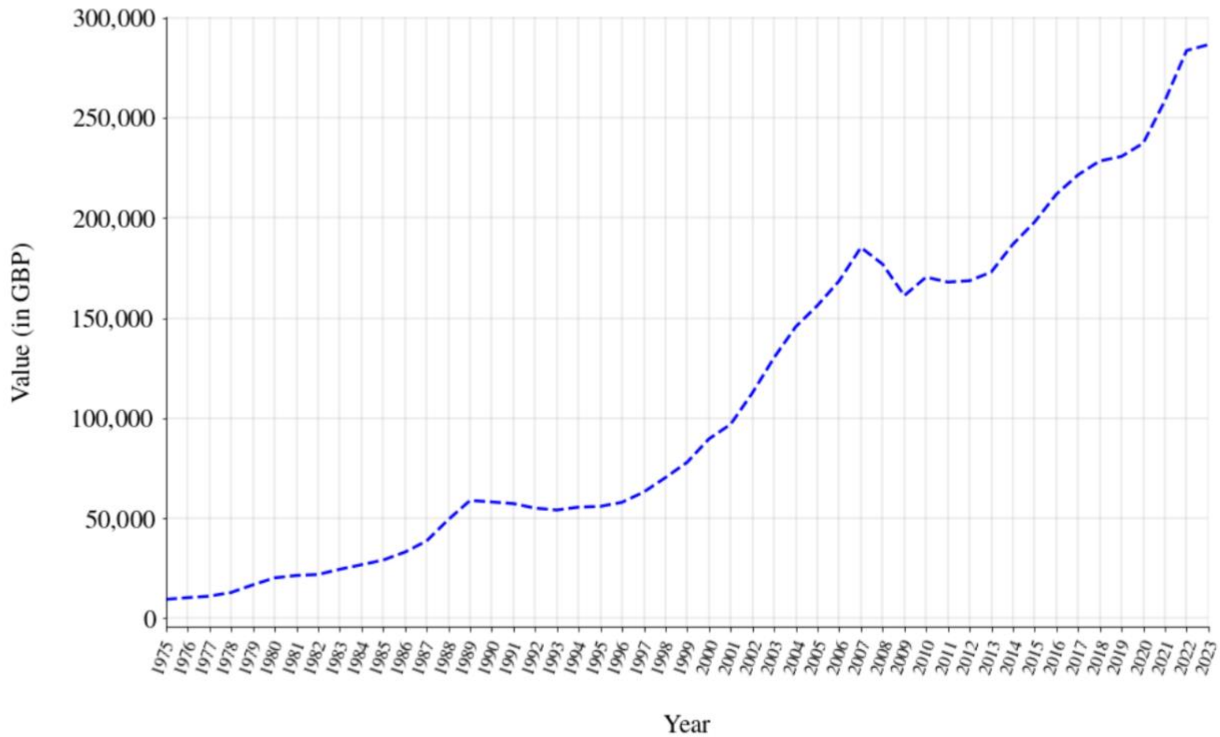

Figure 1. Residential house prices (UK HPI) from 1975 to 2023

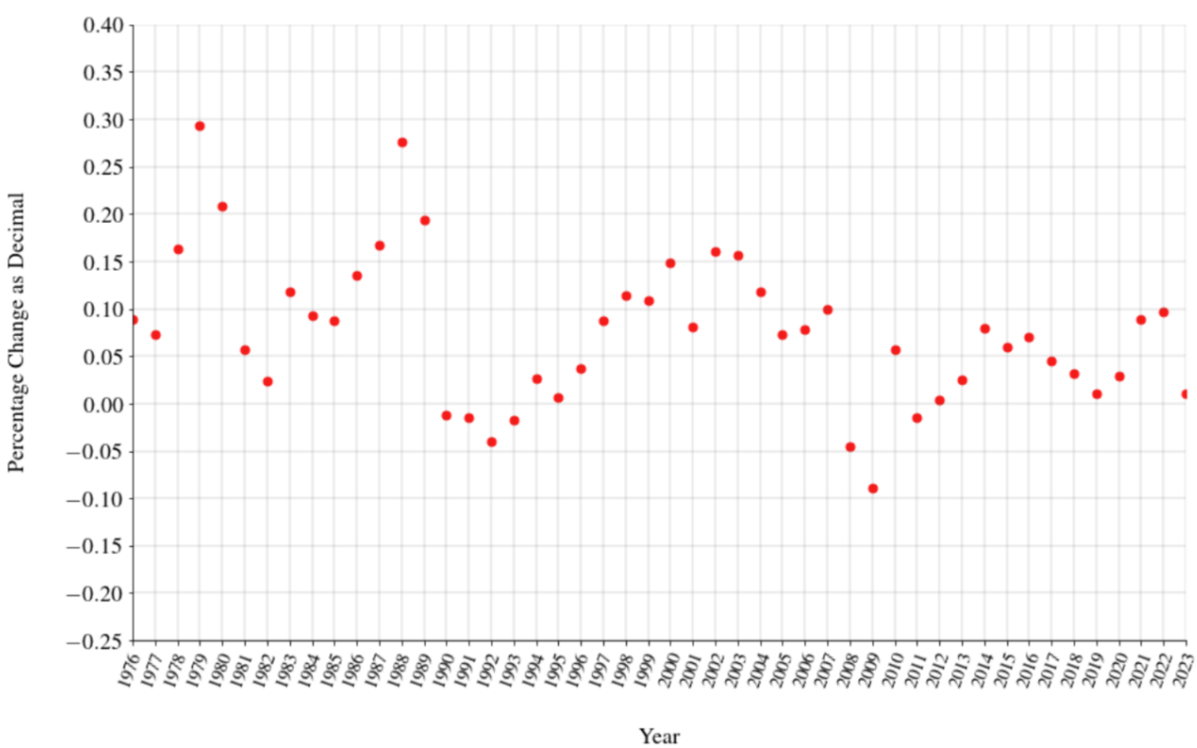

Figure 2. Year on Year percentage change for residential house prices (UK HPI) from 1976 to 2023

Interest Rates

An important variable that is expected to have an impact on house prices is Interest Rates. The logic follows, that if interest rates are high, then consumers will have to pay more (in interest) for the same value property. This in turn, lowers demand, which leads to downward pressure on house prices. When interest rates are low, consumers will have to pay less for the same value property. This availability of cheap credit leads to an increase in housing demand, which in turn leads to an upward pressure on house prices.

Interest rates are often used as a measure to keep down inflation. The Bank of England sites that their aim is to "keep inflation low and stable." (bankofengland.co.uk, 2024) They also state their inflation target is 2%. (bankofengland.co.uk, 2024).

GDP and Employment Rate

Given that house prices are often a representation of the wider economy, it is expected that other more general economic factors will also play a role in affecting their fluctuation in value. These include GDP and Employment Rate. These are both strong measures of how well the economy is performing in a given year. It is therefore expected that an increase in GDP, should have an upward pressure on house prices (and vice versa). An increase in employment rate should also have an upward pressure on house prices (and vice versa).

Data

House Prices

This paper will use average residential house price data taken from the United Kingdom House Price Index (UK HPI) from the gov.uk website. Data is available from 1968, but because one of our key independent variables, Interest Rate, only has availability from 1975, this is the start year that has been used for the paper's analysis.

Below are summary statistics for the House Price data:

Summary Statistics	Value (pounds GBP)
Min	9529.75
Max	286397.0
Mean	110919.70
Standard Deviation	83402.87

Interest Rates

This paper uses interest rate data taken from the Bank of England. This raw data isn't set at a regular time series cadence. Instead it is populated only when a change in interest rate takes place. This necessitated two data cleansing actions: (1) Aggregating the data to a yearly time series cadence, using a mean average of the year; (2) Where there is a year where no change took place, inputting the interest rate as the last change.

Summary Statistics	Value (percentage)
Min	0.18
Max	15.0
Mean	6.21
Standard Deviation	4.65

GDP

The GDP data used in this paper is chained volume measures: Seasonally adjusted £m data from the Office of National Statistics. This data is taken at a yearly time series cadence.

Summary Statistics	Value (million pounds GBP)
Min	856049.0
Max	2270764.0
Mean	1537641.5
Standard Deviation	445021.04

Employment Rate

The Employment Rate data was Employment rate (aged 16 to 64, seasonally adjusted): %. This was also taken from the Office of National Statistics.

Summary Statistics	Value (percentage)
Min	65.9
Max	75.8
Mean	71.45
Standard Deviation	2.39

Analysis

House Prices and Interest Rates
The analysis starts by comparing house prices (our dependent variable) against our first independent variable (Interest Rate), and T = 49. Let HP denote House Prices, and IR denote Interest Rate. The dependent variable will be HP and the independent variable will be IR:

$$HP_t = \beta_0 + \beta_1 IR_t + u_t$$

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                     HP   R-squared:                       0.709
Model:                            OLS   Adj. R-squared:                  0.703
Method:                 Least Squares   F-statistic:                     114.5
Date:                Wed, 17 Apr 2024   Prob (F-statistic):           3.46e-14
Time:                        18:31:56   Log-Likelihood:                -594.03
No. Observations:                  49   AIC:                             1192.
Df Residuals:                      47   BIC:                             1196.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       2.047e+05   1.09e+04     18.761      0.000    1.83e+05    2.27e+05
IR         -1.509e+04   1410.688    -10.699      0.000   -1.79e+04   -1.23e+04
==============================================================================
Omnibus:                       11.088   Durbin-Watson:                   0.395
Prob(Omnibus):                  0.004   Jarque-Bera (JB):               10.931
Skew:                           0.991   Prob(JB):                      0.00423
Kurtosis:                       4.193   Cond. No.                         13.1
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

R^2 measures the goodness of fit of the model:

$$1 - \frac{\sum \hat{u}_t^2}{\sum (HP_t - \overline{HP})^2}$$

R^2 = 0.709, meaning the model is well fit, and that a relatively high proportion of the variation in HP can be explained by the model. The intercept and IR variable also show strong t-statistics, at 18.761 and -10.699 respectively. This means that they both have P-Values of 0.000, meaning they are statistically significant and we reject the null that the coefficients = 0. The fact that the coefficient is < 0 makes economic sense, because we would expect house prices to fall when interest rates rise (as explained in the previous section).

The Skew indicates whether the residuals follow a normal distribution. The Skew = 0.991 (where 0 would mean the residuals are normally distributed). The kurtosis = 4.193 (where 3 would mean the residuals are normally distributed). This means that the residuals don't follow a perfect normal distribution. This can also be seen from the Jarque-Bera, which has a P-Value of 0.00423. Given that it is less than 0.05 means we reject the null hypothesis, that the residuals have a normal distribution.

Figure 3 below shows a plot of this model. The relatively good fit (shown by R^2) can be seen, given that the observations fall relatively near to the line. This demonstrates that Interest Rate is a reasonable predictor of House Prices.

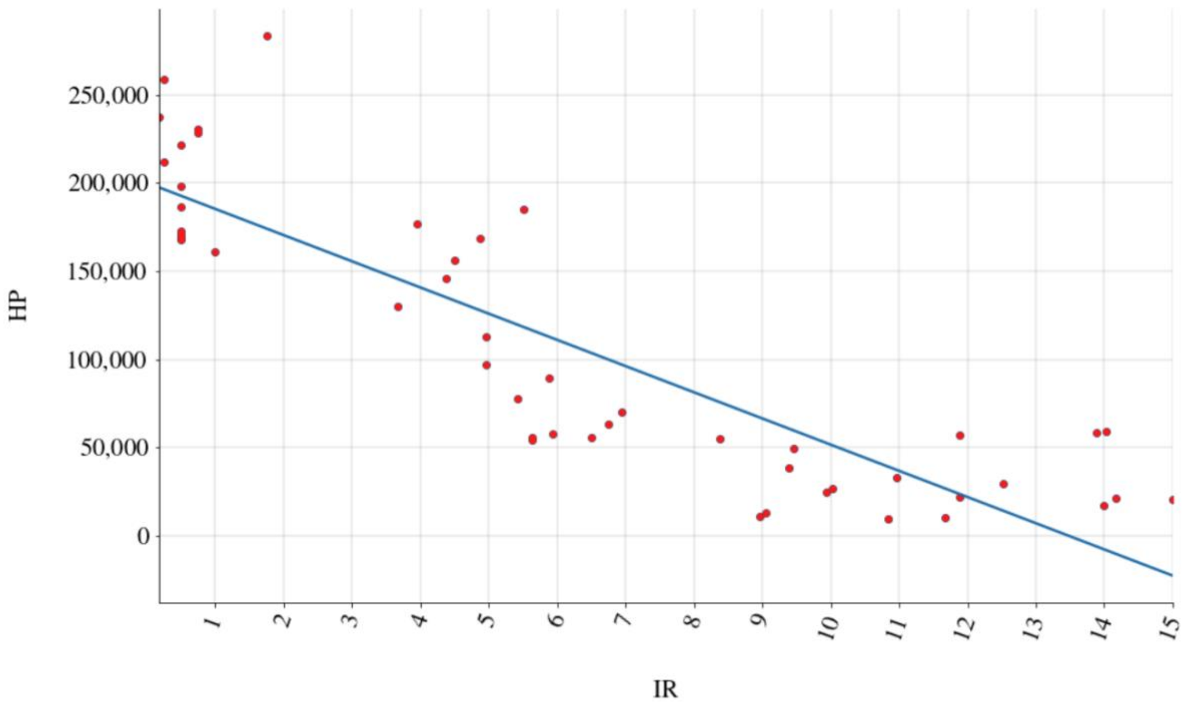

Figure 3. House Prices (HP) plotted against Interest Rates (IR) from 1975 to 2023, with regression line.
Notes: HP is UK HPI data measured in GBP. IR is Bank of England data measured in percentages.

Logging House Prices

The next model aims to resolve these issues of non-normality in the residuals. To do this, The natural logarithm of the dependent variable has been taken. The model now becomes this:

$$ln\, HP_t = \beta_0 + \beta_1 IR_t + u_t$$

As well as making sense from a model specification perspective, taking the log of HP makes sense from an intuitive economic perspective. This is because logs approximate the percentage change of a variable. The aim of this model is to identify the relationship between a particular interest rate, and its effect on the change of Houses Prices. Therefore using a logged dependent variable will model this relationship.

Figure 4 shows these variables plotted as a line graph below:

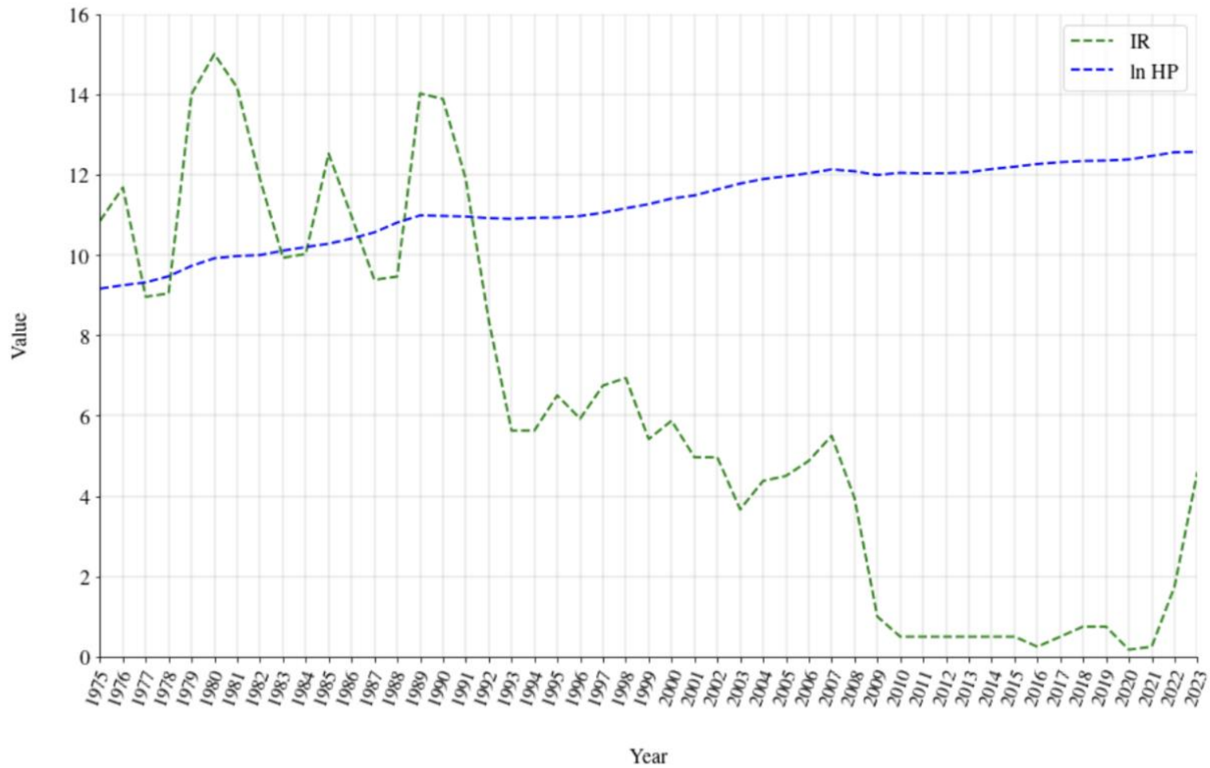

Figure 4. Interest Rate (IR) and Logged House Prices (ln HP) from 1975 to 2023.
Notes: ln HP is UK HPI data measured in GBP. IR is Bank of England data measured in percentages.

This new model's output is displayed below. It should be noted that R^2 should not be compared between this model and the last one, because the dependent variable is now different. Again, the intercept and IR variable show strong t-statistics, at 96.134 and -10.825 respectively. They both have P-values of 0.000, meaning they both reject the null hypothesis that the coefficients equal zero. This model does however bring the Skew closer to zero (now -0.367) and the kurtosis closer to 3 (now 4.180). The Jarque-Bera P-value of 0.139 means that we now fail to reject the null hypothesis that the residuals are normally distributed. This means that the residuals now more resemble a normal distribution. Normally distributed errors (estimated by the residuals) isn't a strict Gauss Markov assumption of the Ordinary Least Squares estimator, but it does mean that our t-statistics and P-Values will be more accurate.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  ln HP   R-squared:                       0.714
Model:                            OLS   Adj. R-squared:                  0.708
Method:                 Least Squares   F-statistic:                     117.2
Date:                Wed, 17 Apr 2024   Prob (F-statistic):           2.33e-14
Time:                        18:33:10   Log-Likelihood:                -37.885
No. Observations:                  49   AIC:                             79.77
Df Residuals:                      47   BIC:                             83.55
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         12.3476      0.128     96.134      0.000      12.089      12.606
IR            -0.1798      0.017    -10.825      0.000      -0.213      -0.146
==============================================================================
Omnibus:                        4.559   Durbin-Watson:                   0.406
Prob(Omnibus):                  0.102   Jarque-Bera (JB):                3.942
Skew:                          -0.367   Prob(JB):                        0.139
Kurtosis:                       4.180   Cond. No.                         13.1
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Figure 5 below shows a plot of this model:

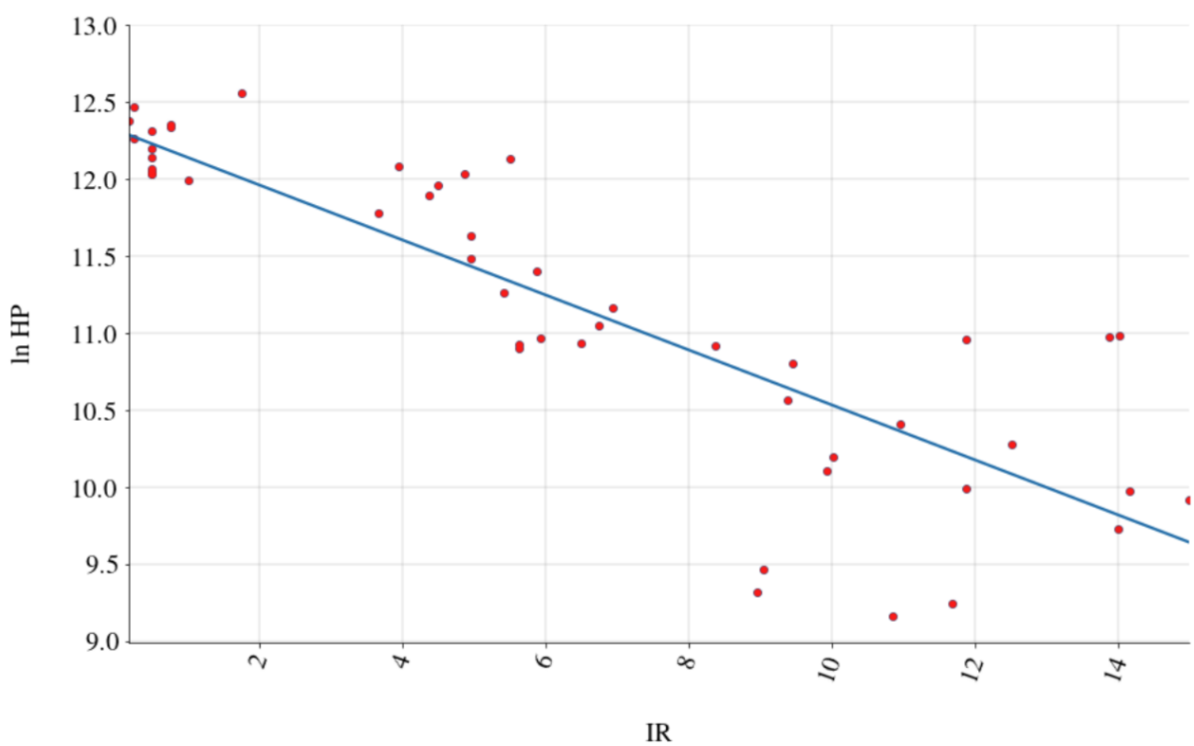

Figure 5. Logged House Prices (ln HP) plotted against Interest Rate (IR) from 1975 to 2023, with regression line. Notes: HP is UK HPI data measured in GBP. IR is Bank of England data measured in percentages.

Gauss-Markov assumption that should be followed is heteroscedasticity of the errors. This means that they follow constant variance:

$$E\left[u_t^2\right] = \sigma^2$$

Now heteroskedasticity is tested, by regressing the squared residuals on the regressor:

$$\widehat{u}_t^2 = a + b'x_t + v_t$$

The null hypothesis is that *b = 0*, meaning that there is no relationship between the squared residuals and the regressor. If *b = 0*, then the squared residuals equals the constant and there is no heteroskedasticity.

The test on this model, gives this output:

```
[('Lagrange multiplier statistic', 6.958938797389006),
 ('p-value', 0.008340148572815828),
 ('f-value', 7.779778010384054),
 ('f p-value', 0.007606065456469129)]
```

The P-value is lower than 0.05, meaning that the null hypothesis is rejected, and there is evidence of heteroskedasticity.

Adding GDP as an Independent Variables

In aiming to improve the model further, additional dependent variables are now added. These are GDP and Employment Rate, denoted by GDP and ER respectively. These new variables are also expected to have an effect on the change in house prices. The model can now be written as follows:

$$ln\, HP_t = \beta_0 + \beta_1 IR_t + \beta_2 GDP_t + \beta_3 ER_t + u_t$$

Note that GDP data availability is only up to the year of 2022. For this reason, the remainder of the analysis will be from the date range of 1975 – 2022 (T = 48).

Taking the natural log of GDP seems logical. This is because the scale of GDP is vastly greater than House Prices, meaning that a small change in GDP is unlikely to have a significant impact on House Prices. Taking logs of GDP, models an elasticity between the two variables, which means there are no units of measurement. This elasticity can be written as follows:

$$\frac{dHP / HP}{dGDP \ / \ GDP}$$

It's important to note that IR and ER have not been logged. This decision has been made, to have the equation model how a change in Interest Rate (or Employment Rate) results in a percentage change in House Prices.

This makes intuitive economic sense, because these independent variables don't continuously increase across time. An employment rate of 0.99 is as good today, as it was in 1975. This holds for Interest Rates as well.

These variables can be seen from the line graph below in Figure 7 (note that ER has been divided by 10, to improve readability of the graph):

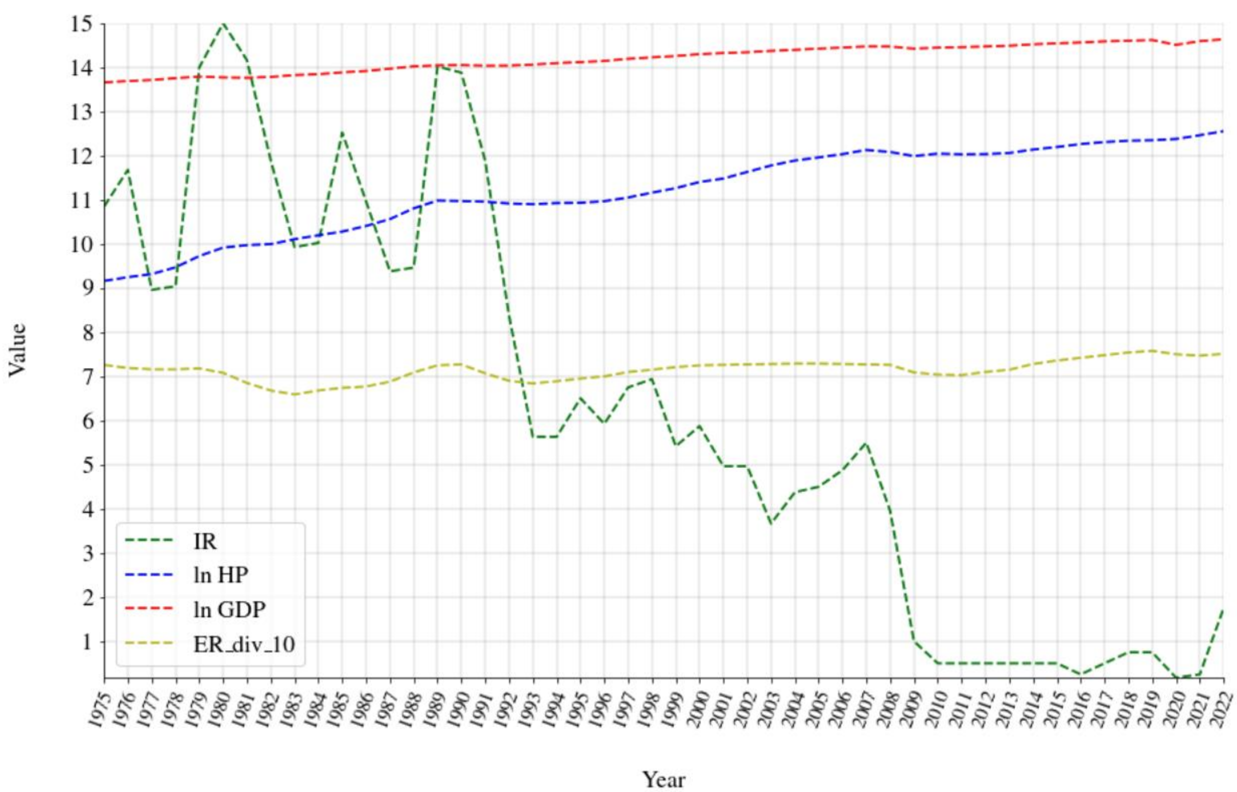

Figure 6. Interest Rate (IR), Logged House Prices (ln HP), Logged GDP (ln GDP) and Employment Rate Divided by 10 (ER div 10) from 1975 to 2022.
Notes: In HP is UK HPI data measured in GBP. IR is Bank of England data measured in percentages. ln GDP is ONS data measured in million pounds GBP. ER is ONS data measured in percentages.

Where all of the variables are used in one model, the equation would be written as follows:

$$ln\ HP_t = \beta_0 + \beta_1\ IR_t + \beta_2\ ln\ GDP_t + \beta_3\ ER_t + u_t$$

Given that now three independent variables have been introduced, measuring their effect on the model becomes more difficult. In order to better identify how much effect a new variable has on the model, a regression has been run on each possible combination of the variables. The outputs have been described and divided into three groups below: one independent variable, two independent variables, and three independent variables (the equation shown above).

Where the coefficients or intercepts are statistically significant (at the 5% level), the cells have been highlighted green. Where they are not statistically significant, they are highlighted red.

	NUMBER OF VARIABLES						
	1			2			3
VARIABLES:							
Interest Rate	-0.1798			0.036	-0.1565		0.0435
	0.016			0.01	0.018		0.007
Logged GDP		3.1802		3.6785		3.3994	4.0442
		0.074		0.148		0.087	0.126
Employment Rate			0.2442		0.0789	-0.0423	-0.0508
			0.049		0.036	0.011	0.008
Constant	12.3476	-33.9617	-6.2414	-41.2637	6.5406	-34.0507	-42.8732
	0.128	1.051	3.481	2.154	2.64	0.923	1.633
DIAGNOSTIC TESTS:							
R-Squared	0.727	0.976	0.353	0.981	0.753	0.982	0.99
Durbin-Watson	0.414	0.314	0.071	0.612	0.299	0.468	1.089
Jarque-Bera P-Value	0.0507	0.551	1.01E-05	0.523	1.93E-07	0.0279	6.69E-06
Strong Multicollinearity	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE

Figure 7 (previous page). Every iteration of the regression model, using Logged House Prices as the dependent variable, grouped by the amount of regressors.
Notes: The top number for each variable is the coefficient, whilst the bottom number is the standard error.

Because the table has been divided into groups of the same amounts of variables, means that R^2 can be compared within its group.

It should firstly be noted that the bivariate model using only Employment Rate as the regressor should not be used, because it has a very poor R^2 of only 0.353. This shows that only a small proportion of the variation in Logged House Prices is explained by this model.

All of the models using two and three regressors, despite all having significant coefficients, have other various issues. They all have Jarque-Bera P-Values below 0.05, meaning they reject the null hypothesis that the residuals of the model are normally distributed (meaning the residuals are not normally distributed).

All of the multivariate models suffer from Strong Multicollinearity. This is shown by the regression output message below:

```
[2] The condition number is large, 8.13e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

This is likely because the three independent variables are highly correlated (to differing degrees). An increase in GDP usually leads to high employment rates, whilst an increase in interest rates often sees a fall in GDP (and employment rate). The interconnectedness of these three variables is leading to this multicollinearity. Fortunately, however, there is no perfect multicollinearity in any of the models, meaning that for each model, the OLS estimator exists. For each model therefore, the matrix of regressors X has full rank and $(X'X)^{-1}$ exists.

The Durbin-Watson Statistic (formula below) tests for autocorrelation:

$$\frac{\sum_{t=2}^{T} (u_t - u_{t-1})^2}{\sum_{t=1}^{T} u_t^2}$$

The Durbin-Watson should range from 1.5 to 2.5, for autocorrelation not to be a concern. A value of < 1 should be extreme cause for concern. All of the models suffer from a low Durbin-Watson statistic. This means they all suffer from autocorrelation. This will be addressed in the next section.

R^2 is particularly high on the GDP bivariate model, at 0.976. Another interesting point is that adding additional independent variables to GDP doesn't change its coefficient very much, nor does it increase R^2 very substantially. For this reason, this bivariate model has been carried forward into the next section as the model of choice.

Introducing Lagged Variables

As discussed in the previous section, the Durbin-Watson statistic showed that many of the models suffered from autocorrelation. The GDP bivariate model was no different, with a Durbin-Watson of 0.071. In order to resolve this issue, in this section an Autoregressive distributed lag (ARDL) has been run. This will include lagged variables for both GDP and House Prices. Running this ARDL also makes sense from an intuitive economic perspective. A change in GDP might take a year or two until the effect can be seen in $ln\ HP$. Furthermore, a change in $ln\ HP$ could have a relationship with $ln\ HP$ in previous years, due to market cycles.

It should be noted that now there are two fewer observations, because the “lag 2” variables are two years shifted. Therefore T = 46. The model now becomes this:

$$ln\ HP_t \ = \ \beta_0 \ + \ \beta_1\ ln\ GDP_t \ + \ \beta_2\ ln\ GDP_{t-1} \ + \ \beta_3\ ln\ GDP_{t-2} \ + \ \beta_4\ ln\ HP_{t-1} \ + \ \beta_5\ ln\ HP_{t-2} \ + \ u_t$$

And the regression output is as follows:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  ln HP   R-squared:                       0.997
Model:                            OLS   Adj. R-squared:                  0.997
Method:                 Least Squares   F-statistic:                     2809.
Date:                Sat, 20 Apr 2024   Prob (F-statistic):           8.57e-50
Time:                        08:10:17   Log-Likelihood:                 71.875
No. Observations:                  46   AIC:                            -131.8
Df Residuals:                      40   BIC:                            -120.8
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -3.2851      2.114     -1.554      0.128      -7.558       0.988
ln HP(-1)      1.5659      0.142     11.045      0.000       1.279       1.852
ln HP(-2)     -0.6529      0.157     -4.162      0.000      -0.970      -0.336
ln GDP         0.6732      0.316      2.129      0.039       0.034       1.312
ln GDP(-1)    -0.8800      0.408     -2.158      0.037      -1.704      -0.056
ln GDP(-2)     0.5053      0.336      1.504      0.140      -0.174       1.184
==============================================================================
Omnibus:                        2.030   Durbin-Watson:                   1.866
Prob(Omnibus):                  0.362   Jarque-Bera (JB):                1.474
Skew:                          -0.437   Prob(JB):                        0.479
Kurtosis:                       3.064   Cond. No.                     7.75e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.75e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

The R^2 remains strong (which is expected, given that additional regressors have been added). Introducing these lags has also improved the autocorrelation. The Durbin-Whatson is now 1.866, which is within the acceptable range between 1.5 and 2.5. All coefficients are statistically significant and reject the null hypothesis that they equal 0, except for the Constant and GDP Logged lag 2.

The output below tests for heteroskedasticity in this model. The P-Value for this model is now greater than 0.05, meaning that we fail to reject the null hypothesis, and there is no evidence of heteroskedasticity:

```
[('Lagrange multiplier statistic', 0.398056039245251),
 ('p-value', 0.528094910560942),
 ('f-value', 0.3846602949740375),
 ('f p-value', 0.5381802141268273)]
```

Figure 8 below shows the resultant change in house prices, due to a 1% change in each significant regressor. Note that each case is a log-log, meaning that they are elasticities.

Change in Dependent Variable (by 1%)	Change in logged House prices
ln HP(-1)	1.5659%
ln HP(-1)	-0.6529%
ln GDP	0.6732%
ln GDP(-1)	-0.8800%

Figure 8. The effect in ln HP due to a 1% change in each regressor. ln HP is UK HPI data measured in GBP. Notes: ln GDP is ONS data measured in million pounds GBP.

Summary and Conclusion

From the analysis conducted in this paper, it can clearly be seen that there is a positive linear relationship between Logged House Prices and Logged GDP. From the final ARDL model, it can also be seen that both the previous period's Logged House Prices help predict today's logged house prices, as well the previous period's logged GDP helping predict today's logged House Prices.

All of the regressors in this final regression were statistically significant at the 5% level, with the exception of the constant and GDP logged lag 2. The R^2 was also very high, demonstrating a high proportion of logged house prices that was explained by the model.

This model is certainly not without fault however. Much of this high R^2 could be attributable to including so many variables in the model. The bivariate GDP model had a R^2 of 0.976, and every time a regressor is added will always increase R^2, meaning the high value for this number could be misleading.

There is another potentially misleading aspect of the high R^2 in the initial bivariate GDP model. There is a considerable amount of interconnectedness between the three initial variables that were used as regressors. This was discussed in the previous section in relation to the multicollinearity identified in the multivariate models. The fact that these three variables show high correlation means that the bivariate GDP model's error term will be capturing some effects from other variables. Because of this correlation between variables, GDP will be correlated with its error term, meaning that exogeneity (one of the Gauss Markov assumptions) fails.

In conclusion, whilst there is certainly evidence of a relationship between logged house prices and logged GDP, there is too much interconnectedness between these variables and other factors, in order to identify any statistically significant causal relationship.

Literature Survey

The subject of house price fluctuation has received lots of academic interest. Many papers have attempted to draw a causal relationship between various independent variables and house prices.

The paper "What Drives House Prices?" (Jacobsen et al., 2005) analysed these relationships in the Norwegian housing market. He found interest rates, housing construction, unemployment and household income to be the most important factors.

"Assessing the role of income and interest rates in determining house prices" (McQuinn, 2008) discusses more specific determinants, in the form of disposable income and interest rates. He explains that many other previous models have struggled to find significant causal relationships.

In recent years, there have been attempts to predict house prices with the use of Machine Learning techniques (Adetunji, et al. 2022). Using a Random Forest model, allowed for the analysis of 14 dependent variables.

This paper draws a narrow focus on only the housing market within the United Kingdom. Whilst using only key independent variables, it aims to find a causal relationship between them and house price fluctuation.

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