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Exam report
Predictive Analytics

Predicting the Swedish Real Estate Price Index

In the Greater Stockholm Area

Exam: Predictive Analytics [redacted] Home Assignment (UC)

Examiners: [redacted]

Program: MSc Business Administration and Data Science

Names: Axel Olausson

Student Numbers: [redacted]

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Introduction

Stockholm is Sweden's largest city and its main economic hub (EBSCO, 2024). The capital concentrates high-value jobs, headquarters, and knowledge-intensive services making it an attractive place for workers and firms. At the same time, Stockholm is routinely criticized for unattainably high housing prices and persistent unaffordability. As of august 2025, Svensk Mäklar Statistik (2025) presented that while the average house in Sweden costs 3 982 000 SEK, the average price for a house in Stockholm is 7 180 000 SEK[1]. Yet, the capital continued to attract people in 2024, with 81 030 moved in and 72 522 moved out, resulting in a net inflow of 8 508 residents.

With many Swedes moving into Stockholm, a key consideration for others who are curious to pursue a similar path is: What housing prices will look like once they take the chance and move to the capital? Not only that, but governmental institutions as well as the Swedish Riksbank need to know the housing price for policy decisions, as they can have a big effect on prospects for some, and the worth of asset prices for others.

The subject has been studied previously, and researchers such as Claussen (2012), have asked themselves the question of whether Swedish houses are overpriced? Compared to those studies however, this study will be based on newer data, in which more recent shocks, policy changes and other factors have had their effect. The study aims to forecast the Inflation Adjusted Real Estate Price Index (REPI) for the coming 12 quarters using ARIMA and dynamic regression model, to evaluate their ability to capture the structure of the data and to forecast going forward. The dataset underwent Box Cox transformations, differencing and structural break analysis.

The result shows that neither model captured the temporal patterns well enough and that a probable cause behind this poor forecast is that unexpected shocks strongly affected the data's structure. For future studies, including more explanatory variables could potentially ensure better fits and forecasts.

1. Dataset Description

This project uses the Real Estate Price Index (REPI) from the Swedish Statistical Central Bureau to measure price development of one- and two-dwelling buildings for permanent living in the Greater Stockholm Area. The index measures price on actual sales that occurred some months before the registration date. The time series neither adjusted for seasonality nor inflation adjusted and covers

[1] The average may also be affected by abnormally high prices in an area. However, unable to find the mean, this was the best approximation for average.

quarterly observations during the period Q1 1986 till Q1 2025, thereby containing 157 observations (SCB, 2025). The time series will also be deflated using the Consumer price Index with Fixed Interest Rate (CPIF) to reflect real house prices as advised by Hyndman and Athanasopolous (2021). Adjusting the index by CPIF has also been common practice in previous reports published by the Swedish Riksbank (Claussen, 2012). The CPIF data is not as extensive as the REPI data and contains only 154 observation which causes the adjusted REPI dataset to range from 1987 Q1 to 2025 Q1 with values of 138.1131 and 466.8517 respectively, a rough 238% increase.

The time plot reveals several interesting features. Firstly, there is a long period of sustained growth starting in 1996 and continuing onwards up till 2020, thereby showing a trend. As for seasonality, nothing is apparent from time-plot alone. Very little seasonality is also apparent from the seasonality-plot, given that the slopes do not precisely align. However, the time-graph reveals cyclicality related to several significant macroeconomic events in Sweden and abroad. Firstly, there is a sharp decline in housing prices following the 1990-1994 recession, during which Swedish interest rates reached 500% in September 1992 (Sveriges Riksbank, na.). Similar shocks (some less potent) occurred in 2008, 2020 and 2022, following events such as the 2008 financial crisis, the COVID-19 Pandemic and Russian invasion of Ukraine. The first two crises were combatted by quantitative easing measures presented by the Riksbank to stimulate economic activity (Riksbanken, 2008) (Riksbanken, n.a.). The war instead caused inflation, caused by the strain on global supply chains which the Riksbank combatted by raising interest rates (Riksbanken, 2022).

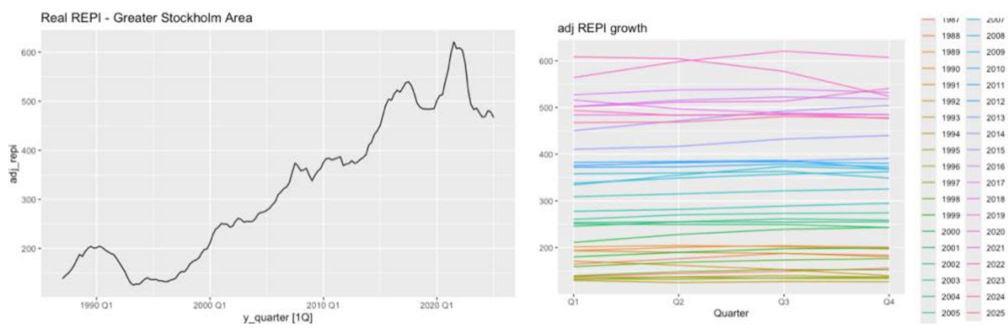


Figure 1 & 2

In previous studies (Abildgren et al., 2024) (Claussen, 2012), interest rate has been accounted for as an exogenous variable which could explain the development of real estate prices and this study aims to do the same, given the strong effect that interest rate development seems to have on real estate prices. Following this decision, data on the Swedish policy rate (styrräntan), was downloaded. The data had 124 observations, ranging from 7% in Q3 1994 to 2.23% in Q2 2025.

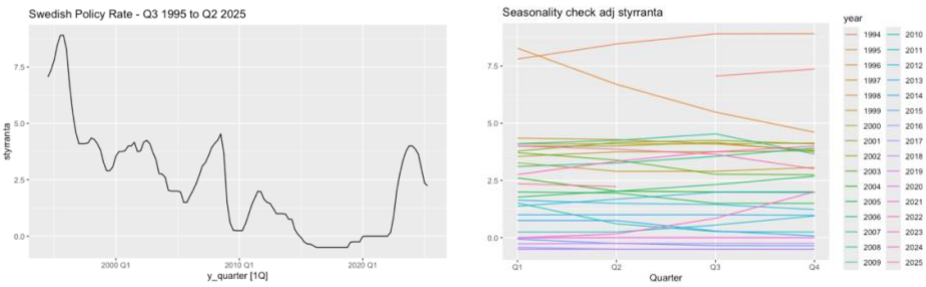


Figure 2 & 3

The data reveals a vague downwards going trend from the late nineties till 2008, but it is not as apparent as it was in the case of REPI. There is also no clear sign of seasonality.

After combining the real REPI data with the policy rate data, the final dataset has 124 observations, ranging from Q3 1994 till Q1 2025.

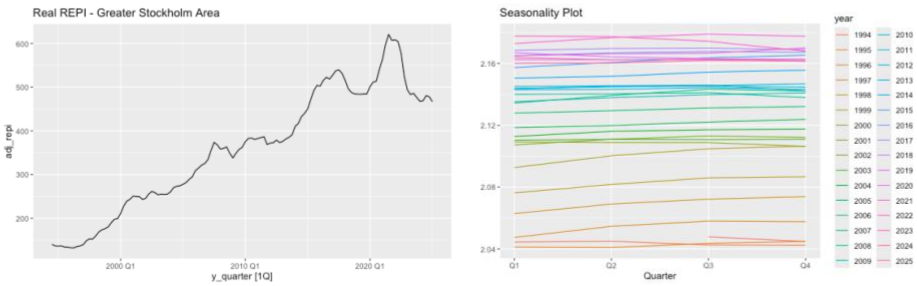


Figure 4 & 5

Before concluding this section, it is important to mention that because of limited space, the transformations and formatting of the external regressor will be discussed to a lesser extent than the forecasting data. Nonetheless, similar proper measures that were applied to ensure appropriability of the dependent time series data have also been applied to the external regressor. To see the result of those tests, please refer to the R-notebook attached.

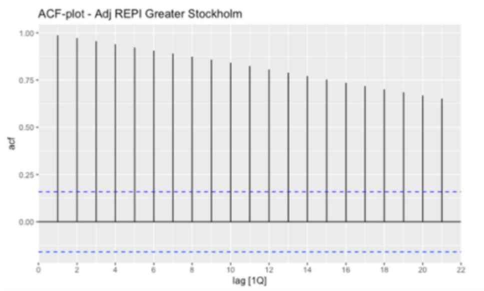
2. Methodology

2.1 Mathematical Transformations, patterns and overview

After having finished the preprocessing, various forms of visuals and tests were executed to gain a better understand the data prior to defining the most appropriate models. This happened accordance with the tidy forecasting workflow proposed by Hyndman and Athanopolous (2021).

Given that the level of the data changed from 1995 till 2025, potentially leading to changing variation throughout the time series, the lambda value was calculated to then be used in a power-transformation. Power-transformations such as the box-cox transformation are meant to result in consistent variation across the time series, which makes forecasting the data easier (Hyndman and Athanopolous, 2021). In the case with the REPI data, the lambda value was -0,43, which is like applying a stronger logarithmic transformation of the data. The result from the box cox led to the series having even more accentuated troughs, potentially since the box cox transformation leads to a “stretch” of smaller values and a compression of large values, thereby causing the troughs to appear more pronounced.

After the mathematical transformation, following the insights given from the time-plot, an ACF (Autocorrelation Function)-plot was constructed to gain further insights regarding the seasonality and trend of the data. Data which is trended tends to have positive values slowly decreasing with each lag, which is evident in the ACF as well. Seasonal variations also become apparent in ACF-plots, as seasonal lags become larger than others. However, this was not evident from the plot (Hyndman & Anthanopolous, 2021). Seasonality is however slightly more evident in figure 5, given the alignment of the slopes. Nonetheless, optical inspection alone is inadequate for trend and seasonality measurements, meaning that more testing is needed.



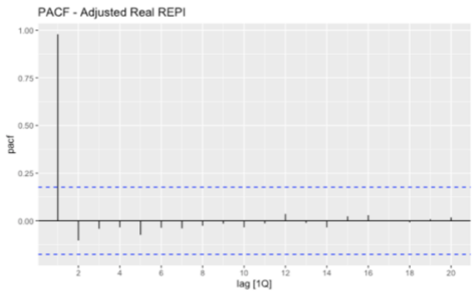


Figure 6 & 7

To further investigate the patterns in the data, an STL (Seasonal and Trend Decomposition using Loess) decomposition was pursued. STL was mainly picked due to its versatility, its ability to handle seasonality which changes over time and because it can be robust to outliers.

The STL features show a trend strength of 0.996608 and a seasonal strength of 0.44, indicating that the main driving component of the time series is the trend. However, there is moderate seasonality present, despite of it being non-apparent from the ACF-plot. An important observation to mention is that while the trend steadily increases throughout the time series, it does so in damped way, meaning that there is no constant increase continuing into the indefinite future. The remainder plot appears to have relatively small, zero mean white noise with no persistent structure. Nonetheless, spikes and dips do occur in the remainder during periods of financially significant events such as the 2008 financial crisis and the COVID-19 pandemic, reflecting a potential need to add structure beyond a univariate model.

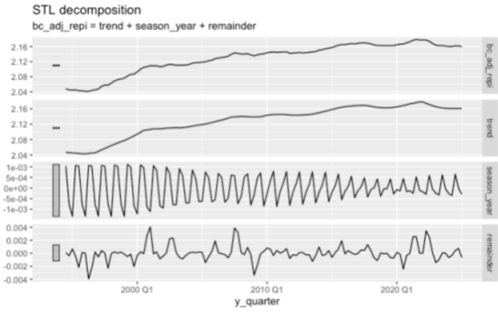


Figure 8

2.2 Stationarity

Having completed an initial inspection of the data, several tests were carried out for stationarity. Stationary time series have constant mean and variance over time, making them easier to model and forecast (Hyndman & Athanasopoulos, 2021). An initial plot (Figure 3) suggested non-stationarity, but this was verified using the KPSS (Kwiatkowski–Phillips–Schmidt–Shin) and ADF (Augmented Dickey–Fuller) tests. The tests have different null hypotheses, as the KPSS test states that the time series is stationary while the ADF instead claims that there is a unit root in its null hypothesis. The tests also rely on different assumptions which can cause them to land in different and sometimes opposing conclusions. Therefore, several tests with different parameters were carried out to truly assure stationarity. First, the series was tested with trend and drift (KPSS tau, ADF "trend"). The KPSS τ statistic (0.4897) exceeded the 1% critical value (0.216), rejecting stationarity. The ADF τ_3 statistic (−1.091) was above the 1% critical value (−3.99), so the unit root null could not be rejected. φ_2 (4.3525) and φ_3 (3.7546) were also below their 1% critical values (6.22, 8.43), showing no strong evidence for a deterministic trend. Testing for a random walk with drift (KPSS mu, ADF "drift") gave KPSS $\mu = 2.2429$ (> 0.739), again rejecting stationarity. The ADF τ_2 (−2.7511) failed to reject the unit root, though φ_1 (6.5822) slightly exceeded its 1% critical (6.52), suggesting weak evidence against no drift. The ADF "none" test ($\tau_1 = 2.2484 > -2.58$) reinforced the presence of a unit root. See appendix for test results.

Given the evidence, first order differencing was needed to create a stationary time series. Using the "unitroot_ndiffs" and "unitroot_nsdiffs" features, the suggested order of differencing was two and zero respectively. However, differencing was applied conservatively, starting with one first order differencing and then testing thereafter. This time, the tests all provided evidence for stationarity at the 1% significance level. However, conflicting evidence was presented by the "unitroot_ndiffs" feature, suggesting that yet another first-order difference was to be taken. Nonetheless, these tests can be conflicting as mentioned previously and the decision to difference can be subjective. However, taking too many differences may introduce false dynamics or autocorrelation which does not exist in the time series, making conservative differencing a recommended method (Hyndman & Athanopolous,2 2021). Thus, the decision to limit the differencing to the first order seemed objectively best given the overwhelming evidence in its favor.

2.3 Structural Breaks

Structural breaks occur when the underlying process of a time series shifts significantly, potentially altering its statistical properties. If left unidentified, they may lead to misleading conclusions and flawed forecasts. In this analysis, two complementary approaches were applied: the QLR (supF) test, which is the generalized version of the Chow test and the SIS test (based on impulse saturation) to identify potential breaks and outliers.

The QLR test was implemented by estimating the model for each potential breakpoint and comparing the F-statistics against critical boundaries. The F-statistic curve (Figure 9) crosses the upper boundary around the year 2000, and the hypothesis test supports this, with a p-value of 0.0276 — below the 5% significance level. This indicates statistical evidence for a structural break, corresponding to the second quarter of 2000. The SIS test, which incorporates dummy variables to capture possible location shifts and outliers, did not reveal any additional significant persistent breaks. While impulse indicators captured short-lived fluctuations in the dataset, these do not constitute structural breaks in the strict sense. Given these results, there is moderate statistical evidence for a single structural break in the early 2000s. However, as both methods rely on model-specific assumptions, the interpretation should be made with caution, especially given that the break occurs near the beginning of the sample period, where fewer pre-break observations may affect robustness (Hyndman & Athanasopoulos, 2021; Zeileis et al., 2002). Nonetheless, to adhere to the conservative practices that were applied in section 2.2 regarding stationarity, this project will operate under the premises that there is a structural break that needs to be taken into consideration.

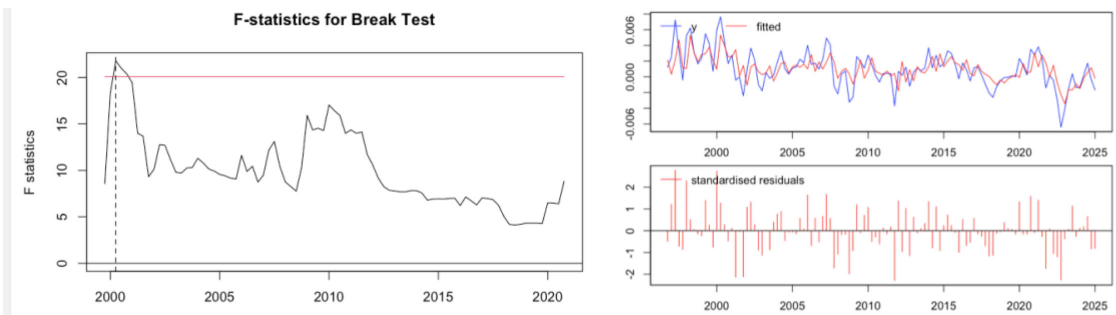


Figure 9 & 10

When handling structural breaks, Pesaran and Timmermann (2007) suggest caution. The inclusion of the structural break can as mentioned lead to misleading forecasts if left unattended. However, while only keeping data post-break can lead to less biased forecasts, it can also cause increased variance and less precise forecasts. This is particularly important to consider in the case of this prediction, given that there is not a particularly large amount of data to train on. Therefore, following Pesaran and Timmermann, the structural break is handled by excluding some data pre-break, but not all, as to take away some bias while not increasing variance.

2.4 Forecasting Models

Given the patterns and evidence shown in previous data, along with common practice in financial and macroeconomic forecasting, this report chose to pursue two models, the ARIMA (Autoregressive Integrated Moving Average) and the Dynamic Regression model.

ARIMA models aim at modelling autocorrelation in the data via three components. The first component is the autoregressive component, aimed at forecasting the value of a variable based of a linear combination of its past values. The moving average component instead uses past errors in a way adjacent to past errors. Combining them creates an ARMA model and the ARIMA is then formed by taking a difference. Naturally, the appropriate ARIMA model depends on the nature of the data and so, to find the appropriate order of the ARIMA terms, an autocorrelation function and a partial autocorrelation function were taken on the differenced REPI-data. The figures (11 & 12) reveal mixed patterns. The ACF-plot decreases rapidly at its first lag but beyond the seasonal lag, no significant autocorrelation arises. Instead, the data moves in a sinusoidal way. The PACF shows a similar pattern, with rapid decay after the first lag, then continues moving sinusoidally. As such, there is no clear indication whether ARIMA (p,d,0) or ARIMA (0,d,q) should be tested. Therefore, many models are fitted and evaluated according to their AIC, AICc and BIC.

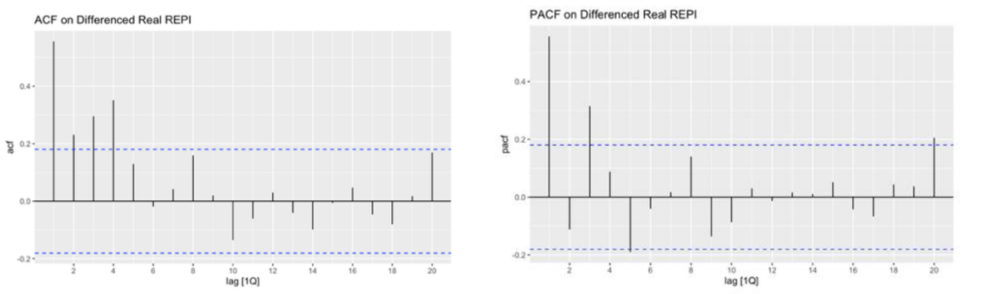


Figure 11 & 12

The Dynamic Regression model with ARIMA errors extends the ARIMA framework by including exogenous regressors, in this case, the differenced Swedish policy rate. This allows the model to capture relationships between the REPI series and relevant macroeconomic variables, while the ARIMA error structure accounts for autocorrelation in the residuals. This approach is often preferred when there is economic theory or empirical evidence suggesting that certain variables can improve forecast accuracy. (Hyndman & Athanasopoulos, 2021).

The models will be estimated using three separate train/test -sets based of the points made in the previous section. All datasets are however, split according to the 80/20 % rule, where training makes up 80% of the dataset and 20% is left for testing and validating the results. The first dataset disregards the structural break, enabling the use for more datapoints (94 training, 24 testing) while perhaps introducing bias from the structural break. The second dataset uses only uses data from the post break period, thereby eliminating bias but limiting datapoints (79 training, 20 test). The final dataset aims to mitigate both effects by having some pre-break data but not all (88 training, 23 test).

3. Results

The overall best performing dataset overall was the third dataset, following Peseran and Timmermanns (2007) recommendations. Within this dataset, several ARIMA models were tested given the ambiguity explained in the past section, including the automatic ARIMA, which is estimated using the Hyndman-Khandakar algorithm. The three most successful models for the ARIMA model were the ARIMA_110, ARIMA_111 and the ARIMA_210.

Model	AIC	AICc	BIC
ARIMA_110	-854.6136	-854.1258	-844.75
ARIMA_111	-853.5916	-852.5416	-838.7962
ARIMA_210	-853.0601	-852.0101	-838.2647

Table 1

To verify that the ARIMA_110 was appropriate for forecasting, a residual-plot was constructed giving an indication of whether the innovation residuals of the model are autocorrelated. If a fitted model has residuals which are autocorrelated, it is systematically missing some structure in the data, meaning that the model has been unsuccessful in capturing that pattern (Hyndman & Athanopolous, 2021). Upon optically inspecting the plot, autocorrelation in the residuals was not evident (see figure 13). However, to substantiate this claim, a Ljung Box test was performed, using 4 degrees of freedom and 10 lags. The null-hypothesis of the Ljung Box test is that there is no autocorrelation amongst the residuals, so with a result of 0.87, there was no evidence to reject this. Following this evidence (or rather lack thereof), the forecast could be produced for the duration of the test set(see plot 14).

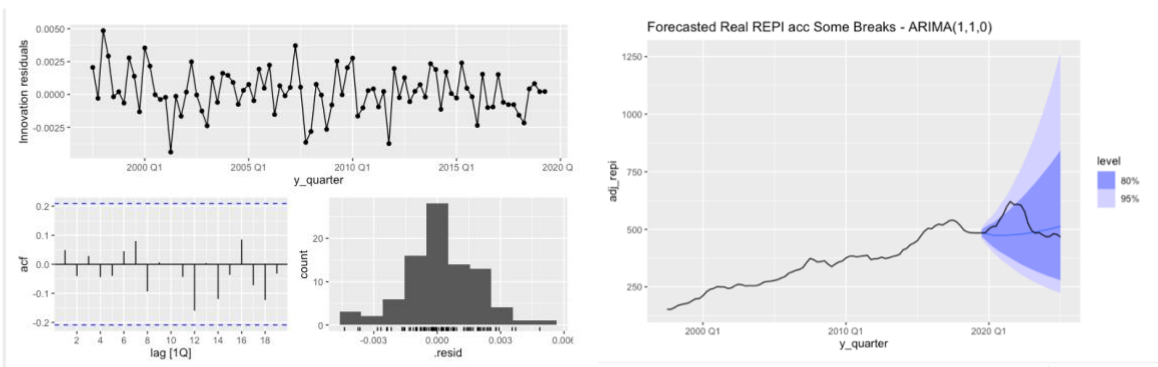


Figure 13 & 14

Following the plot, the following accuracy measures could be presented:

Model	RSME	MAE	MPE	MAPE	ACF1
ARIMA_110	72.15475	54.57534	6.186975	9.718032	0.89655

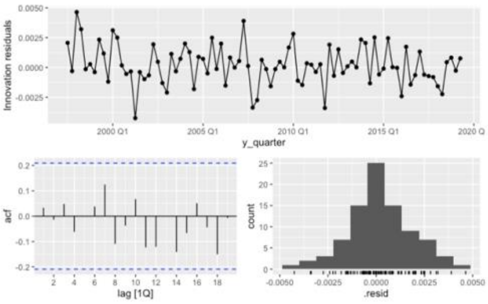
Table 2

Having fit the ARIMA, various kinds of Dynamic Regression models, also known as ARIMAX, were fitted.

Model	AIC	AICc	BIC
ARIMAX(1,1,0)(2,0,0)	*-858.3035*	*-857.5627*	*-845.9739*
ARIMAX(2,1,0)	*-854.7102*	*-853.2925*	*-837.488*
ARIMAX(2,1,1)	*-853.2666*	*-851.4104*	*-833.5393*

Table 3

Where the best performing model was the ARIMAX(1,1,0)(2,0,0). Once again, to maintain integrity of the forecast, the residual plot was constructed. Just as last time, residuals appear non-correlated but to ensure that this intuition is indeed true, the ljung box test was constructed, using 4 degrees of freedom and 10 lags. The test rendered a p-value of 0.65, showing that autocorrelation is not present in the residuals. The forecast showed the following trajectory, when predicted over the period of the test set (see figure 16).



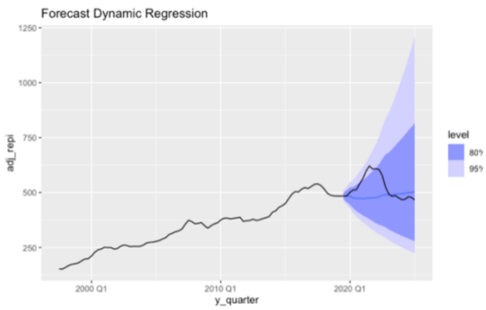


Figure 15 & 16

Following the Dynamic regression plot, the accuracy figures of both models are:

Model	RSME	MAE	MPE	MAPE	ACF1
ARIMA_110	*72.15475*	*54.57534*	***6.186975***	*9.718032*	***0.89655***
Dynamic Regression	***71.1657***	***52.36418***	*6.283549*	***9.266725***	*0.8990481*

Table 4

Both models do a poor job of predicting the adjusted real estate price index over the test set period. Nonetheless, the dynamic regression improves slightly over the Root Mean Square Error, the Mean Average Error and the Mean Average Percentage Error, improving upon previous performance by 1.4%, 4.2% and 4.6% respectively. Nonetheless, the improvement does not disregard the fact that models systematically under-forecast, just to a varying degree. There is also strong autocorrelation in the residual terms, showcasing the failure to capture some structure in the data.

In defense of the models however, the period into which they are trying to estimate reflect shocks which are highly unpredictable. The forecast starts in 2020, during which an unanticipated global pandemic caused major disruption to global markets, as well as a rapid rise in Swedish house prices. According to the Riksbank (2021) however, this rise is atypical for periods of recession and the Riksbank stresses that the surge deviates from historical patterns, which are traditionally explained by variables such as disposable incomes and interest rates. Instead, they state that several non-conventional drivers have jointly acted and strengthened each other to drive up prices. First, they mention that the main cause is a demand-supply mismatch of one and two-dwelling houses, caused by the fact that far more apartments are built than houses. What caused this demand surge is uncertain, however, reasons such as temporarily lifted amortization demands, surging stock prices and more disposable income left due to cancelling other consumption. They also lift the fact that working from home could have caused an increase in the demand of houses opposed to apartments, further contributing to the supply and demand mismatch highlighted before. Nonetheless, the best performing model was the dynamic regression model, suggesting the following forecast 12 quarters after the test period, showing an increase of 13.72% between 2019 Q3 and 2028 Q1.

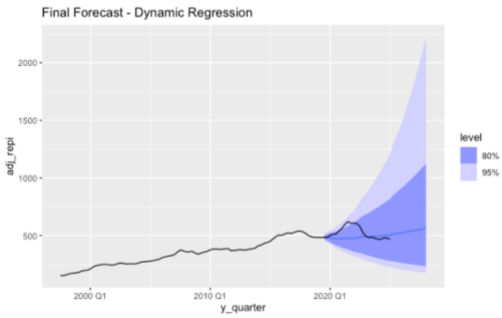


Table 17

Therefore, people looking into purchasing a house in the greater Stockholm area can expect a nice return on their investment according to the prediction. Nonetheless, due to the model's poor performance, cautionary buyers should also consider other predictions, in which models accounting for other external factors have been applied, as such models could potentially provide more accurate forecasts.

4. Conclusion

This study set out to project real house prices in Greater Stockholm using quarterly REPI data. After a Box–Cox transform, first differencing, and conservative treatment of an early-2000 break, we compared low-complexity ARIMA models with a parsimonious dynamic-regression variant (ARIMA errors + policy rate). The dynamic model delivered small but consistent accuracy gains on the holdout, yet both approaches under-predicted the 2020–2022 surge and left residual dependence, pointing to missing drivers during a pandemic-era demand shift. These results suggest the current specifications are useful baselines rather than full explanations. Improving performance likely requires a few targeted covariates (saving, WFH/mobility, credit conditions, wealth) and, if needed, modest time-varying dynamics while keeping the overall design lean.

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APPENDIX

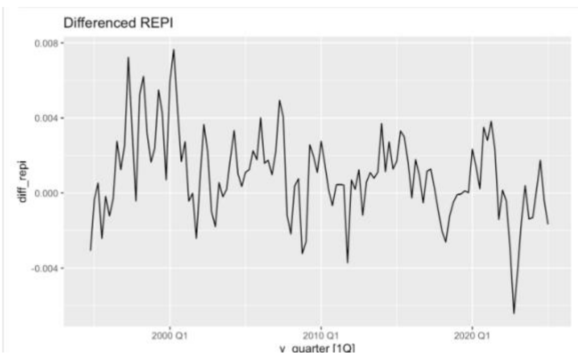
```
#######################
# KPSS Unit Root Test #
#######################

Test is of type: mu with 4 lags.

Value of test-statistic is: 2.2429

Critical value for a significance level of:
                10pct  5pct 2.5pct  1pct
critical values 0.347 0.463  0.574 0.739
```

```
#######################
# KPSS Unit Root Test #
#######################

Test is of type: tau with 4 lags.

Value of test-statistic is: 0.4897

Critical value for a significance level of:
                10pct  5pct 2.5pct  1pct
critical values 0.119 0.146  0.176 0.216
```

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression trend


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
      Min        1Q    Median        3Q       Max
-0.004867 -0.001116  0.000008  0.001056  0.004588

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.784e-02  2.435e-02   1.143    0.255
z.lag.1     -1.288e-02  1.180e-02  -1.091    0.278
tt           8.843e-07  1.352e-05   0.065    0.948
z.diff.lag   5.085e-01  7.848e-02   6.479 2.27e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.001862 on 117 degrees of freedom
Multiple R-squared:  0.3529,	Adjusted R-squared:  0.3364
F-statistic: 21.27 on 3 and 117 DF,  p-value: 4.563e-11


Value of test-statistic is: -1.091 4.3525 3.7546

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -3.99 -3.43 -3.13
phi2  6.22  4.75  4.07
phi3  8.43  6.49  5.47
```

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression drift


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0048592 -0.0011119  0.0000054  0.0010707  0.0045831

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.026372   0.009431   2.796  0.00604 **
z.lag.1     -0.012161   0.004420  -2.751  0.00688 **
z.diff.lag   0.507183   0.075454   6.722 6.73e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.001854 on 118 degrees of freedom
Multiple R-squared:  0.3529,	Adjusted R-squared:  0.342
F-statistic: 32.18 on 2 and 118 DF,  p-value: 7.022e-12


Value of test-statistic is: -2.7511 6.5822

Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.46 -2.88 -2.57
phi1  6.52  4.63  3.81
```

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression none


Call:
lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0052151 -0.0010635 -0.0002018  0.0010771  0.0054197

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
z.lag.1    1.974e-04  8.778e-05   2.248   0.0264 *
z.diff.lag 5.562e-01  7.546e-02   7.371 2.45e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.001906 on 119 degrees of freedom
Multiple R-squared:  0.4128,	Adjusted R-squared:  0.4029
F-statistic: 41.82 on 2 and 119 DF,  p-value: 1.758e-14


Value of test-statistic is: 2.2484

Critical values for test statistics:
      1pct  5pct 10pct
tau1 -2.58 -1.95 -1.62
```



```
##############################################
# Augmented Dickey-Fuller Test Unit Root Test #
##############################################

Test regression trend


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0046704 -0.0010295 -0.0001027  0.0009939  0.0049670

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.388e-03  4.027e-04   3.447 0.000791 ***
z.lag.1     -5.648e-01  9.052e-02  -6.239 7.41e-09 ***
tt          -1.385e-05  5.272e-06  -2.628 0.009757 **
z.diff.lag   1.229e-01  9.002e-02   1.365 0.174790
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.001864 on 116 degrees of freedom
Multiple R-squared:  0.2677,	Adjusted R-squared:  0.2488
F-statistic: 14.14 on 3 and 116 DF,  p-value: 6.48e-08


Value of test-statistic is: -6.239 13.0294 19.543

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -3.99 -3.43 -3.13
phi2  6.22  4.75  4.07
phi3  8.43  6.49  5.47
```

```
#######################
# KPSS Unit Root Test #
#######################

Test is of type: tau with 4 lags.

Value of test-statistic is: 0.0497

Critical value for a significance level of:
                10pct  5pct 2.5pct  1pct
critical values 0.119 0.146  0.176 0.216
```

```
#######################
# KPSS Unit Root Test #
#######################

Test is of type: mu with 4 lags.

Value of test-statistic is: 0.5341

Critical value for a significance level of:
                10pct  5pct 2.5pct  1pct
critical values 0.347 0.463  0.574 0.739
```

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression drift


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0051191 -0.0010890 -0.0002458  0.0011050  0.0054300

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0004530  0.0001933   2.344   0.0208 *
z.lag.1     -0.4788343  0.0865125  -5.535 1.94e-07 ***
z.diff.lag   0.0890659  0.0913109   0.975   0.3314
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.001911 on 117 degrees of freedom
Multiple R-squared:  0.2241,	Adjusted R-squared:  0.2109
F-statistic:  16.9 on 2 and 117 DF,  p-value: 3.568e-07


Value of test-statistic is: -5.5349 15.3184

Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.46 -2.88 -2.57
phi1  6.52  4.63  3.81
```

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression none


Call:
lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0045113 -0.0007038  0.0001664  0.0014945  0.0056915

Coefficients:
           Estimate Std. Error t value Pr(>|t|)
z.lag.1    -0.39147    0.07954  -4.922 2.81e-06 ***
z.diff.lag  0.04831    0.09133   0.529    0.598
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.001947 on 118 degrees of freedom
Multiple R-squared:  0.1877,	Adjusted R-squared:  0.174
F-statistic: 13.64 on 2 and 118 DF,  p-value: 4.7e-06


Value of test-statistic is: -4.9216

Critical values for test statistics:
      1pct  5pct 10pct
tau1 -2.58 -1.95 -1.62
```