Copenhagen Business School
Master in Business Administration and Data Science

Course: Predictive Analytics

Course Code: KAN-CDSCO1005U

Title: Forecast of apartments ready for occupancy on a monthly basis in Poland

Student Number: 158370

Examiners: Andrea Tafuro

Submission Details:

Date of submission: 18.08.2023

Number of characters: 23205

Number of pages: 10

Table of Contents:

Abstract

This study zooms into the realm of predictive analytics by addressing the issue of housing development in Poland. Urban development and housing availability have become pressing concerns in the European landscape. The objective of this research is to analyse historical trends and patterns to forecast the supply of new residential units on a monthly basis for a two-year horizon.

The study's foundation lies in a comprehensive analysis of a dataset that spans from January 2000 to June 2023, facilitating predictions from July 2023 to June 2025. Extensive exploratory data analysis is employed, involving visualisations, non-linearity assessments, and seasonality investigations. Logarithmic transformations and seasonal differentiation provide insights into underlying trends and patterns.

Time series forecasting models are crucial components of this study. Exponential Smoothing (ETS) and ARIMA models are examined. A variety of ETS models are evaluated with ETS(M,Ad,A) emerging as the most fitting. The ARIMA(2,0,1)(1,1,1)[12] model is also considered, with ETS ultimately chosen as the more suitable option after comprehensive evaluations.

Forecast of Apartments ready for Occupancy on a monthly basis in Poland

Introduction

Urban development plays a pivotal role in current societies, and the urgency escalates during housing crises across various European nations. Amidst this context, this study delves into the pressing issue of housing scarcity, focusing on Poland. The objective of this paper is to analyse and predict the availability of new residential units, including both apartments and houses, over a two-year horizon on a monthly basis.

Poland's dynamic housing landscape required a comprehensive analysis of the construction efforts. By analysing historical trends and patterns, this paper seeks to anticipate the future supply of housing solutions. The recent credit holidays and Ukrainian Refuges influx put the housing market in an abnormally difficult situation (Lepcha, 2022). The analytical approach aims to clarify the impending challenges and opportunities linked to residential expansion.

The exploration encompasses statistical forecasting techniques, with a focus on ARIMA and ETS models, to capture the intricate dynamics of new living spaces entering the market. These models are chosen for their capability to comprehend underlying trends, seasonality, and irregularities in the data.

In a society where access to suitable living spaces is crucial for societal well-being, this paper contributes to the discourse by providing insights into the potential trajectory of housing development in Poland. The findings will enable a proactive approach to managing housing challenges, and the forecasted figures will serve as a foundation for strategic planning to mitigate the impact of housing crises.

Data and Pre-processing[1]

The utilised dataset was sourced from the authoritative statistical, governmental website of Poland (Główny Urząd Statystyczny, n.d.), thereby establishing a robust foundation of data reliability. The temporal scope of the dataset includes a span from January 2000 extending through June 2023, thereby facilitating the prognosis of the period from July 2023 to June 2025.

Having in mind the efficiency of data analysis, a series of preparatory measures were executed in Excel, a transposition of the dataset and deletion of specific columns among others. The final dataset, attached alongside the report, includes two columns: Date, in the format Month Year, and Value, which is expressed as a quantity of the housing units released for use in that month.

Exploratory Data Analysis and Initial Transformations

1. Initial Visualisation

The first visualisation (Fig1), effectively conveys the time series information. It portrays an upward trend over the years, interspersed with distinct outlier occurrences around 2004 and 2009.

[1] All of the results which are mentioned in the text as well as graphs that did not have a significant value for the analysis can be found in the appendix.

These outliers provide a hint towards a possible structural breaks and imply further analysis.

2. Non-Linearity Assessment

To select the appropriate forecasting techniques it is crucial to assess the potential non-linearity of the data. In order to do so, there is a logarithmic transformation applied to the Values column. The comparison of the original and log-transformed data suggests that the log transformation captures the underlying trend more effectively as Fuqua School of Business (n.d.) suggests and therefore, will be used for further analysis. As can be seen in Figure 2 there is a much clearer upward trend after the logarithmic transformation (on the right).

3. Seasonality and Decomposition

The classical multiplicative decomposition, which can be seen in Figure 3 presents a clear seasonality within the data, which indicates a need for differentiation on a seasonal basis as a further action. The analysis also reveals a notable ascending trend starting from 2015, indicating the possibility of structural shifts around that time, which will be checked by the structural break analysis later. Additionally, the presence of irregularities in the residuals around 2004 and 2009 draws attention to potential anomalies during these periods.

The seasonality visualisation (Figure 4) reinforces the earlier observation of pronounced seasonality in the dataset. Furthermore, the presence of occasional outliers within the seasonal pattern becomes more evident.

4. Autocorrelation and Stationarity

The assessment of autocorrelation done with the ACF plot on logarithmically transformed data highlights significant autocorrelation, particularly at the 12th, 24th, 36th and 48th lags, which

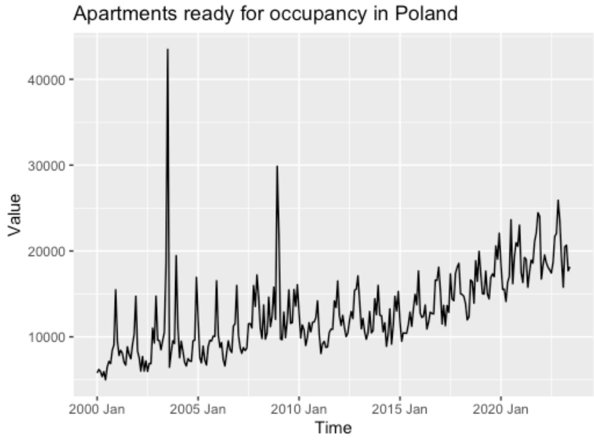


Figure 1: Initial Visualisation

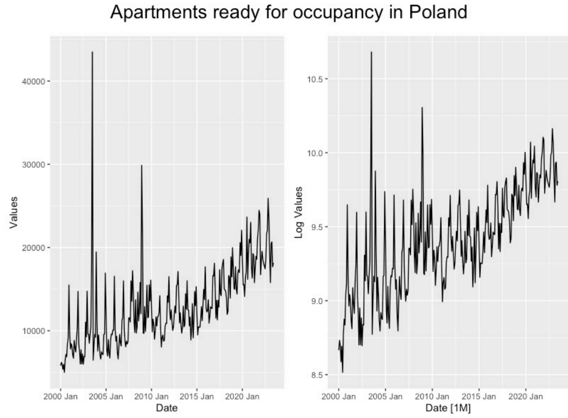


Figure 2: Comparison initial vs log data

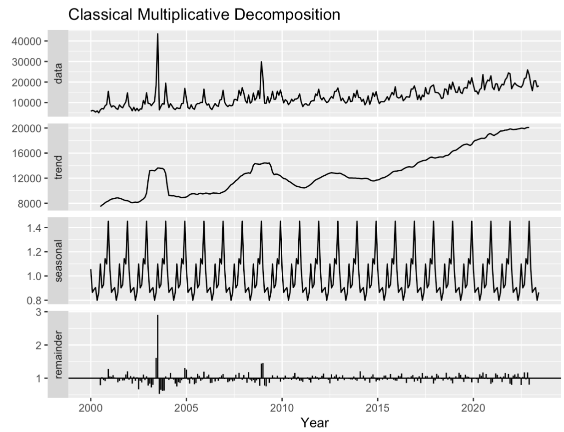


Figure 3: Decomposition Plot

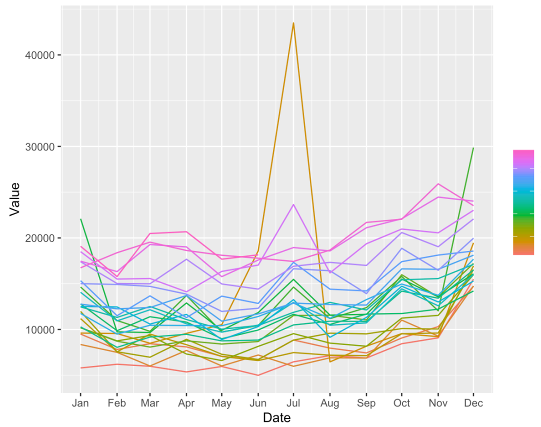


Figure 4: Seasonality Analysis

correspond to the annual seasonality. This observation corroborates the non-stationary nature of the data, as the autocorrelations do not decrease beyond significance levels over time. There is an overall decreasing trend in the autocorrelation graph (Figure 5) which maybe indicating non-stationarity or due to trend.

To further investigate stationarity, two unit root tests namely ADF and KPSS are employed. The ADF test results in the rejection of the null hypothesis is indicating non-stationarity. The test statistic of -8.5963 significantly exceeds the critical values for all significance levels. Furthermore, the presence of a statistically significant time trend component (coefficient: 0.0017238) suggests a potential deterministic trend within the data. In contrast, the KPSS test yields contradictory outcomes, indicating stationarity. The test statistic of 0.1432 is lower than the critical values for all significance levels. This discrepancy may imply the presence of a trend-stationary process. The contradiction of the test results raises the possibility of a trend-stationary process, however, the high seasonality that has been discussed in the previous section and high autocorrelation on the repetitions of the 12th lag would imply the non-stationary assumption. Therefore, the analysis will be repeated after differentiating on 12 lags to make sure to account for seasonality.

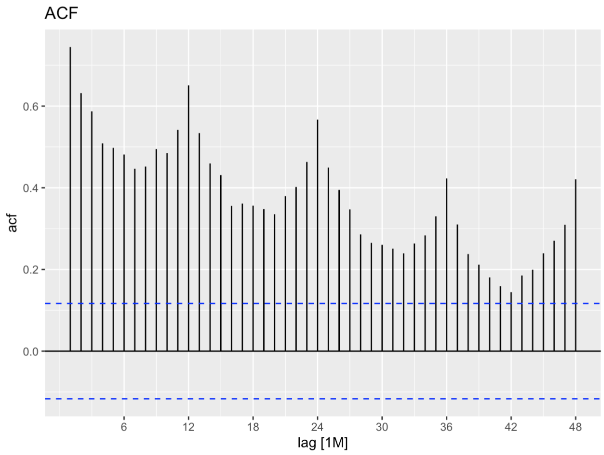


Figure 5: ACF

5. Differentiation of the Data

The first applied differentiation involves a lag of 12, accounting for the yearly seasonality. The resulting differentiated data is plotted and there is a clearly more flat trend and the ACF plot presents much lower autocorrelation where the most outlying bars are located around 40% at most and the rest being very close to the significance levels around 12%. There is still a 0 and 12th lag with high autocorrelation which is decreasing to below significance after that. The ADF and KPSS tests are repeated after seasonal differentiation to determine whether there is a need for additional differentiation that would make the data stationary.

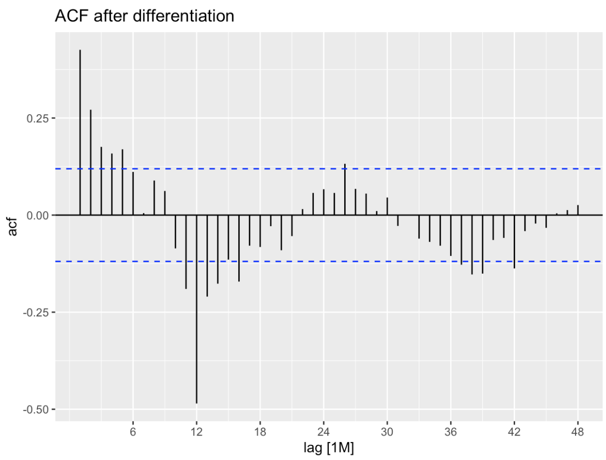


Figure 6: ACF after differentiation

The results of the ADF test show that the intercept is not statistically significant which further implies no drift or trend, while the lag 1 high negative value signifies presence of stationarity in the time series and lastly, the tt coefficient with high p-value indicate no statistically significant time trend.The F-statistic is 37.08, with an extremely low p-value (< 2.2e-16), indicating the overall significance of the model. The test-statistic for the ADF test is -7.84, significantly lower than the critical values for all levels of significance, suggesting strong evidence against the presence of a unit root and indicating the series' stationarity.

The test-statistic for the KPSS test is 0.0564, which is notably lower than the critical values for all levels of significance. This indicates that the null hypothesis of stationarity is not rejected, implying that the series is likely stationary around a deterministic trend.

In conclusion, based on the results of both the ADF and KPSS tests, there is strong evidence to suggest that the time series, after seasonal differentiation, is stationary without a unit root. Therefore, the analysis will now move forward without any further differencing.

6. Structural Break Detection

Furthermore, the analysis extends to detecting potential structural breaks within the data. A structural break test is applied, assessing whether there are significant changes in the data's behaviour over time. The QLR test suggests the presence of a structural break at observation number 38, corresponding to a specific date. The data after the structural break is extracted for further examination.

Summary

Upon an initial visual inspection, the time series displayed a distinctive upward trend, interwoven with distinct outlier occurrences around 2004 and 2009. These outliers hinted at possible structural breaks within the data, thus prompting the need for further examination. In pursuit of selecting appropriate forecasting techniques, a logarithmic transformation was applied. Comparison between the original and log-transformed data revealed that the log transformation effectively captured the underlying trend. The classical multiplicative decomposition unraveled a pronounced seasonality within the dataset. Furthermore, the presence of an ascending trend from 2015 suggested the potential occurrence of structural shifts around that time, which were eventually not found. Autocorrelation assessment on log-transformed data, unveiled significant autocorrelation, particularly at lags corresponding to the annual seasonality. This persistent autocorrelation suggested the non-stationary nature of the data. Contrasting ADF and KPSS unit root tests provided conflicting outcomes. The ADF test hinted at non-stationarity, yet the KPSS test indicated stationarity. This contradiction illuminated the potential presence of a trend-stationary process. To reconcile this discrepancy, a differentiation with a lag of 12, accounting for yearly seasonality, was applied. The resulting differentiated data exhibited a flatter trend and substantially reduced autocorrelation, confirming the influence of seasonality. Revisiting the ADF and KPSS tests post differentiation revealed consistent evidence of stationarity. The ADF test emphasised the absence of a unit root, substantiated by the significantly low test-statistic, while the KPSS test reaffirmed the series' likely stationary behaviour. The application of a Structural Break test has pinpointed a significant alteration in the data's behaviour and resulted in the cut off point of the data one data point after the break.

Analysis of Time Series Forecasting Models

The transformed dataset was split into training and testing subsets using an 80-20 split. The first 80% of the data were used for training (train), while the remaining 20% were used for testing (test).

1. ETS Models

The Exponential Smoothing (ETS) models are applied to a given dataset. Four different ETS models are tested: ETS Guess Model 1, ETS Guess Model 2, ETS Guess Model 3, and ETS Auto Model. The analysis compares the models between each other to then pick the best one. Among the four ETS models considered, namely ETS(A,N,A), ETS(M,A,M), ETS(A,N,M), and ETS(M,Ad,A), a comparison is drawn based on the AIC, AICc, and BIC criteria. The specification for the first model is chosen based on the fact that there is no clear trend in the data after differentiation, however, clear indication of seasonality. The decision was made to check both additive and multiplicative patterns for seasonality, which the latter can be seen in the second guessed model. Based on the decomposition plot (Figure 3) there is significant but steady seasonality. Nevertheless, the model with multiplicative trend is an interesting model to examine. And lastly, the third model was chosen as a combination of the previous two, where the error term was assumed to be additive and seasonality multiplicative and no trend.

Upon analysis, it becomes evident that the ETS(M,Ad,A) model consistently achieves the lowest values across all three evaluation criteria. The AIC, AICc, and BIC for this model are substantially lower than those for the alternative models, signifying a superior trade-off between capturing data dynamics and model simplicity. This model's favourable performance is attributed to its incorporation of additive errors, additive damped trend, and additive seasonality. The AIC, AICc, and BIC values for the ETS(M,Ad,A) model are, respectively, 365.1781, 369.0644, and 424.0921.

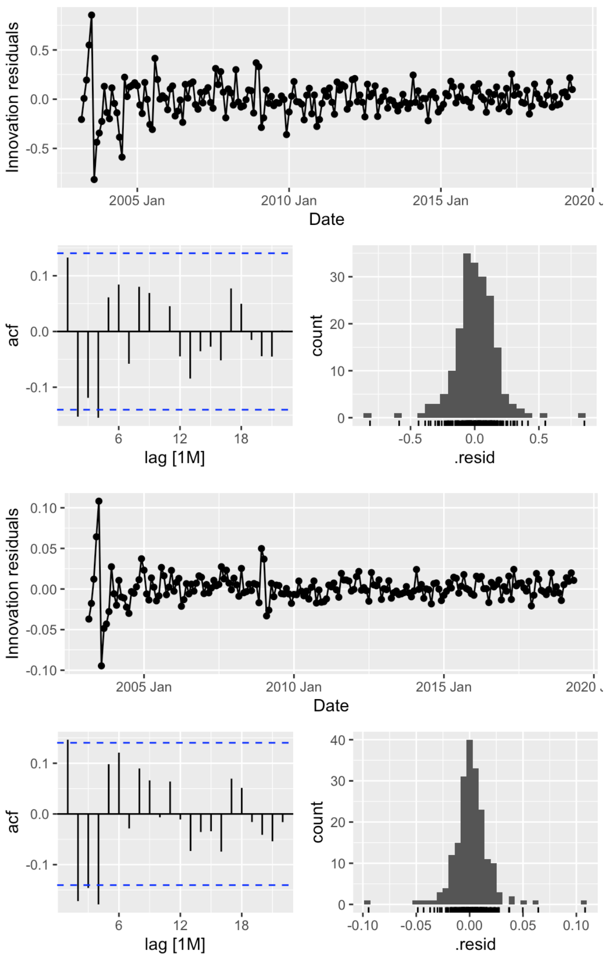


Figure 8: Evaluation of the residuals for ETS Auto

The Ljung-Box test assesses the null hypothesis that the residuals are independent. In the ETS(M,Ad,A) the hypothesis is rejected what implies a certain autocorrelation between residuals. For ETS Guess Model 1, the Ljung-Box test returned a p-value of 0.0259. Although higher than the previous case, this p-value remains below conventional significance thresholds. While the model demonstrates some capacity to capture data patterns, there are indications of residual autocorrelations, signifying potential areas for model refinement. ETS Guess Model 2 exhibited a notably lower p-value of 0.000725. This result robustly rejects the null hypothesis, highlighting significant residual autocorrelations. The test for ETS Guess Model 3 yielded a p-value of 0.0341. Although it is relatively higher than for the other models, it still suggests some evidence against residual independence. In this context, ETS Guess Model 1 exhibits relatively better conformity in terms of independence compared to the other models. However, it is important to emphasise that the presence of residual autocorrelations does not inherently render the models invalid. Instead, it underscores the potential for enhancements to more accurately capture temporal patterns.

When looking at the residuals analysis the ACF graph presents the lowest degree of forecasting error, with almost none of the bars reaching the significance level for the ETS(A,N,M). However, the distribution of the residuals is better for the ETS(M,Ad,A).

Summing up, the ETS(M,Ad,A) model yields the best results when it comes to the AIC, AICc and BIC analysis and ETS(A,N,A) has the best results of the Ljung-Box test. While the residuals visual analysis presents inconclusive results when it comes to the models, with ETS(A,N,M) and ETS(M,Ad,A) being the front runners for the best model picks. Therefore, the three models will be compared visually together to make a final decision. As can be seen on Figure 9, all three models that were being considered in due to the numerical results seem to be a good fit for the forecast. Therefore, because in the previous results the ETS(M,Ad,A) was dominating so it will be chosen for further comparison.

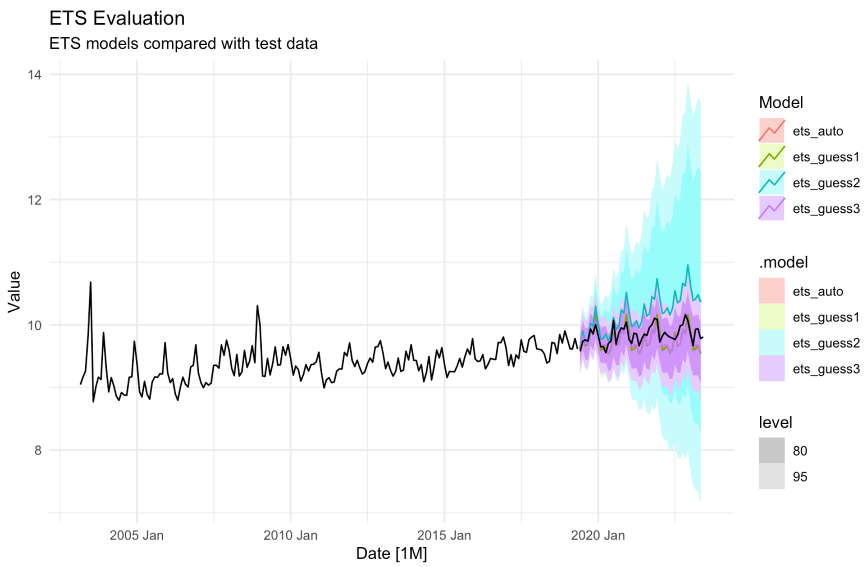


Figure 9: Visual Analysis of ETS models

2. ARIMA Models

ARIMA is a popular time series forecasting method used to model and predict future values in a time series data set. ARIMA models are flexible and can handle data with trends, seasonality, and autocorrelation.

The first model, referred to as ARIMA Guess 1 is an ARIMA(0,0,0)(0,1,1)[12] model, the values have been chosen as all zeros for the non-seasonal component due to lack of indication in the previous analysis of any lagged terms, only seasonal differencing applied and no lagged forecast errors. However, when discussing the seasonal part the model is closed without lagged terms of the dependent variable but with seasonal differencing and including a moving average. The coefficient estimates for this model's seasonal moving average (SMA) component and the constant term are approximately -0.8460 and 0.0278, respectively. The estimated sigma squared, representing the variance of the residuals, is 0.04075. The AIC, AICc, and BIC values for this model are -47.32, -47.19, and -37.69, respectively.

The second model, denoted as ARIMA Guess 2 model is an ARIMA(1,0,0)(0,1,1)[12] model the values have been chosen with an indication of possible lagged term of dependent variable, while the other. The other values remain the same as in the first model. The coefficient estimates for the autoregressive term, seasonal moving average component, and the constant term are approximately 0.4733, -0.7866, and 0.0149, respectively. The estimated sigma squared is 0.03245. The AIC, AICc, and BIC values for this model are -91.25, -91.02, and -78.41, respectively.

The third model, labeled Auto ARIMA model is an ARIMA(2,0,1)(1,1,1)[12] model. This model incorporates both autoregressive and moving average components, along with seasonal autoregressive and seasonal moving average components. The estimated sigma squared is 0.03224. The AIC, AICc, and BIC values for this model are -92.31, -91.84, and -73.06, respectively.

In the case of the three ARIMA models examined, we observe that the Auto ARIMA model consistently exhibits the lowest AIC, AICc, and BIC values among the three models. This indicates that the Auto ARIMA model is the most appropriate model for this dataset, according to these criteria.

Additionally, the Ljung-Box test is employed to assess the independence of the residuals. For the ARIMA Guess 1 model, the Ljung-Box test yields a p-value of 0, which is extremely low. This suggests that there is significant autocorrelation present in the residuals. In contrast, the ARIMA Guess 2 model shows a Ljung-Box test p-value of 0.0000545. Although this p-value is relatively small. This suggests that while there might be some residual autocorrelation, the model's performance in terms of capturing temporal dependencies is relatively better compared to the first model. Similarly, the Auto ARIMA model demonstrates a Ljung-Box test p-value of 0.000545. This indicates the presence of residual autocorrelation, but again, the model's performance appears to be relatively better than the first model. However, it's worth noting that both the ARIMA Guess 2 and Auto ARIMA models exhibit some level of residual autocorrelation, potentially indicating room for improvement in model fit. Both the graphical and statistical analyses suggest that the Auto ARIMA model is the most promising among the three models in terms of residual behaviour. However, all three models exhibit some degree of residual autocorrelation. Lastly, among the other visualisations the ARIMA Auto presents to be the least autocorrelated and the normal distributions of the said residuals is the most coherent. Therefore, the ARIMA Auto model will be chosen for visual comparison with the chosen ETS model.

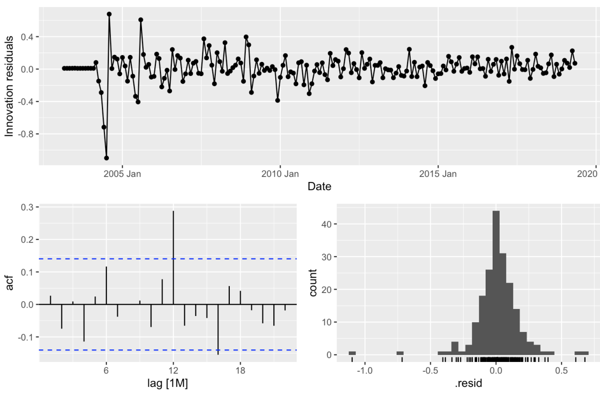


Figure 10: Evaluation of the residuals ARIMA Auto

3. Final Model Selection

In the final model selection there will be a accuracy measure comparison as well as visual one to determine which of the models should be chosen for the final forecast. The ARIMA model demonstrates a ME of 3090, an RMSE of 3675, and a MAE of 3139. Additionally, it exhibits a MPE of 15.4%, and a MAPE of 15.8%. On the other hand, the ETS model showcases a ME of 1478, an RMSE of 2609, and a MAE of 2019. The MPE for this model is 6.90%, while the MAPE is 10.2%. Comparing the two, the ETS model outperforms the ARIMA model with lower RMSE and MAE values, suggesting its superior accuracy in predicting the test dataset.

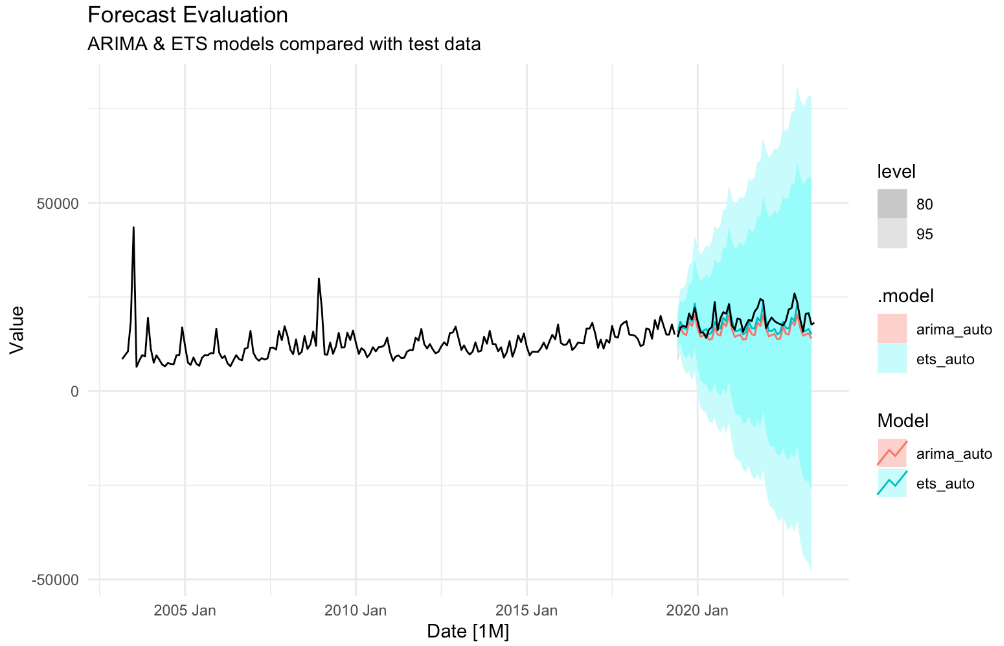


Figure 11: Visual comparison of the ARIMA and ETS models

Based on the visual comparison of the models the ETS model seems to be a better fit for the forecast as well. The better performance can be seen visually as the ETS follows the data more closely and has more correct peeks. Therefore it will be chosen for the final forecast.

Forecast

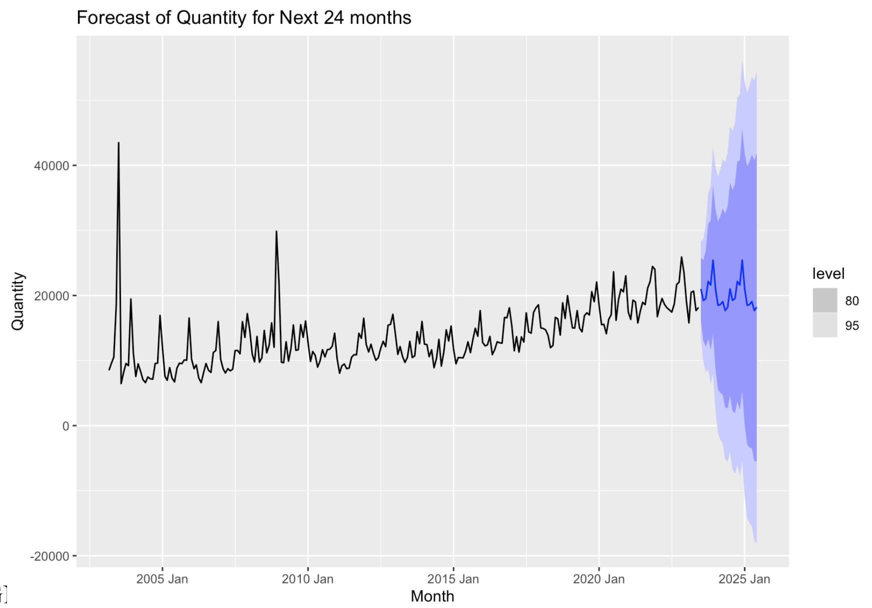


Figure 12: Final Forecast

The forecast has been performed on the untransformed data using the ETS(M,Ad,A) model. Overall, the forecast seems to follow a similar trend as the data before with a slightly lower magnitude. The predictions for the first and second twelve months visually look the same, what could require further inspection or usage of different models, outside of the ARIMA or ETS scope.

Conclusions

This paper embarked on a journey to address the critical issue of housing availability, focusing on Poland, where urban development and housing scarcity have become pressing concerns. Through a meticulous analysis of historical trends and patterns, this research aimed to forecast the supply of new residential units on a monthly basis, with a two-year horizon, using time series forecasting techniques.

The comprehensive analysis of time series forecasting models, specifically focused on Exponential Smoothing (ETS) and ARIMA models. The ETS models, encompassing different configurations, were evaluated using criteria such as AIC, AICc, and BIC. Among these models, ETS(M,Ad,A) emerged as the most balancing model complexity and goodness of fit. The Ljung-Box test illuminated potential residual autocorrelations within these models, emphasizing areas for potential refinement.

The ARIMA models followed suit, with ARIMA Guess 1, ARIMA Guess 2, and Auto ARIMA models being considered. Through a thorough analysis of AIC, AICc, BIC, and residual independence, the Auto ARIMA model demonstrated its superiority in capturing the dataset's dynamics. The Ljung-Box test highlighted residual autocorrelations, prompting a critical evaluation of model performance. Finally, a visual comparison of the chosen ETS model and the Auto ARIMA model took place. Through this final comparison, the ETS model emerged as the most suitable choice for forecasting. Its comprehensive analysis, incorporating trend, seasonality, and irregularities, displayed a better fit for the dataset's intricacies.

In conclusion, this study has contributed to the predictive analytics domain by offering a comprehensive methodology for forecasting housing availability on a monthly basis in Poland. By examining historical trends and employing time series forecasting techniques, the paper provides valuable insights for policymakers, urban planners, and real estate developers to address housing challenges proactively. The chosen ETS model, validated through various assessments and comparisons, promises a robust foundation for strategic planning and policy formulation in the context of housing crises. As housing dynamics continue to evolve, this research could improve the predictive analytics sphere to mitigate the impact of housing scarcity and guide sustainable urban development.

References

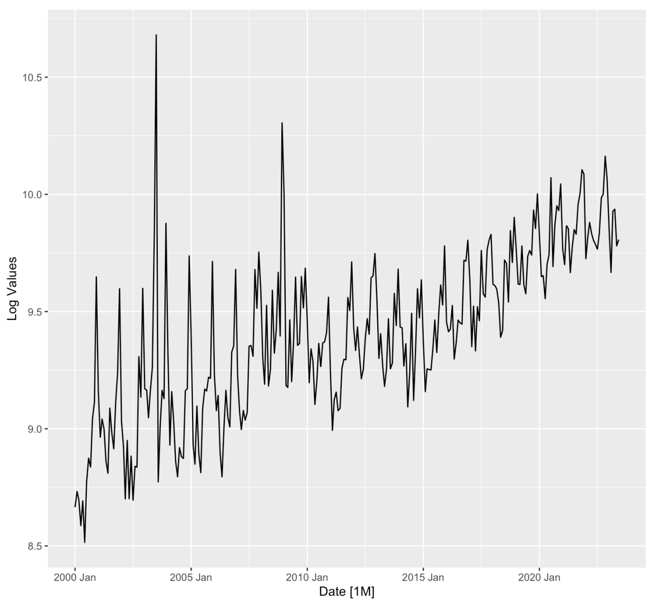
Autocorrelation | Forecasting: Principles and Practice (2nd ed). (n.d.). https://otexts.com/fpp2/autocorrelation.html

Fuqua School of Business. (n.d.). Steps in choosing a forecasting model: deflation? log transformation? seasonal adjustment? regression variables? random walk? exponential smoothing? ARIMA?https://people.duke.edu/~rnau/411fcst.htm

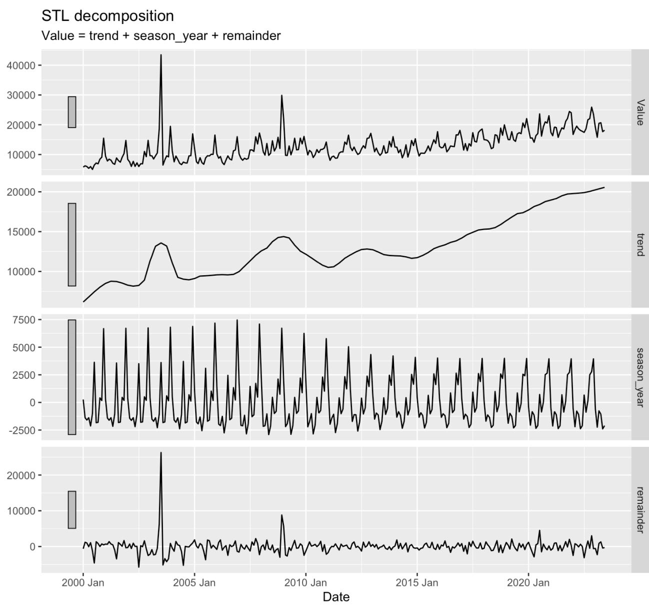
Główny Urząd Statystyczny. (n.d.). *Bank Danych Makroekonimicznych* [Dataset]. https://bdm.stat.gov.pl

Lepcha, M. (2022, October 21). Poland house price crash: Rising rates squash mortgage applications despite government-imposed credit holidays. *Capital Com SV Investments Limited*. https://capital.com/poland-house-price-crash-mortgage-applications-rates-rising

Appendix



Appendix Figure 1: Log Plot of initial data



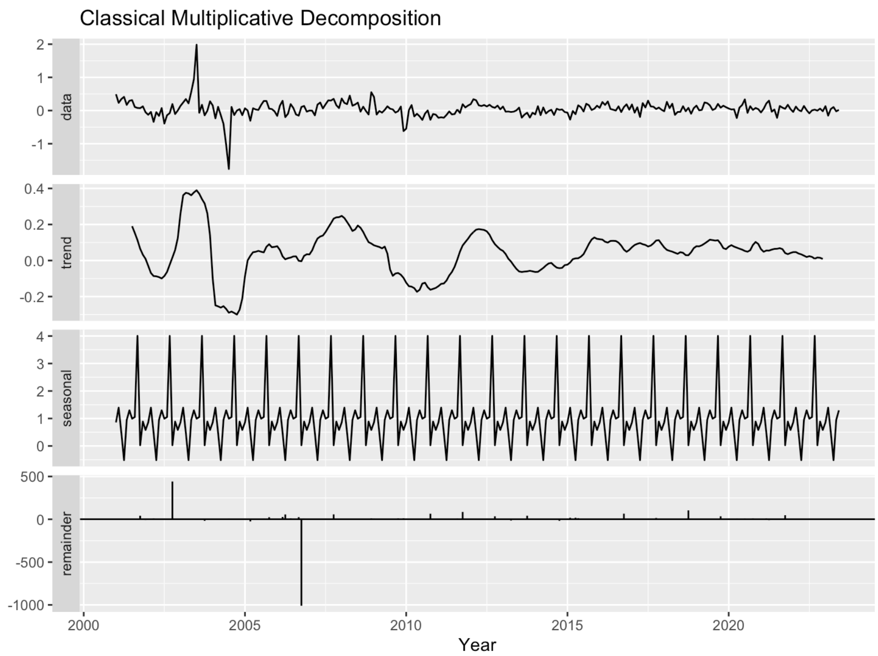
Appendix Figure 2: STL Decomposition of the log data

```
###############################################
# 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
-1.03643 -0.12207 -0.02192  0.10375  1.25800

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  4.8452597  0.5631805   8.603 5.94e-16 ***
z.lag.1     -0.5407097  0.0629001  -8.596 6.24e-16 ***
tt           0.0017238  0.0002583   6.675 1.36e-10 ***
z.diff.lag  -0.0179370  0.0600213  -0.299    0.765
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2144 on 276 degrees of freedom
Multiple R-squared:  0.2763,	Adjusted R-squared:  0.2684
F-statistic: 35.12 on 3 and 276 DF,  p-value: < 2.2e-16


Value of test-statistic is: -8.5963 24.6937 36.965

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -3.98 -3.42 -3.13
phi2  6.15  4.71  4.05
phi3  8.34  6.30  5.36
```

Appendix Figure 3: Initial ADF Test Results

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

Test is of type: tau with 5 lags.

Value of test-statistic is: 0.1432

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

Appendix Figure 4: Initial KPSS Results



Appendix Figure 5: Decomposition Plot after differentiation

```
###############################################
# 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
-1.34746 -0.08025 -0.00286  0.10590  1.54308

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.187e-02  2.767e-02   0.791   0.4299
z.lag.1     -5.113e-01  6.522e-02  -7.840 1.11e-13 ***
tt           1.577e-06  1.760e-04   0.009   0.9929
z.diff.lag  -1.105e-01  6.081e-02  -1.817   0.0704 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2229 on 264 degrees of freedom
Multiple R-squared:  0.2964,    Adjusted R-squared:  0.2884
F-statistic: 37.08 on 3 and 264 DF,  p-value: < 2.2e-16


Value of test-statistic is: -7.84 20.4995 30.7432

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -3.98 -3.42 -3.13
phi2  6.15  4.71  4.05
phi3  8.34  6.30  5.36
```

Appendix Figure 6: ADF after differentiation

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

Test is of type: tau with 5 lags.

Value of test-statistic is: 0.0564

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

Appendix Figure 7: KPSS after differentiation

```
> # QLR test with monthly lags
> qlr1 <- Fstats(Lag0 ~ Lag1 + Lag12, data = sb_data, from = 0.15)
> test1 <- sctest(qlr1, type = "supF")
> breakpoints(qlr1, alpha = 0.05)

	 Optimal 2-segment partition: 

Call:
breakpoints.Fstats(obj = qlr1, alpha = 0.05)

Breakpoints at observation number:
38 

Corresponding to breakdates:
0.1434109 
> #Breakpoints at observation number: 38
```

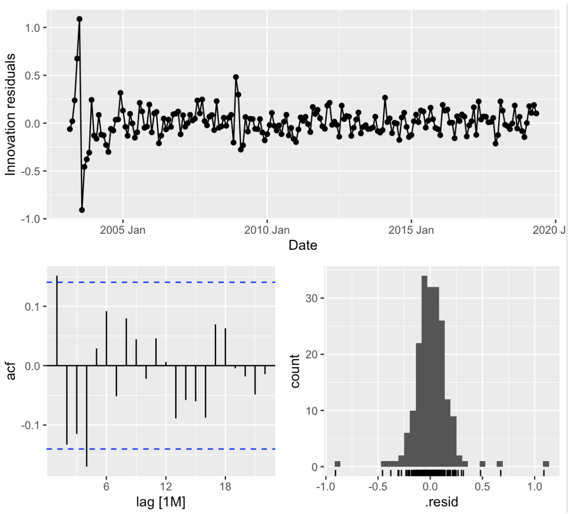
Appendix Figure 8: Structural Break Analysis

```
> report(models_ets%>%select(ets_guess1))
Series: Log_Values 
Model: ETS(A,N,A) 
  Smoothing parameters:
    alpha = 0.2654165 
    gamma = 0.000102216 

  Initial states:
     l[0]       s[0]      s[-1]      s[-2]      s[-3]      s[-4]       s[-5]       s[-6]
 9.253203 -0.1657363 0.1584349 0.4042883 0.1262053 0.1309268 -0.06643827 -0.09221974
     s[-7]      s[-8]      s[-9]      s[-10]     s[-11]
 0.1074116 -0.1502139 -0.2185105 -0.09031799 -0.1438301

  sigma^2:  0.0318

     AIC     AICc      BIC 
371.0263 373.7078 420.1213 
> report(models_ets%>%select(ets_guess2))
Series: Log_Values 
Model: ETS(M,A,M) 
  Smoothing parameters:
    alpha = 0.208781 
    beta  = 0.03853999 
    gamma = 0.0001218219 

  Initial states:
     l[0]       b[0]      s[0]     s[-1]     s[-2]     s[-3]     s[-4]      s[-5]      s[-6]
 9.702485 -0.0147983 0.9846821 1.010451 1.041936 1.011799 1.017676 0.9927318 0.9909206
    s[-7]      s[-8]      s[-9]     s[-10]     s[-11]
 1.011157 0.9857424 0.9774492 0.9903002 0.9851544

  sigma^2:  4e-04

     AIC     AICc      BIC 
378.0429 381.5005 433.6839 
```

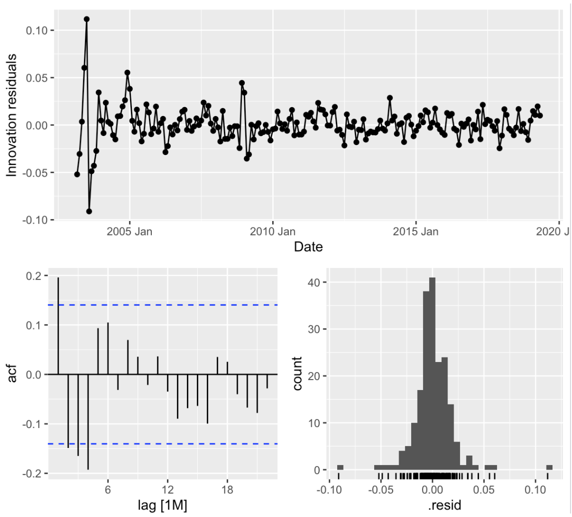
Appendix Figure 9: Results for ETS Guess 1&2

```
> report(models_ets%>%select(ets_guess3))
Series: Log_Values
Model: ETS(A,N,M)
  Smoothing parameters:
    alpha = 0.2660607
    gamma = 0.1728058

  Initial states:
    l[0]      s[0]     s[-1]     s[-2]     s[-3]     s[-4]      s[-5]      s[-6]     s[-7]      s[-8]
 9.38581 0.9855359 1.017232 1.051866 1.003115 1.009775 0.9908524 0.9830577 1.030707 0.9888047
     s[-9]     s[-10]    s[-11]
 0.9715943 0.9816458 0.985815

  sigma^2:  0.0318

     AIC     AICc      BIC
371.1236 373.8052 420.2186
> report(models_ets%>%select(ets_auto))  # --> ANN
Series: Log_Values
Model: ETS(M,Ad,A)
  Smoothing parameters:
    alpha = 0.2583879
    beta  = 0.000663893
    gamma = 0.0001001616
    phi   = 0.9646497

  Initial states:
     l[0]        b[0]        s[0]     s[-1]      s[-2]       s[-3]      s[-4]        s[-5]
 9.538679 -0.0137614 -0.1361877 0.105246 0.3992675 0.09843951 0.1688007 -0.06875347
       s[-6]      s[-7]       s[-8]       s[-9]       s[-10]      s[-11]
 -0.09464806 0.1122073 -0.1473386 -0.2163242 -0.09006147 -0.1306477

  sigma^2:  3e-04

     AIC     AICc      BIC
365.1781 369.0644 424.0921
```

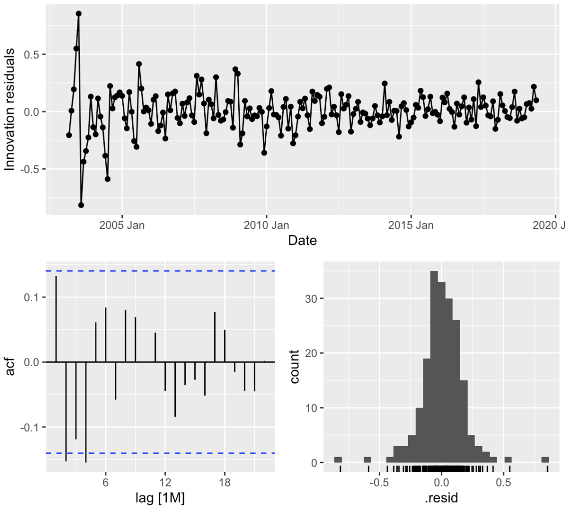
Appendix Figure 10: ETS Guess 3 and ETS Auto Results



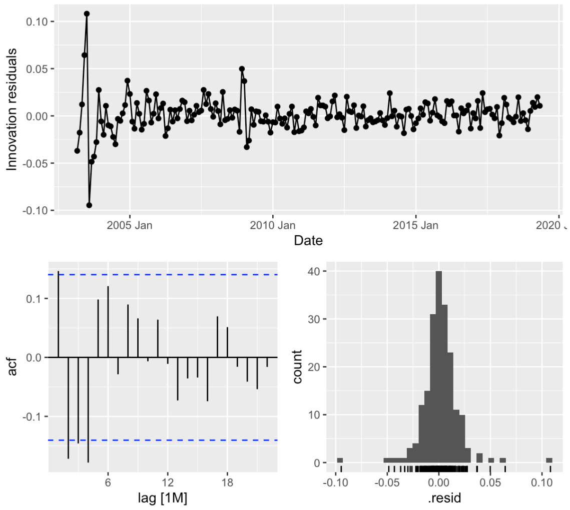
Appendix Figure 11: Residuals analysis ETS G1



Appendix Figure 12: Residuals analysis ETS G2



Appendix Figure 13: Residuals analysis ETS G3



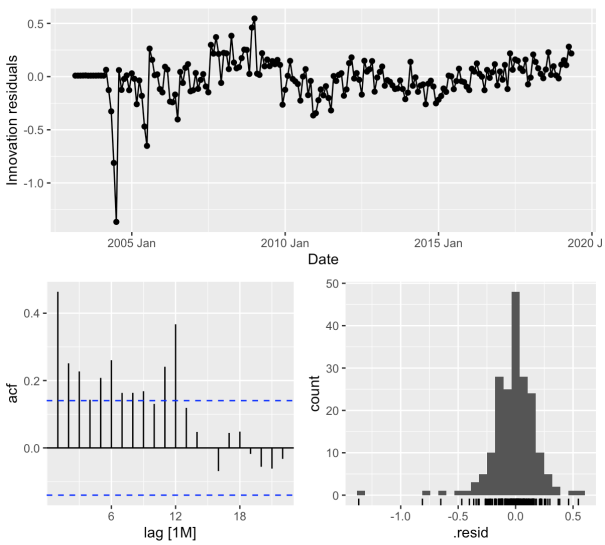
Appendix Figure 14: Residuals analysis ETS Auto

```
> # Ljung Box Test (we want HIGH p-value -> NULL not rejected, then resid. independent)
> models_ets %>%
+   select(ets_auto) %>%
+   residuals()  %>%
+   features(.resid, features = ljung_box, lag = 24, dof = 8)
# A tibble: 1 × 3
  .model    lb_stat lb_pvalue
  <chr>       <dbl>     <dbl>
1 ets_auto     35.4   0.00349
> models_ets %>%
+   select(ets_guess1) %>%
+   residuals()  %>%
+   features(.resid, features = ljung_box, lag = 24, dof = 8)
# A tibble: 1 × 3
  .model      lb_stat lb_pvalue
  <chr>         <dbl>     <dbl>
1 ets_guess1     28.7    0.0259
> models_ets %>%
+   select(ets_guess2) %>%
+   residuals()  %>%
+   features(.resid, features = ljung_box, lag = 24, dof = 8)
# A tibble: 1 × 3
  .model      lb_stat lb_pvalue
  <chr>         <dbl>     <dbl>
1 ets_guess2     40.2  0.000725
> models_ets %>%
+   select(ets_guess3) %>%
+   residuals()  %>%
+   features(.resid, features = ljung_box, lag = 24, dof = 8)
# A tibble: 1 × 3
  .model      lb_stat lb_pvalue
  <chr>         <dbl>     <dbl>
1 ets_guess3     27.7    0.0341
```

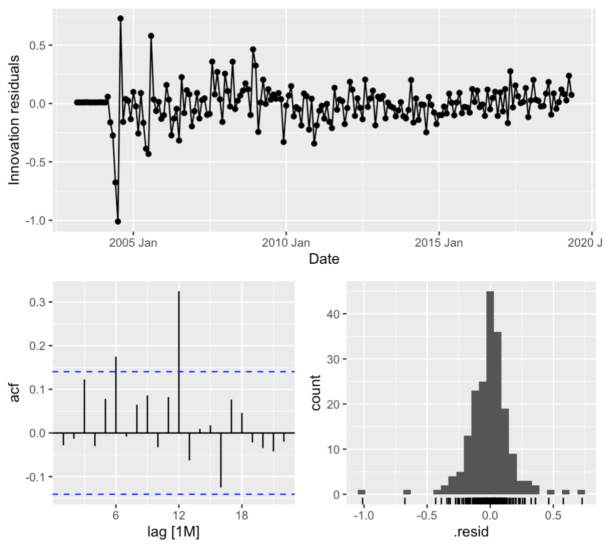
Appendix Figure 15: Ljung-Box for ETS

```
> report(models_arima%>%select(arima_guess1))
Series: Log_Values
Model: ARIMA(0,0,0)(0,1,1)[12] w/ drift

Coefficients:
         sma1  constant
      -0.8460    0.0278
s.e.   0.0823    0.0037

sigma^2 estimated as 0.04075:  log likelihood=26.66
AIC=-47.32   AICc=-47.19   BIC=-37.69
> report(models_arima%>%select(arima_guess2))
Series: Log_Values
Model: ARIMA(1,0,0)(0,1,1)[12] w/ drift

Coefficients:
         ar1     sma1  constant
      0.4733  -0.7866    0.0149
s.e.  0.0652   0.0752    0.0038

sigma^2 estimated as 0.03245:  log likelihood=49.62
AIC=-91.25   AICc=-91.02   BIC=-78.41
> report(models_arima%>%select(arima_auto))
Series: Log_Values
Model: ARIMA(2,0,1)(1,1,1)[12]

Coefficients:
         ar1      ar2      ma1    sar1     sma1
      1.2133  -0.2384  -0.8183  0.0107  -0.7656
s.e.  0.1038   0.0942   0.0646  0.1304   0.0831

sigma^2 estimated as 0.03224:  log likelihood=52.16
AIC=-92.31   AICc=-91.84   BIC=-73.06
```

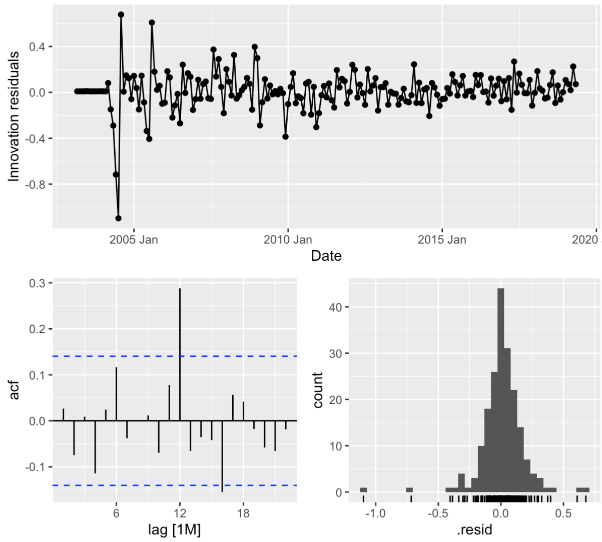
Appendix Figure 16: Reports ARIMA



Appendix Figure 17: Residuals ARIMA Guess 1



Appendix Figure 18: Residuals ARIMA Guess 2



Appendix Figure 19: Residuals ARIMA Auto

```
# A tibble: 1 × 3
  .model       lb_stat lb_pvalue
  <chr>          <dbl>     <dbl>
1 arima_guess1    162.         0
> models_arima %>%
+   select(arima_guess2) %>%
+   residuals()  %>%
+   features(.resid, features = ljung_box, lag = 24, dof = 8)
# A tibble: 1 × 3
  .model       lb_stat lb_pvalue
  <chr>          <dbl>     <dbl>
1 arima_guess2    47.6 0.0000545
> models_arima %>%
+   select(arima_auto) %>%
+   residuals()  %>%
+   features(.resid, features = ljung_box, lag = 24, dof = 8)
# A tibble: 1 × 3
  .model     lb_stat lb_pvalue
  <chr>        <dbl>     <dbl>
1 arima_auto    41.1  0.000545
```

Appendix Figure 20: Ljung-Box ARIMA

```
> accuracy_result <- fabletools::accuracy(forecasts, test_for)
> print(accuracy_result)
# A tibble: 2 × 10
  .model     .type    ME  RMSE   MAE   MPE  MAPE  MASE RMSSE  ACF1
  <chr>      <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1 arima_auto Test  3090. 3675. 3139. 15.4   15.8   NaN   NaN 0.213
2 ets_auto   Test  1478. 2609. 2019.  6.90  10.2   NaN   NaN 0.233
```

Appendix Figure 21: Accuracy results ARIMA vs ETS