Forecast Team Assignment

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Introduction and Company Overview

Starbucks, founded in 1971 in Seattle, expanded under Howard Schultz, who joined in 1982 and later acquired Starbucks through his II Giornale company in 1987. By 2020, Starbucks had grown to over 32,000 stores worldwide, despite a brief dip in 2009 due to the 2008 economic crisis. Initially focused on being the premier coffee purveyor, Starbucks' mission evolved to emphasize nurturing human connection. Their offerings include premium coffees, handcrafted beverages, fresh food, and consumer products such as ready-to-drink beverages, with brands like Seattle's Best Coffee, Teavana, and Evolution Fresh.

Variable One –> Active Starbucks Members

We chose active Starbucks loyalty rewards members as one metric as these patrons accounted for 60% of US retail store sales in the most recent quarter. Loyalty programs are associated with customer retention, increased customer lifetime value, and cost efficiencies (attracting new customers is more costly than retaining existing customers).

Variable Two –> Starbucks Revenue Worldwide

Revenue in billions is a critical metric for Starbucks as it directly reflects the company's financial health, operational efficiency, and global market strategy. Tracking revenue helps assess growth, compare performance across regions, and evaluate the success of new products or services. It also serves as a key indicator for investors, signaling the company's ability to provide returns, while offering a benchmark to measure competitiveness against rivals. Overall, revenue is vital for understanding Starbucks' market position and driving long-term success.

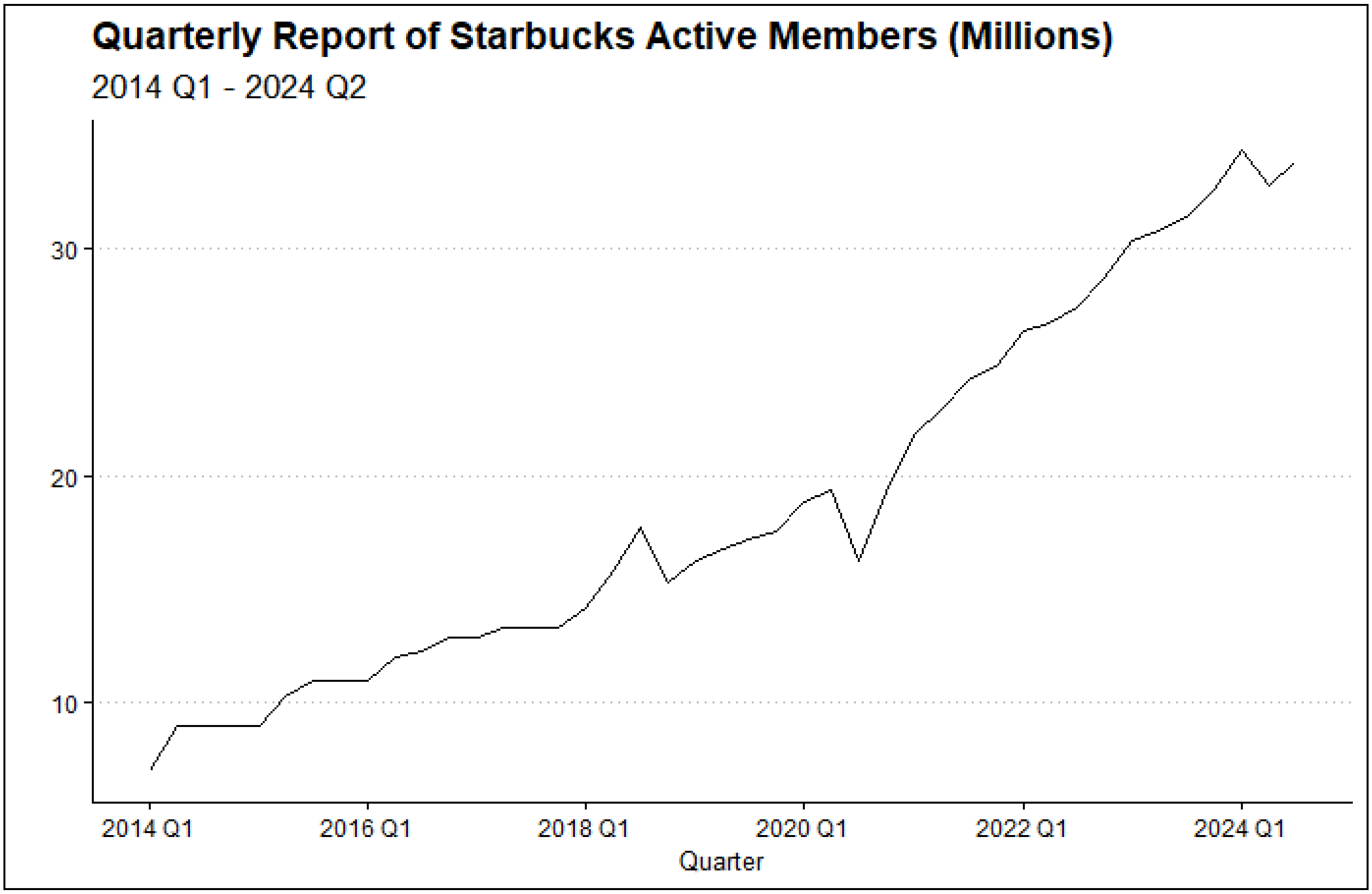
Data and Key Insights

Data Source:

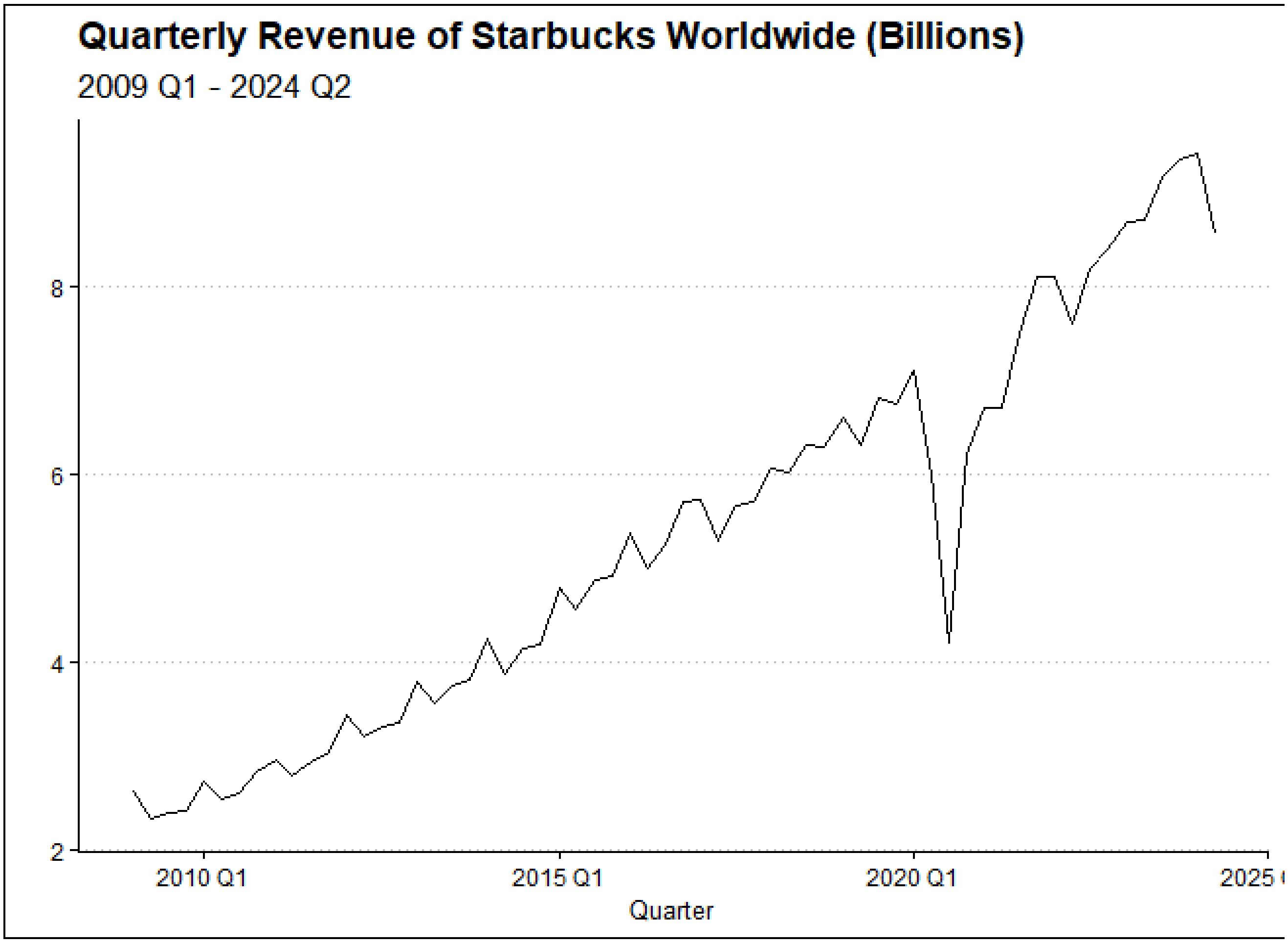
- Membership data for Starbucks' loyalty rewards program was gathered from quarterly earnings releases from Q1 2014 to Q3 2024. Due to unclear definitions in the program's early stages, null values were present, which we addressed using a fill function. This metric is defined as millions of 90-day active members in the United States.
- A dataset published by the Statistic Research Department held values for Quarterly revenue of Starbucks Corporation worldwide from 2009 to 2024.

Initial Observations:

- Upon initial graphing, we noticed in 2018 a steep growth of loyalty members, corresponding to a change in the rewards that increased the rate of point collection and expanded the products available to buy with points. This was followed by a drop in active members. A similar drop was observed that appears to align with the onset of the COVID-19 pandemic.



- The data reveals a consistent upward trend in revenue growth from 2014 to 2024, indicating steady business expansion over the years. However, there is a noticeable and sharp decline in late 2020, which likely corresponds to the global impact of the COVID-19 pandemic. This period was marked by widespread economic disruptions, store closures, and reduced consumer activity, all of which likely contributed to the drop in revenue.



Descriptive Statistics

Active Starbucks Members

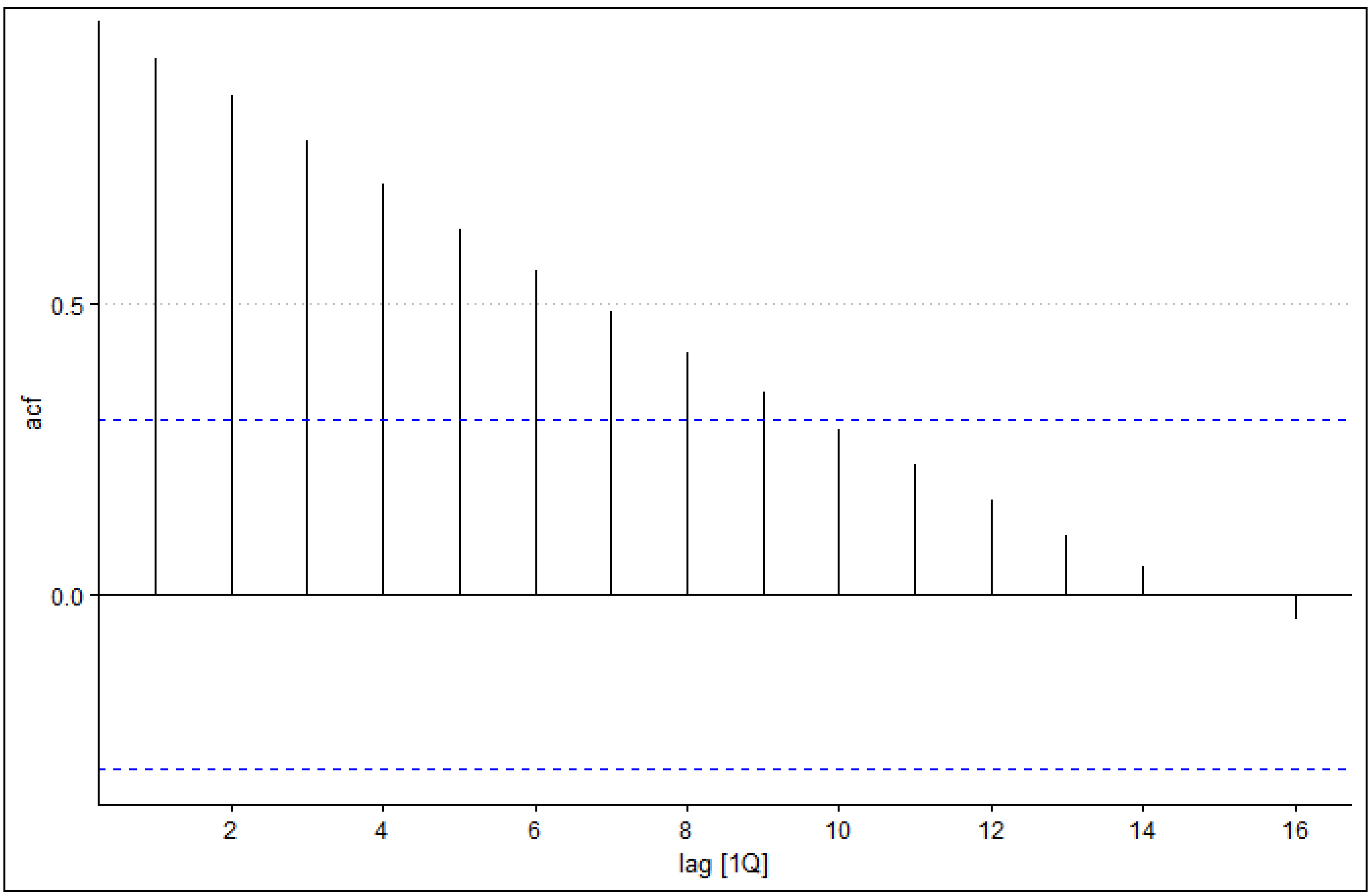
- The data shows that **TSLM2** is the best-performing model across most metrics, including RMSE, MAE, MAPE, and MASE, indicating it provides the most accurate forecasts with minimal bias. In contrast, the **MEAN** model performs the worst, with high errors across all measures. Other models like **ARIMA** and **ETS** also perform well but are slightly less accurate than TSLM2.

.model	.type	ME	RMSE	MAE	MPE	MAPE	MASE	RMSSE	ACF1
TSLM	Training	-2.597960e-16	1.832935	1.5103735	0.33342759	9.366051	0.5708255	0.5999021	0.7930631
TSLM2	Training	0.000000e+00	1.008239	0.6480697	-0.43075181	4.489716	0.2449293	0.3299870	0.4601636
ETS	Training	1.723473e-01	1.077787	0.8075985	-0.04374558	4.819610	0.3052211	0.3527496	0.2056388
ARIMA	Training	1.540853e-04	1.060347	0.7236907	-0.65574978	4.620282	0.2735092	0.3470416	-0.1207070
MEAN	Training	1.127782e-15	7.529960	6.3343248	-18.81267477	41.029091	2.3939736	2.4644844	0.9032065

- **TSLM2** is the best performer shown in the forecast model for the Active Members below, followed by TSLM, ARIMA, and ETS in increasing order of AIC and BIC values.

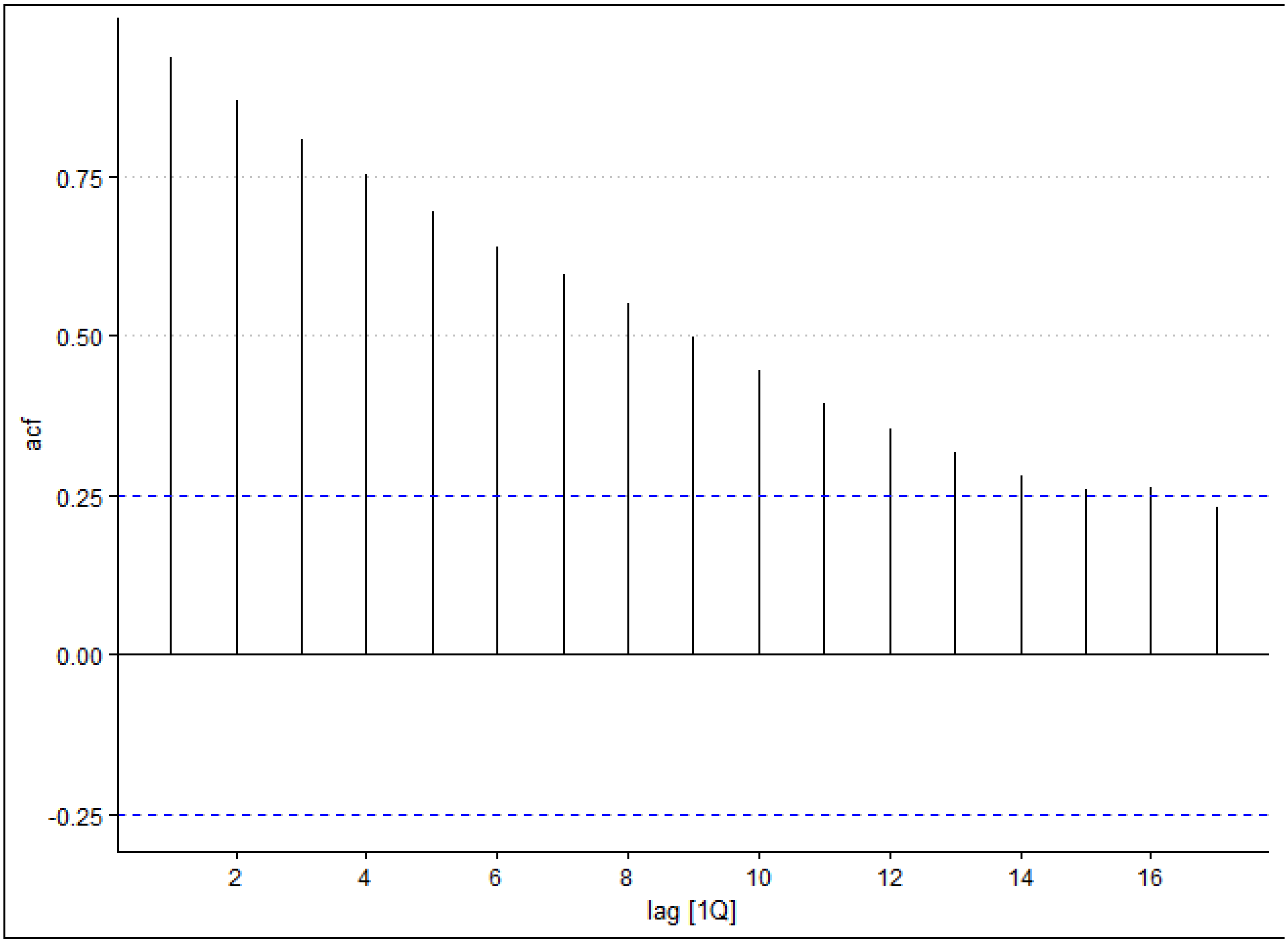
.model	AIC	AICc	BIC
TSLM	61.68530	64.15588	71.96673
TSLM2	14.67281	18.06675	26.66782
ETS	165.67972	167.39401	174.24758
ARIMA	123.19047	123.51479	126.56823

- The ACF analysis shows a strong correlation with the first lag, indicating that past income growth significantly influences the current growth of Active Members for Starbucks. This suggests that effective strategies from previous periods continue to drive member engagement and retention.



Starbucks Revenue Worldwide

- For the revenue, the mean is 5.32 billion per quarter, the median is $5.27 billion per quarter. The ACF graph also shows a strong positive trend in the monthly revenue. The annual spikes during the holiday season are primarily attributed to the popularity of Starbucks' festive beverages and food offerings.



- The table compares several forecasting models, with **ETS** performing the best overall, showing the lowest error rates across most metrics, including RMSE, MAE, MAPE, and MASE. **ARIMA** and **TSLM2** also perform well but are slightly less accurate. In contrast, the **MEAN** model performs the worst, with significantly higher errors, making it the least accurate. Overall, ETS is the most reliable model for minimizing forecast errors.

.model	.type	ME	RMSE	MAE	MPE	MAPE	MASE	RMSSE	ACF1
TSLM	Training	-1.819327e-17	0.4836542	0.2756551	-0.2206900	5.642110	0.4528053	0.5902243	0.63160489
TSLM2	Training	1.456563e-17	0.4494005	0.2467425	-0.6450426	4.764061	0.4053118	0.5484230	0.59561777
ETS	Training	7.556052e-02	0.4309528	0.2276928	0.6939597	4.244837	0.3740199	0.5259104	0.37535526
ARIMA	Training	-7.246430e-03	0.4379995	0.2889253	-1.3976489	5.930286	0.4746035	0.5345098	0.01761482
MEAN	Training	-1.379390e-16	2.0313090	1.7298791	-17.5716549	39.992497	2.8415881	2.4788947	0.92332556

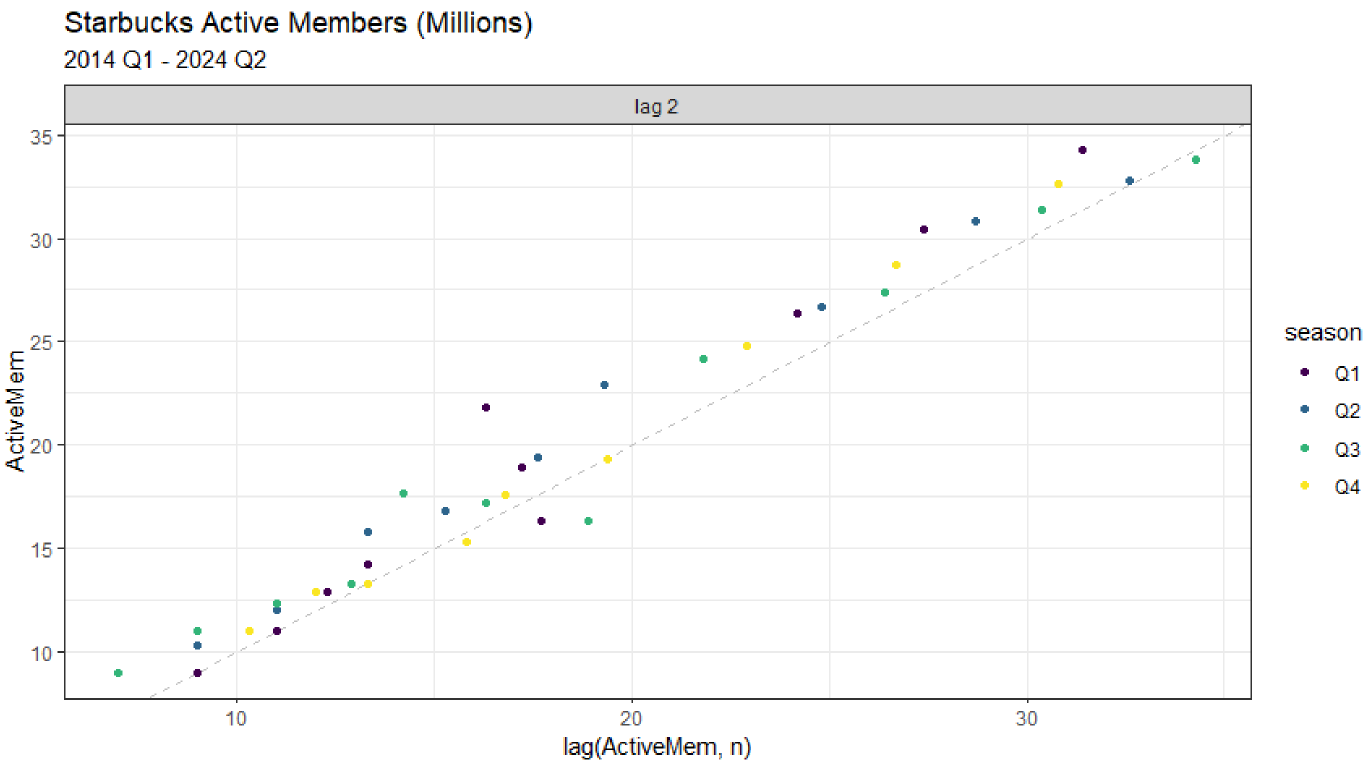
- In the forecast model for the revenue shown below, **TSLM2** is again the top performer, followed by TSLM, ARIMA, and ETS. Lower AIC, AICc, and BIC values indicate a better fit, making TSLM2 the most suitable for both datasets.

.model	AIC	AICc	BIC
TSLM	-76.61897	-75.06341	-63.95373
TSLM2	-83.58058	-81.46737	-68.80446
ETS	130.25884	133.78825	149.25671
ARIMA	80.53540	81.26267	88.91278

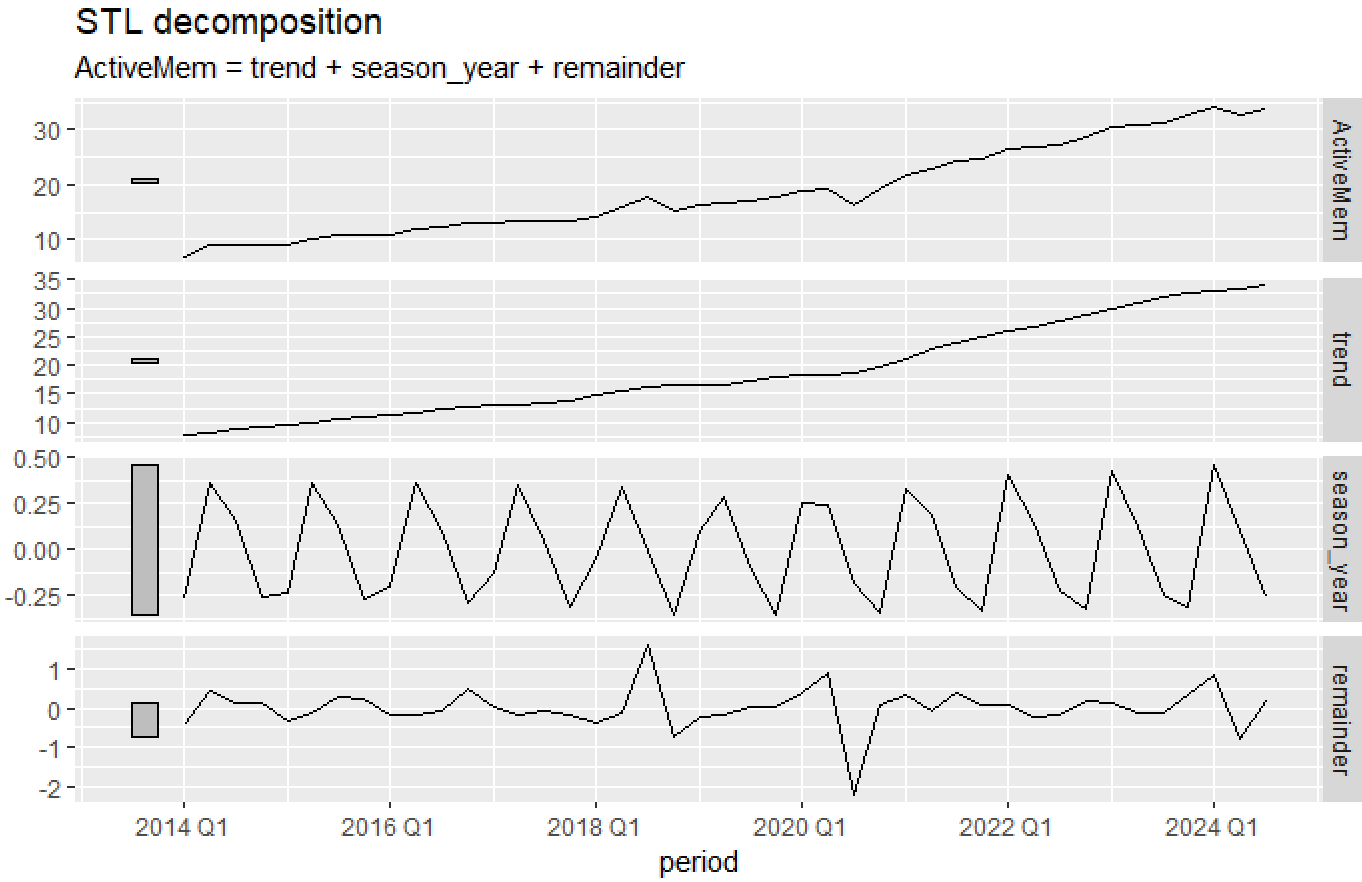
Visualizations

Active Starbucks Members

- In the lag plot, there is a strong linear relationship between the lagged values of Active Members, indicating a high level of autocorrelation, which suggests that previous values of the series are strongly predictive of future values.

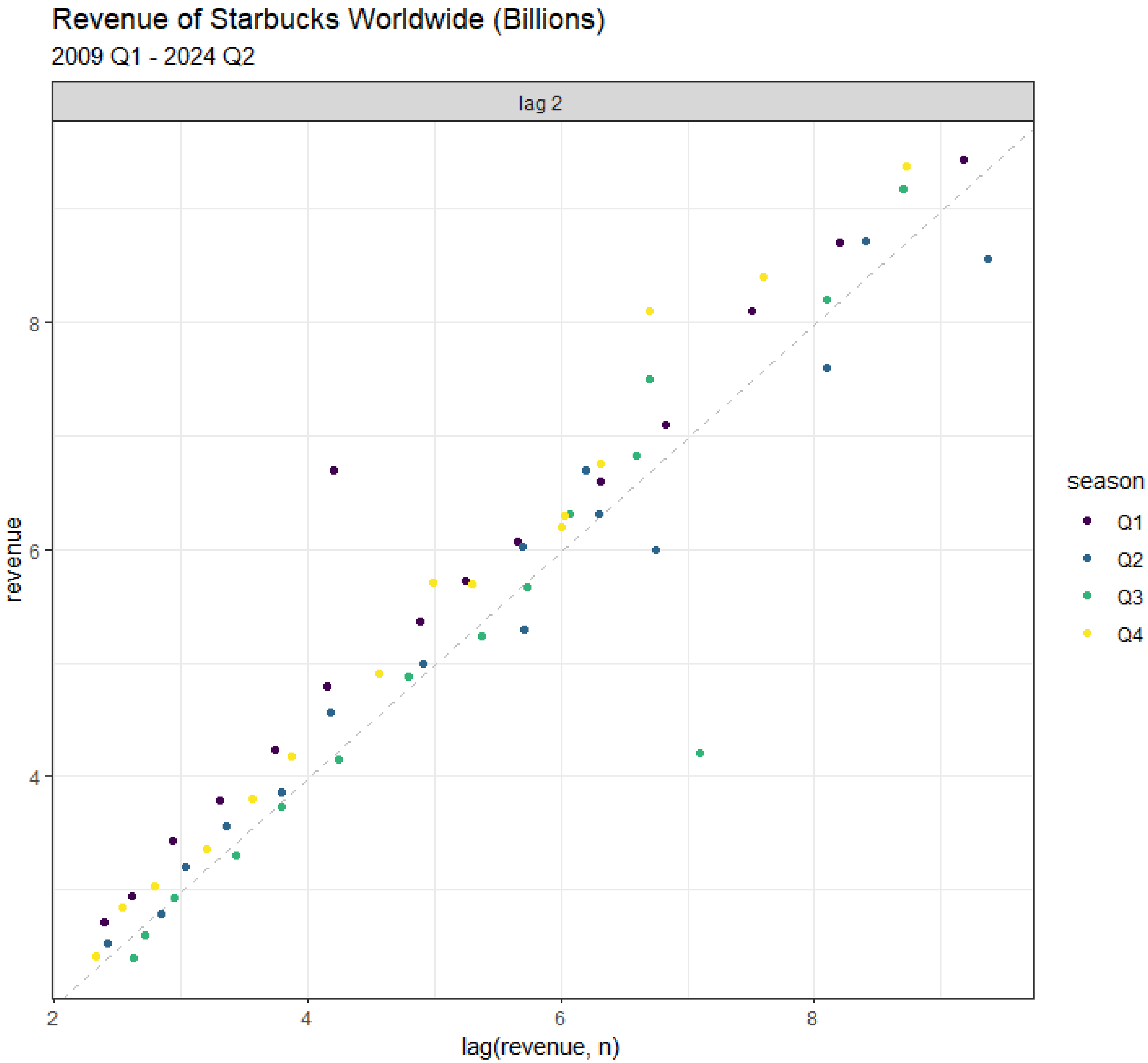


- The STL decomposition plot shows a clear upward trend in Active Starbucks Members over time, with a consistent seasonal pattern repeating each year, and relatively small random fluctuations (remainder).

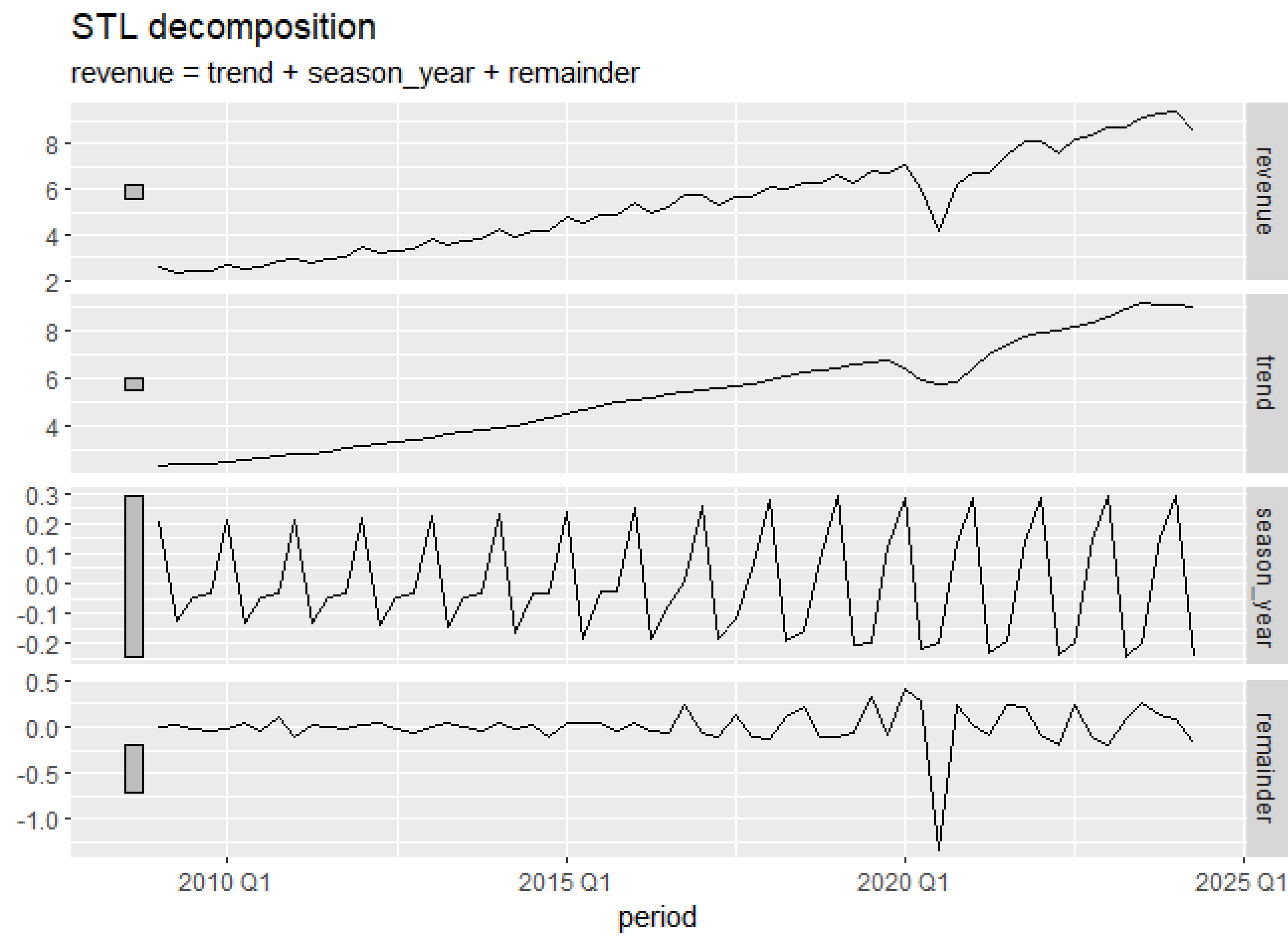


Starbucks Revenue Worldwide

- There is a strong positive correlation between the current month's revenue and the revenue from the two months prior as shown in the lag plot.



- The Seasonal Trend Decomposition shows an overall upward trend, along with regular seasonal fluctuations.



Forecasting Methodology

Forecasting Methods and Model Selection:

1. **ARIMA**: Models autocorrelations and trends in time series. Chosen due to clear autocorrelation in the data (seen in ACF and lag plots).

2. **ETS**: Uses exponential smoothing to model trend and seasonality. Selected because the data displayed strong seasonal patterns and a trend.

3. **TSLM (Linear Model)**: Models the time series as a function of trend and seasonality. Chosen for its simplicity and clear linear trend in the data.

4. **TSLM2 (Polynomial Trend)**: Extends TSLM by adding a quadratic trend. Used to capture slight non-linearity observed in the trend.

5. **Combination Model (ARIMA + ETS)**: Averages ARIMA and ETS forecasts for improved accuracy, balancing strengths of both models.

Justification:

Models were selected based on data characteristics (trend, seasonality, and autocorrelation) and evaluated using accuracy metrics (RMSE, MAE, AIC) to ensure the best fit. The combination model improved forecasting accuracy by blending ARIMA's handling of short-term dependencies with ETS's seasonal strength.

Process Overview

This is the outline of the steps taken for model fitting, data preprocessing, and validation for both the variables:

1. Data Preprocessing: - The dataset was converted into a tsibble for time series analysis and missing values in ActiveMem and revenue were filled. - Time-series data was visualized, highlighting a clear upward trend and seasonality.

2. Exploratory Data Analysis: - **Lag Plot and ACF**: Lag plots and ACF showed autocorrelation, suggesting that past values influence future trends. - **STL Decomposition**: Trend and seasonal components were extracted, confirming a strong seasonal pattern.

3. Model Fitting: - The dataset was split into training (up to 2024 Q1) and test sets (2024 Q2). - Models fitted included **TSLM**, **TSLM2**, **ETS**, and **ARIMA** to capture trend and seasonality. - **Combination Model**: A weighted combination of ARIMA and ETS was also created for improved accuracy.

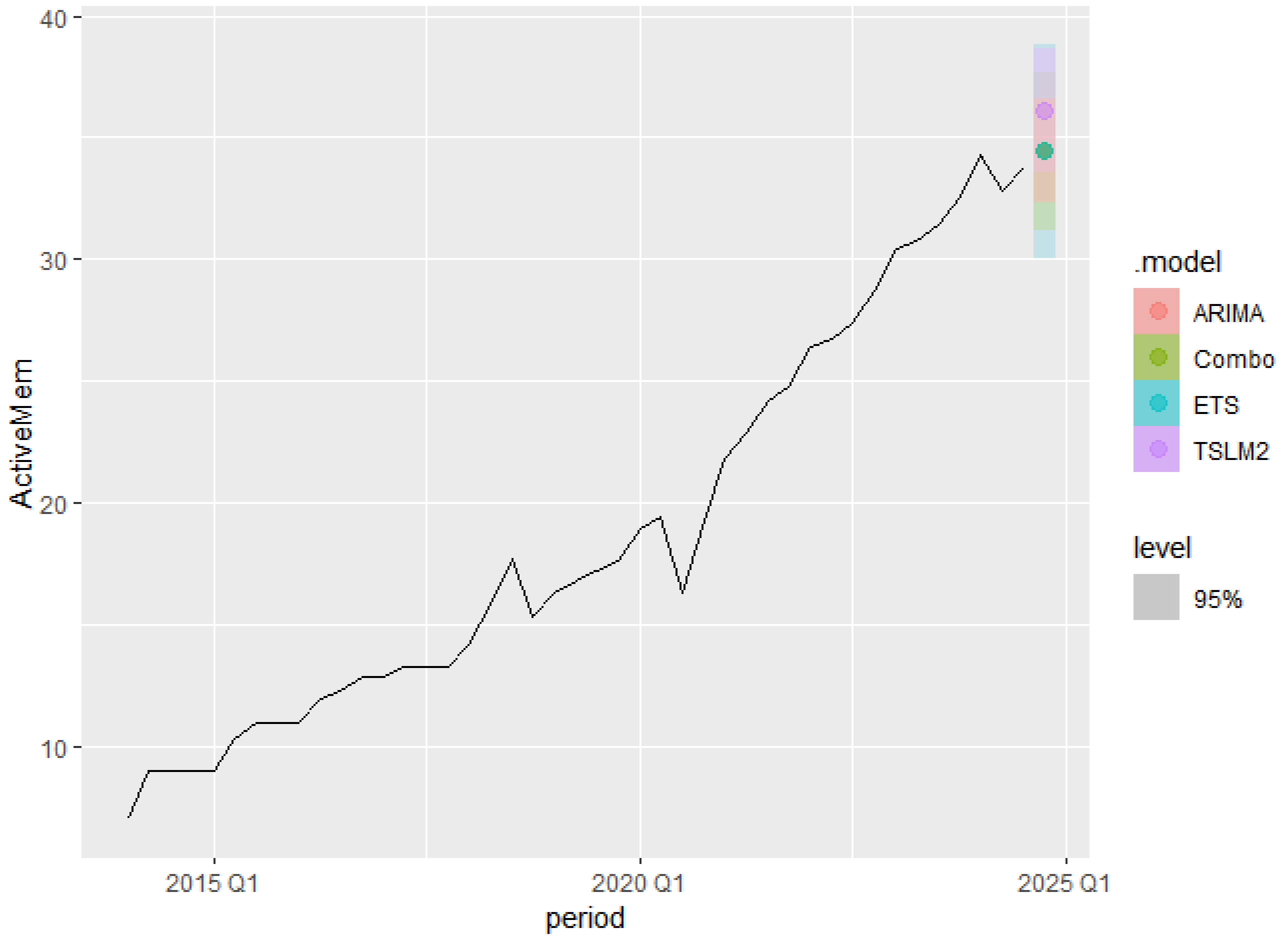
4. Model Validation: - Model performance was evaluated using RMSE, MAE, MAPE, and information criteria (AIC, AICc, BIC). - Residuals were checked to ensure no autocorrelation or patterns remained.

5. Forecasting: - The models were used to forecast Q2 2024 active members and validate against test data. - Forecasts were visualized with 95% confidence intervals, highlighting predicted trends and uncertainty.

Results and Business Impact

Active Starbucks Members

- The forecast graph shows the number of Active Starbucks Members will estimated to increase to around 35 million in the next quarter.



Loyalty Program

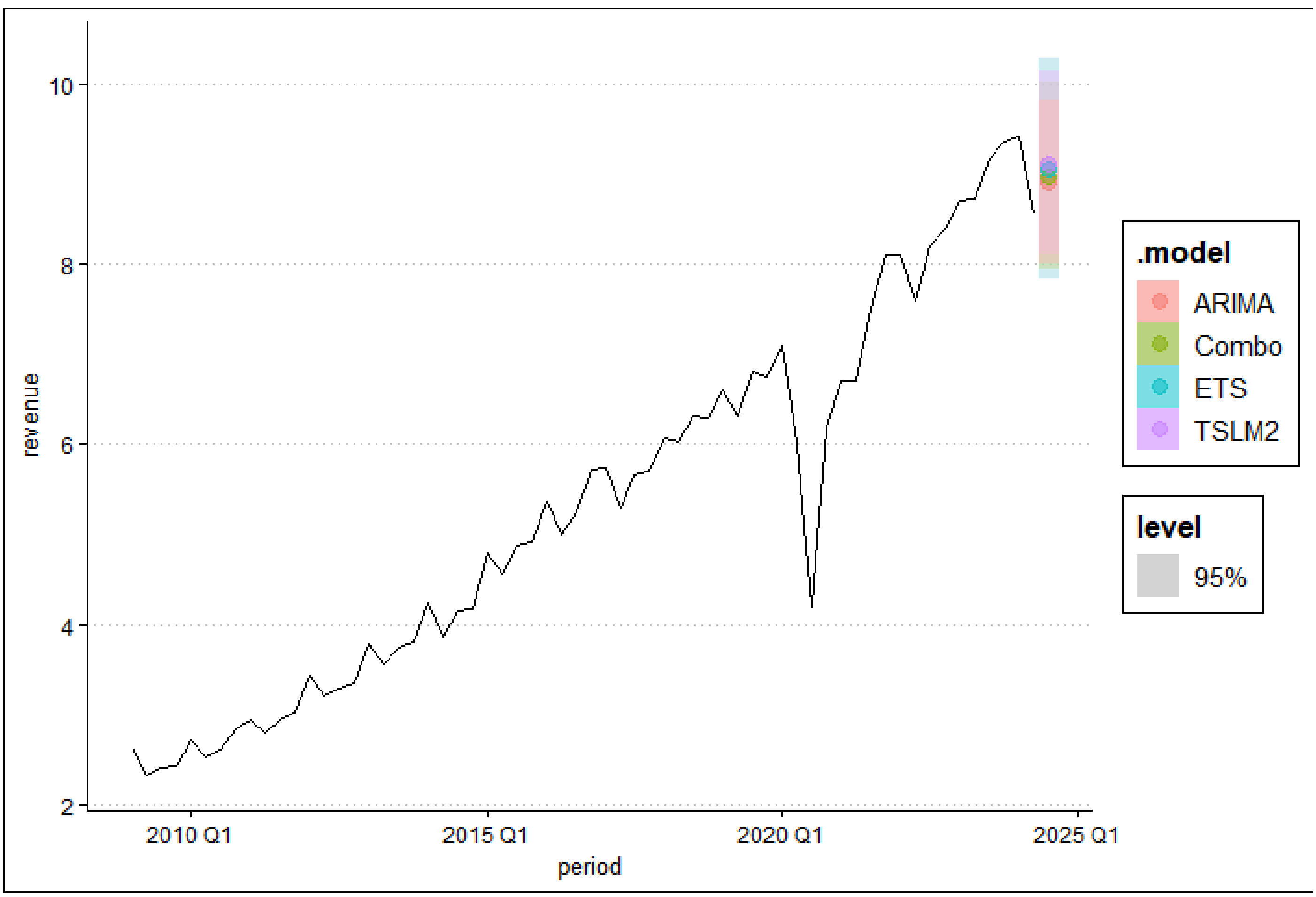
	Q3 FY22	Q4 FY22	Q1 FY23	Q2 FY23	Q3 FY23	Q4 FY23	Q1 FY24	Q2 FY24	Q3 FY24
# of 90-Day Active Members (M) (U.S. Only)	27.4	28.7	30.4	30.8	31.4	32.6	34.3	32.8	33.8
Starbucks Rewards Member Spend % of Tender - Dollars (U.S. Company-Operated Retail Stores Only)	53%	55%	56%	57%	57%	57%	59%	59%	60%

Forecasting of Starbucks rewards loyalty members has clear implications for the business as seen by the percent of sales linked to loyalty rewards accounts. Active rewards members are making purchases and are increasingly a higher proportion of sales dollars. Due to this metric only being reported for the past 9 quarters, we decided to focus on total loyalty members rather than loyalty member spend as a percent of sales. Upon further investigation, we identified the dips in active loyalty reward members were associated with changes to the loyalty reward program. Most recently in February 2023, Starbucks increased the amount of stars (points) required to redeem free items. Future analysis is warranted on how much time needs to pass after a change to the program before engagement resurges. In our worse-case scenario based on our best model (TSLM2), we are confident reduction in loyalty members over the next quarter would be less than 250K (0.74% of current members). Using the same model, the best-case scenario estimates a growth of 4.88M loyalty members over the next quarter (14.44% increase).

.model	period	ActiveMem	.mean	95%
TSLM2	2024 Q4	N(36, 1.7)	36.12377	[33.5620072452269, 38.6855281786987]95
ARIMA	2024 Q4	N(34, 1.2)	34.47999	[32.3329685254417, 36.6270201045087]95
ETS	2024 Q4	N(34, 5)	34.42975	[30.0623930833085, 38.7971078602038]95
Combo	2024 Q4	N(34, 2.7)	34.45487	[31.2080532933766, 37.7016914933547]95

Starbucks Revenue Worldwide

Revenue forecasting is a vital for a company's financial planning and decision making. Accurate forecasts allow for effective budgeting and can allow Starbucks to properly allocate it's resources and wisely invest in growth opportunities and expand it's market. When forecasts indicate potential shortfalls, Starbucks can properly implement cost-cutting measures and reevaluate their strategies to enhance efficiency and increase profits. As seen on the graph, our model estimates that the 2024 Q3 revenue will be 8.9 billion dollars.



In order to select a model to best forecast Starbucks' quarterly revenue. We looked at a number of different model fitting accuracy tests. The ETS model best captured our training data in terms of model accuracy, with the lowest RMSE, MAE, MAPE, MASE, and RMSEE values. Based on other commonly used measures of goodness of fit and model accuracy, the TSLM2 model best balances model complexity and fit with the lowest AIC, AICc and BIC scores. However, the model with the lowest Winkler score was the ARIMA. The model we chose to forecast our revenue was the ARIMA due to it having the lowest Winkler score. We decided that because the ARIMA model forecast best aligned with the actual observed values taking into account magnitude and direction of errors. We wanted to penalize large errors more heavily due to the financial implications of an incorrect forecast with large errors.

.model	.type	winkler
ARIMA	Test	1.776148
ETS	Test	2.590697
TSLM	Test	2.094924
TSLM2	Test	2.044642

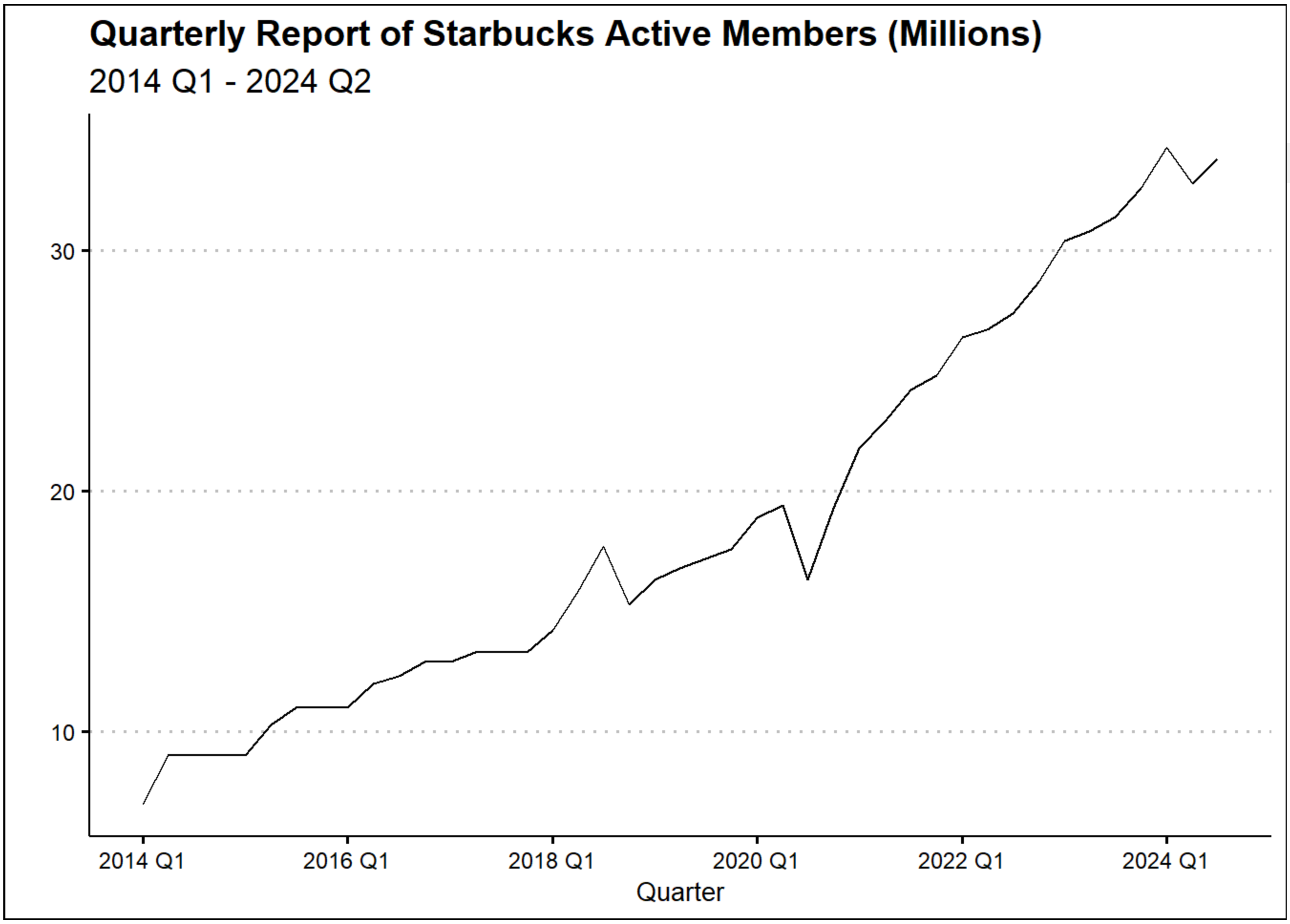
Code

```
rm(list=ls())
suppressPackageStartupMessages({
     library(tidyverse)
     library(fpp3)
     library(ggthemes)
     library(gt)
     library(gtable)})

star<-read_csv("C:/Users/bekfr/OneDrive/Desktop/SM/STAR.csv")
```

```
Rows: 43 Columns: 2
── Column specification ────────────────────────────────────────────────────────
Delimiter: ","
chr (1): period
dbl (1): ActiveMem

ℹ Use `spec()` to retrieve the full column specification for this data.
ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

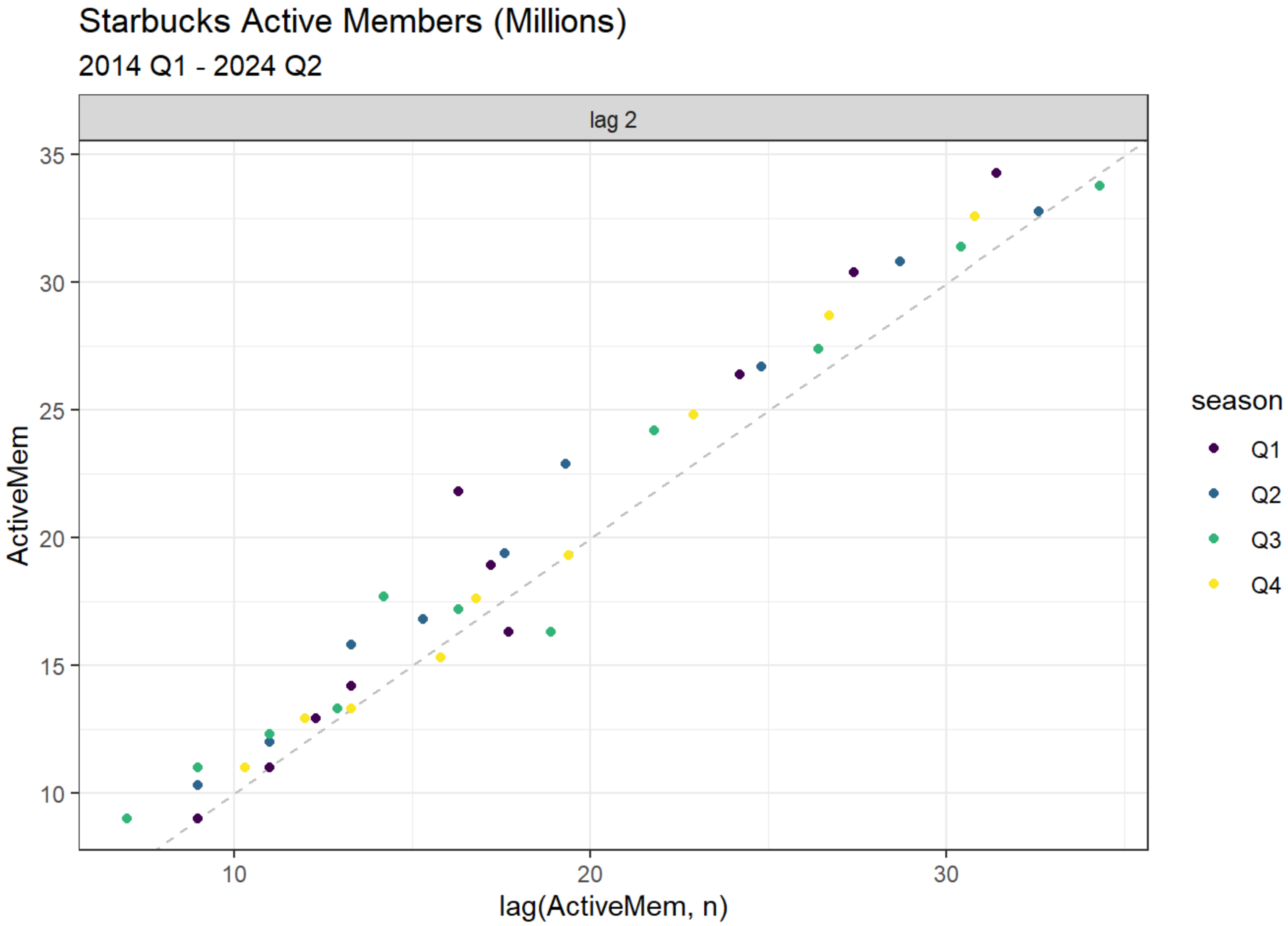
```
star %>%
     mutate(period=yearquarter(period)) %>%
     as_tsibble(index=period) %>%
     fill(ActiveMem, .direction = "up")-> star_ts
```

```
star_ts %>% autoplot(ActiveMem) + theme_clean() + labs(title="Quarterly Report of Starbucks Activ
```

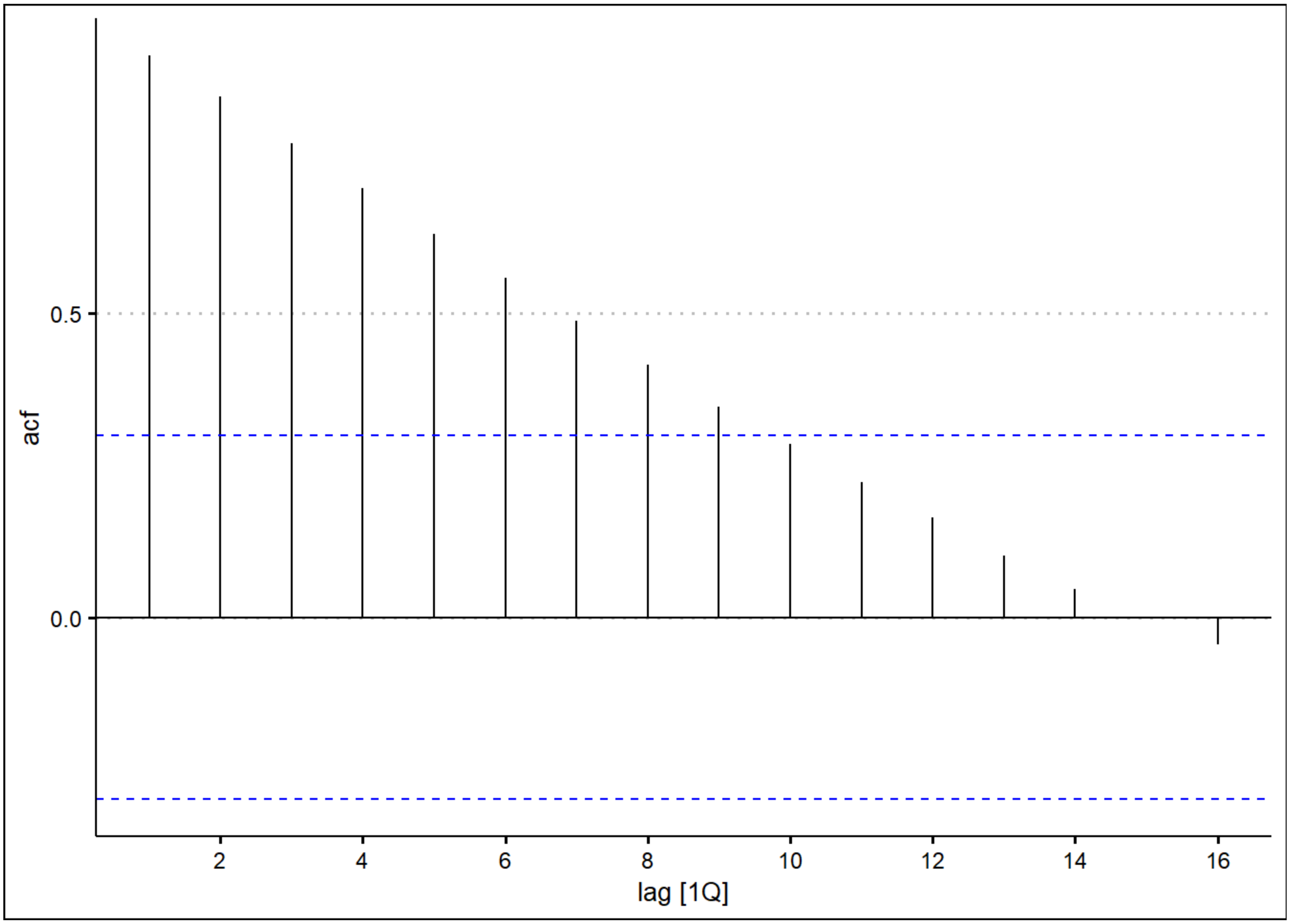



```
star_ts %>% gg_lag(lags=2, geom="point") + theme_bw() + labs(title="Starbucks Active Members (Mil
```

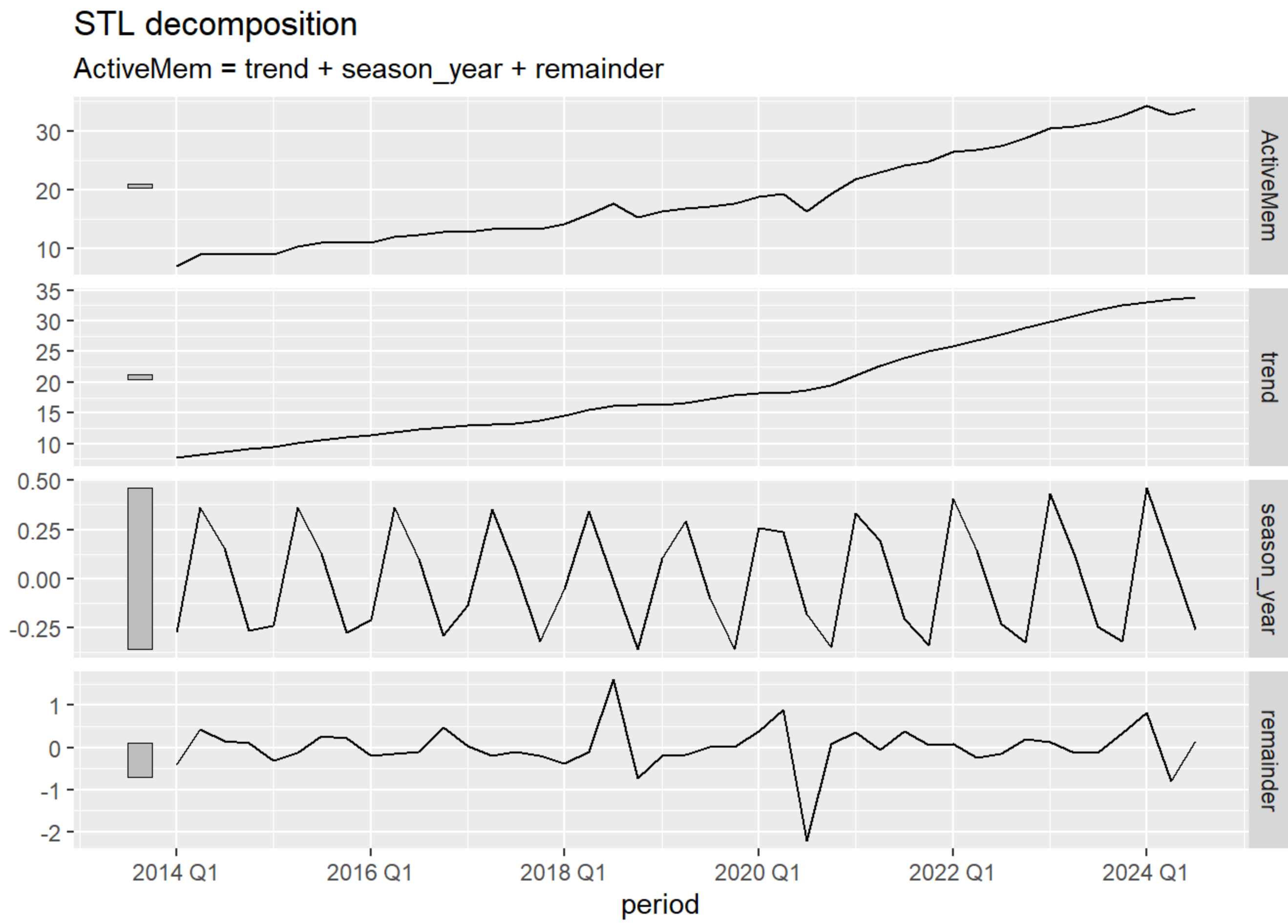
```
Plot variable not specified, automatically selected `y = ActiveMem`
```




```
star_ts %>% ACF(ActiveMem) %>% autoplot() + theme_clean()
```




```
star_ts %>% model(STL(ActiveMem~trend()+season())) %>%
    components() %>% autoplot()
```




```
star_ts %>% filter_index(.~"2024 Q1") -> train_s
star_ts %>% filter_index("2024 Q2") -> test_s

train_s %>% model(TSLM=TSLM(ActiveMem~trend()+season()),
                TSLM2=TSLM(ActiveMem~trend()+ I(trend()^2) + season()),
                ETS=ETS(ActiveMem),
                ARIMA=ARIMA(ActiveMem)) -> fit_star


train_s %>% model(TSLM=TSLM(ActiveMem~trend()+season()),
                  TSLM2=TSLM(ActiveMem~trend()+ I(trend()^2) + season()),
                  ETS=ETS(ActiveMem),
                  ARIMA=ARIMA(ActiveMem),
                  MEAN=MEAN(ActiveMem)) -> fit_star_mean


fit_star_mean %>% accuracy() %>% gt()
```

.model	.type	ME	RMSE	MAE	MPE	MAPE	MASE	R
TSLM	Training	-2.597960e-16	1.832935	1.5103735	0.33342759	9.366051	0.5708255	0.59
TSLM2	Training	0.000000e+00	1.008239	0.6480697	-0.43075181	4.489716	0.2449293	0.32
ETS	Training	1.723473e-01	1.077787	0.8075985	-0.04374558	4.819610	0.3052211	0.35
ARIMA	Training	1.540853e-04	1.060347	0.7236907	-0.65574978	4.620282	0.2735092	0.34
MEAN	Training	1.127782e-15	7.529960	6.3343248	-18.81267477	41.029091	2.3939736	2.46

```
fit_star %>%  accuracy() %>% gt()
```

.model	.type	ME	RMSE	MAE	MPE	MAPE	MASE	RM
TSLM	Training	-2.597960e-16	1.832935	1.5103735	0.33342759	9.366051	0.5708255	0.5999
TSLM2	Training	0.000000e+00	1.008239	0.6480697	-0.43075181	4.489716	0.2449293	0.3299
ETS	Training	1.723473e-01	1.077787	0.8075985	-0.04374558	4.819610	0.3052211	0.3527
ARIMA	Training	1.540853e-04	1.060347	0.7236907	-0.65574978	4.620282	0.2735092	0.3470

```
fit_star %>% glance() %>%
    select('.model',"AIC","AICc","BIC") %>% gt()
```

.model	AIC	AICc	BIC
TSLM	61.68530	64.15588	71.96673
TSLM2	14.67281	18.06675	26.66782
ETS	165.67972	167.39401	174.24758
ARIMA	123.19047	123.51479	126.56823

```
fit_star %>% forecast(test_s) %>%
     accuracy(star_ts, list(winkler = winkler_score)) %>% gt()
```

.model	.type	winkler
ARIMA	Test	6.327148
ETS	Test	8.858461
TSLM	Test	8.345539
TSLM2	Test	4.940277

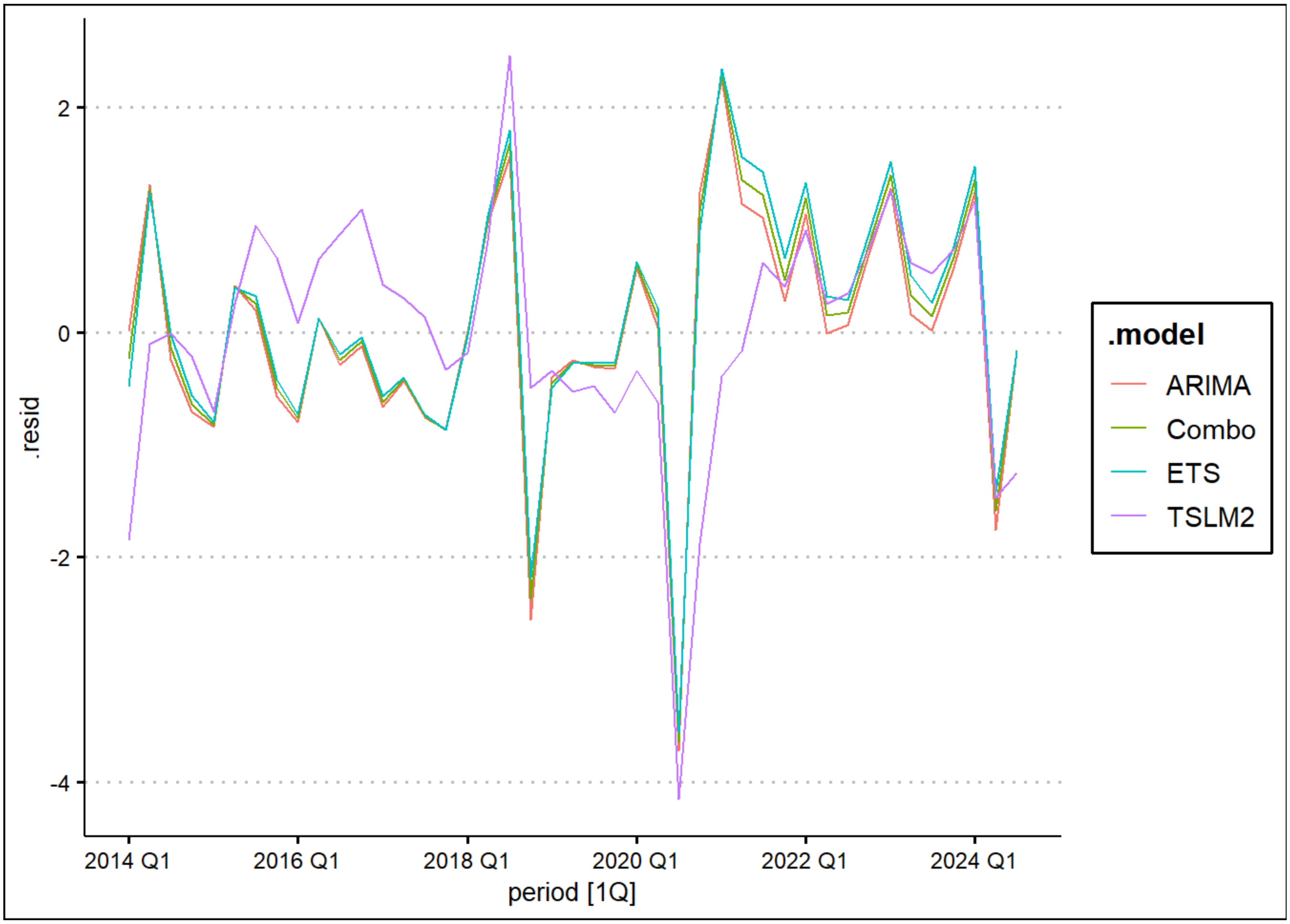
```
star_ts %>% stretch_tsibble(.init = 20, .step=1) %>%
     model(TSLM=TSLM(ActiveMem~trend()+season()),
           TSLM2=TSLM(ActiveMem~trend()+ I(trend()^2) + season()),
           ARIMA=ARIMA(ActiveMem),
           ETS=ETS(ActiveMem)) %>%
     mutate(Combo=0.5*ARIMA+0.5*ETS) %>%
     forecast(h=1) %>%
     accuracy(star_ts) %>% gt()
```

```
Warning: The future dataset is incomplete, incomplete out-of-sample data will be treated as
missing.
1 observation is missing at 2024 Q4
```

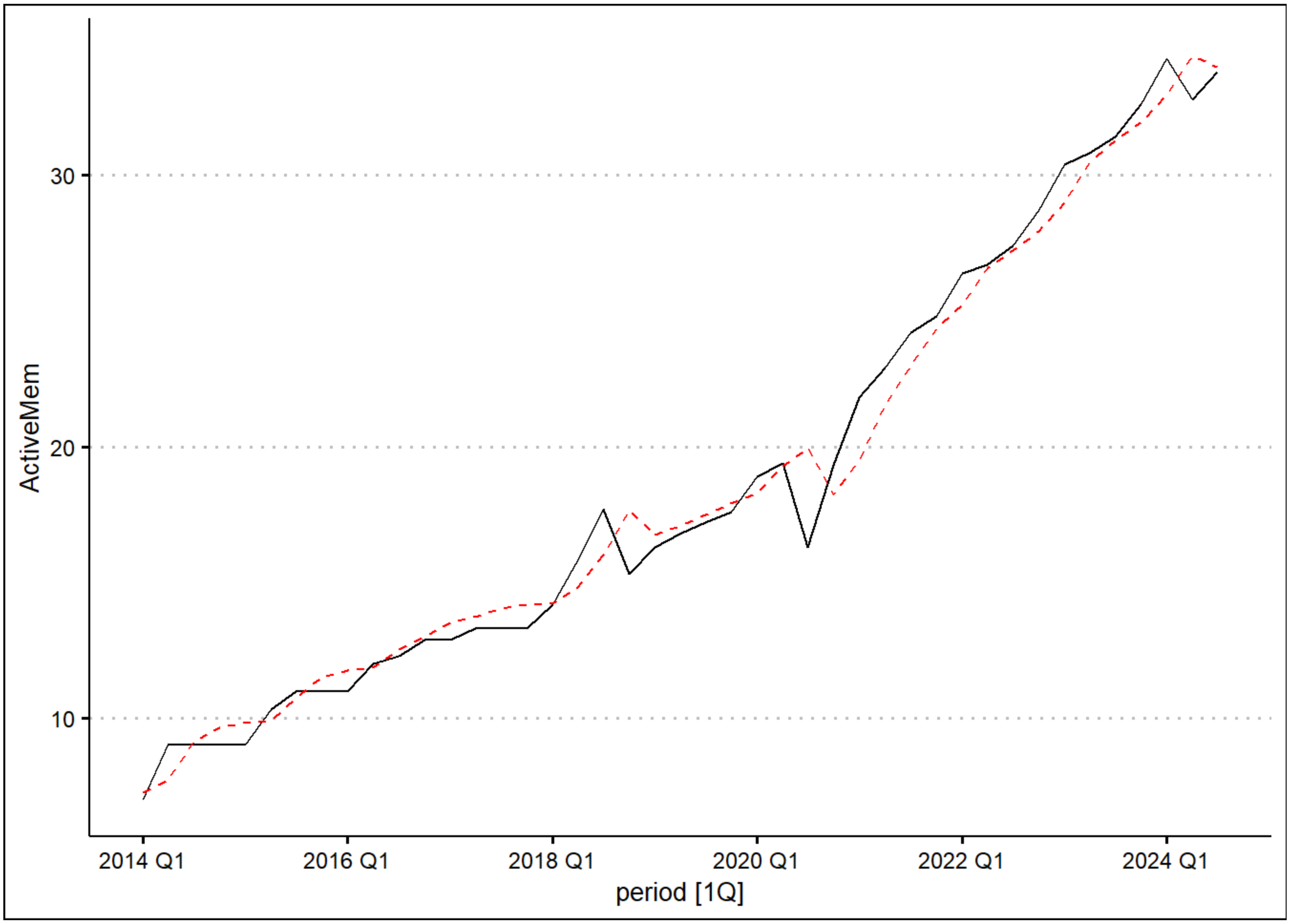
.model	.type	ME	RMSE	MAE	MPE	MAPE	MASE	RMSSE	
ARIMA	Test	0.2981025	1.324322	0.8640413	1.097886	3.842312	0.3293999	0.4388415	-0.24
Combo	Test	0.5000136	1.322418	0.9711539	1.774998	4.174499	0.3702346	0.4382105	0.14
ETS	Test	0.7019246	1.549281	1.1740721	2.452110	4.914395	0.4475935	0.5133864	0.49
TSLM	Test	1.9404881	2.707928	2.3295308	6.548657	8.909016	0.8880909	0.8973281	0.70
TSLM2	Test	0.5577506	1.636992	1.3270034	2.029398	5.648210	0.5058957	0.5424513	0.44

```
star_ts %>% model(TSLM2=TSLM(ActiveMem~trend()+ I(trend()^2) + season()),
                  ARIMA=ARIMA(ActiveMem),
                  ETS=ETS(ActiveMem)) %>%
     mutate(Combo=0.5*ARIMA+0.5*ETS) -> fit2_s
```

```
fit2_s %>% augment() -> resids2_s

resids2_s %>% autoplot(.resid) + theme_clean()
```



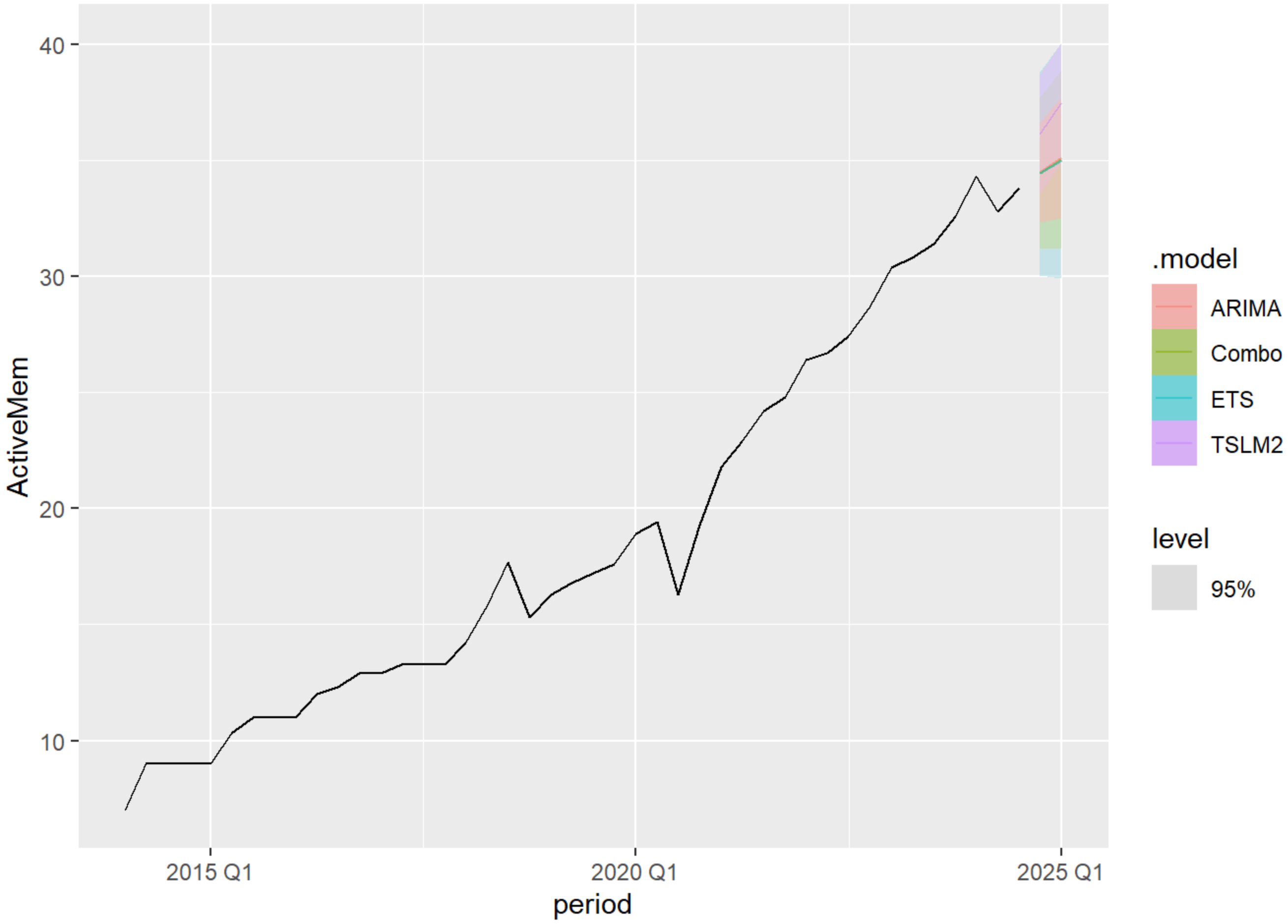

```
star_ts %>% autoplot(ActiveMem) +
    autolayer(resids2_s %>% filter(.model=="Combo"),.fitted,
              lty=2,col="red") +
    theme_clean()
```




```
fit2_s %>% forecast(h=1) %>% hilo(level=95) %>% gt()
```

.model	period	ActiveMem	.mean	95%
TSLM2	2024 Q4	N(36, 1.7)	36.12377	[33.5620072452269, 38.6855281786987]95
ARIMA	2024 Q4	N(34, 1.2)	34.47999	[32.3329685254417, 36.6270201045087]95
ETS	2024 Q4	N(34, 5)	34.42975	[30.0623930833085, 38.7971078602038]95
Combo	2024 Q4	N(34, 2.7)	34.45487	[31.2080532933766, 37.7016914933547]95

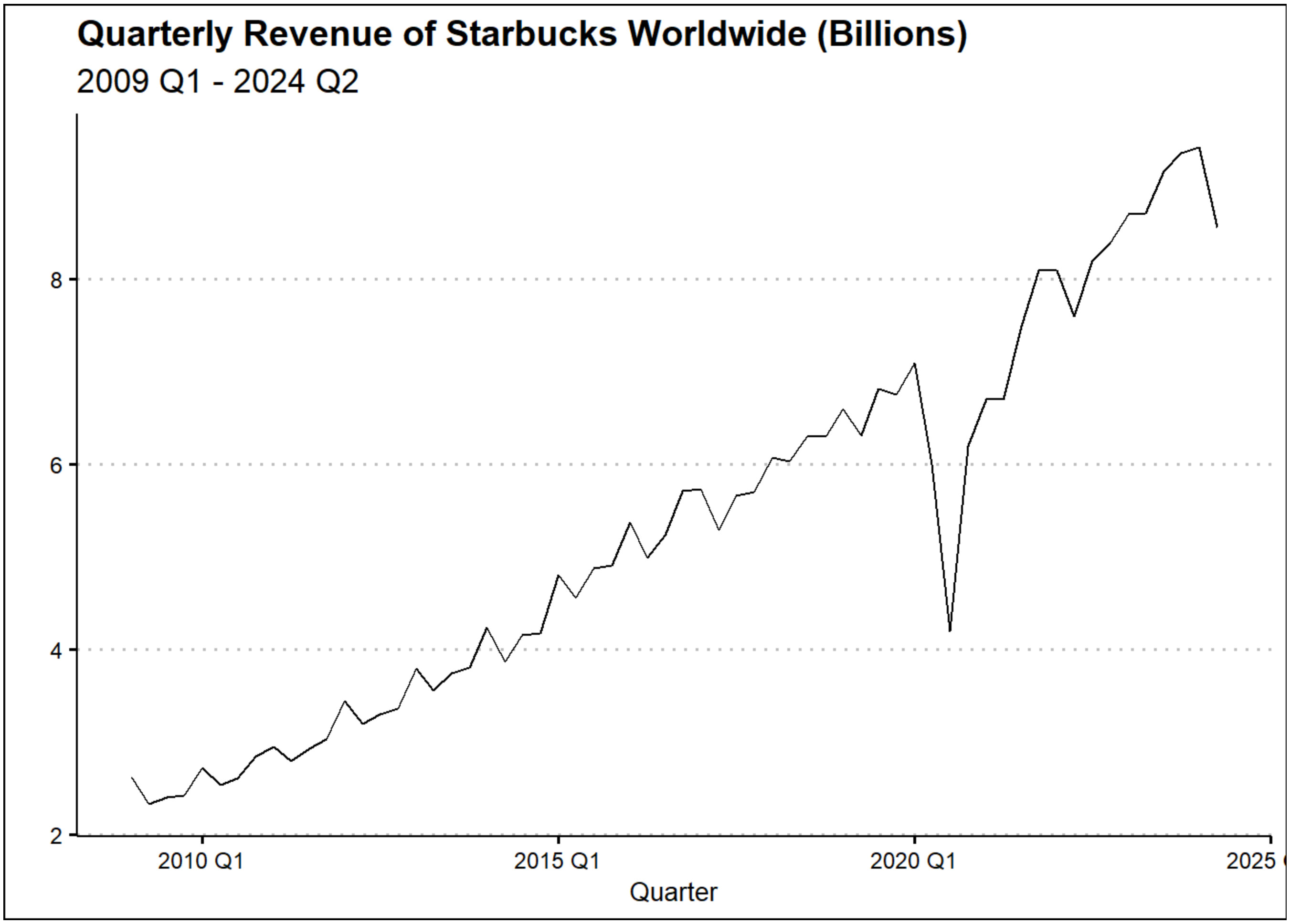
```
fit2_s %>% forecast(h=2) %>% autoplot(level=95, fill = "lightblue", alpha = 0.5) +
    autolayer(star_ts, ActiveMem)
```




```
# Variable 2 - Quarterly revenue worldwide
rev <- read_csv("C:/Users/bekfr/OneDrive/Desktop/SM/starbucksrev.csv")
```

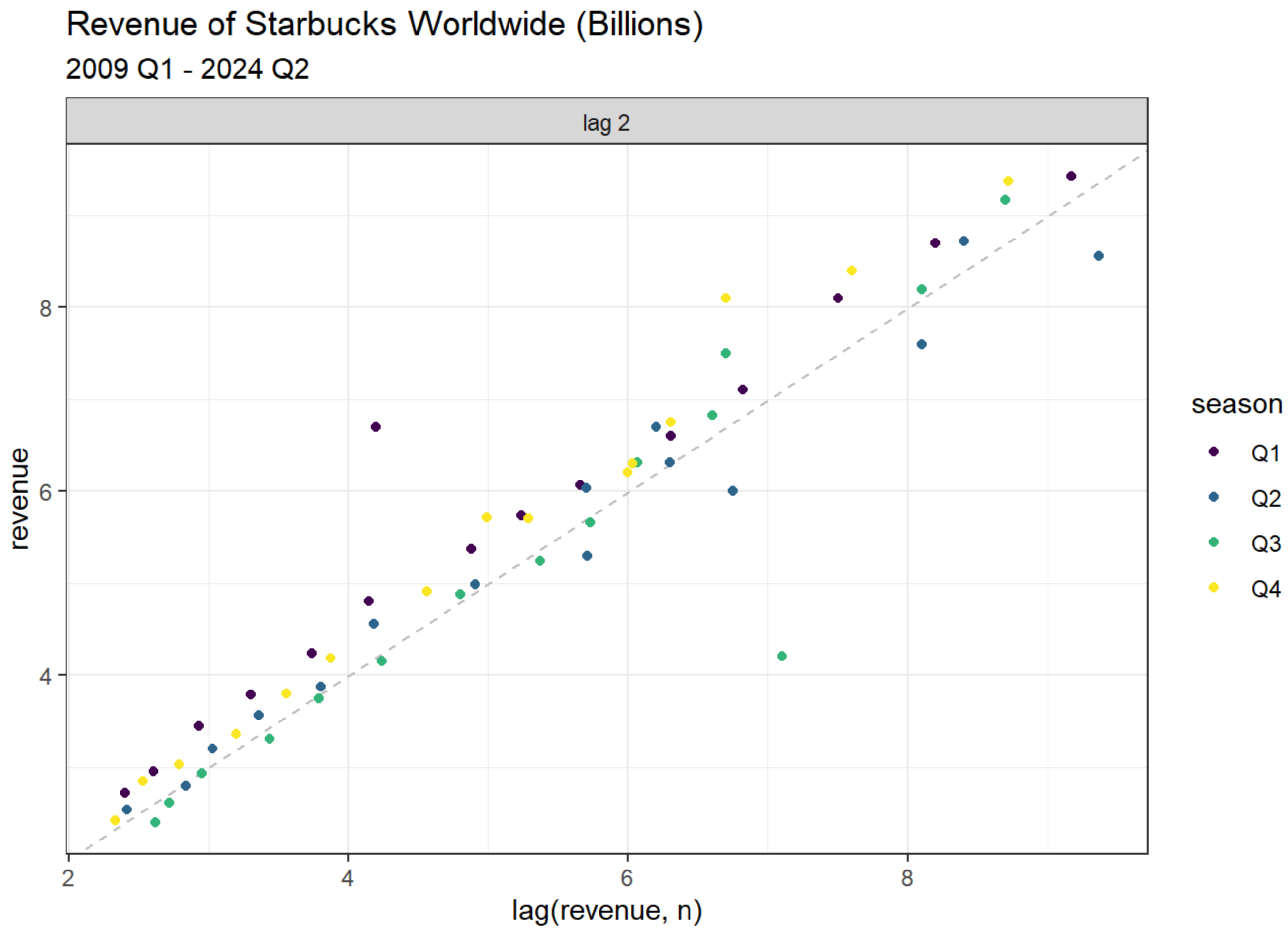
```
New names:
Rows: 62 Columns: 6
── Column specification
──────────────────────────────────────────────────────── Delimiter: "," chr
(1): period dbl (1): revenue lgl (4): ...3, ...4, ...5, ...6
ℹ Use `spec()` to retrieve the full column specification for this data. ℹ
Specify the column types or set `show_col_types = FALSE` to quiet this message.
• `` -> `...3`
• `` -> `...4`
• `` -> `...5`
• `` -> `...6`
```

```
rev %>% select(period, revenue) %>%
     mutate(period = yearquarter(period)) %>%
     as_tsibble(index=period) -> rev_ts

rev_ts %>% autoplot(revenue) + theme_clean() +
     labs(title="Quarterly Revenue of Starbucks Worldwide (Billions)", subtitle="2009 Q1 - 2024 Q
```

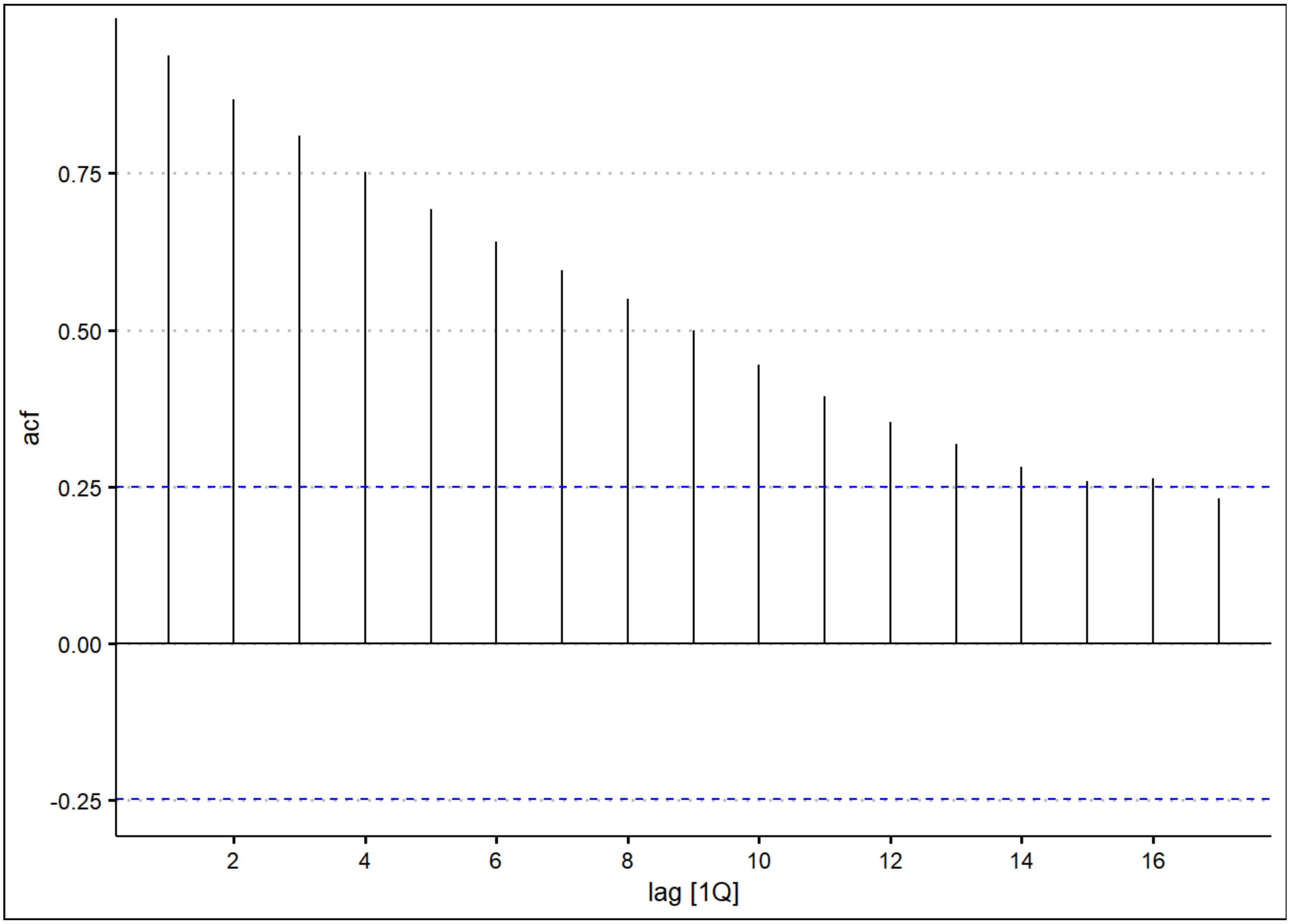



```
rev_ts %>% gg_lag(lags=2, geom="point") + theme_bw() + labs(title="Revenue of Starbucks Worldwide
```

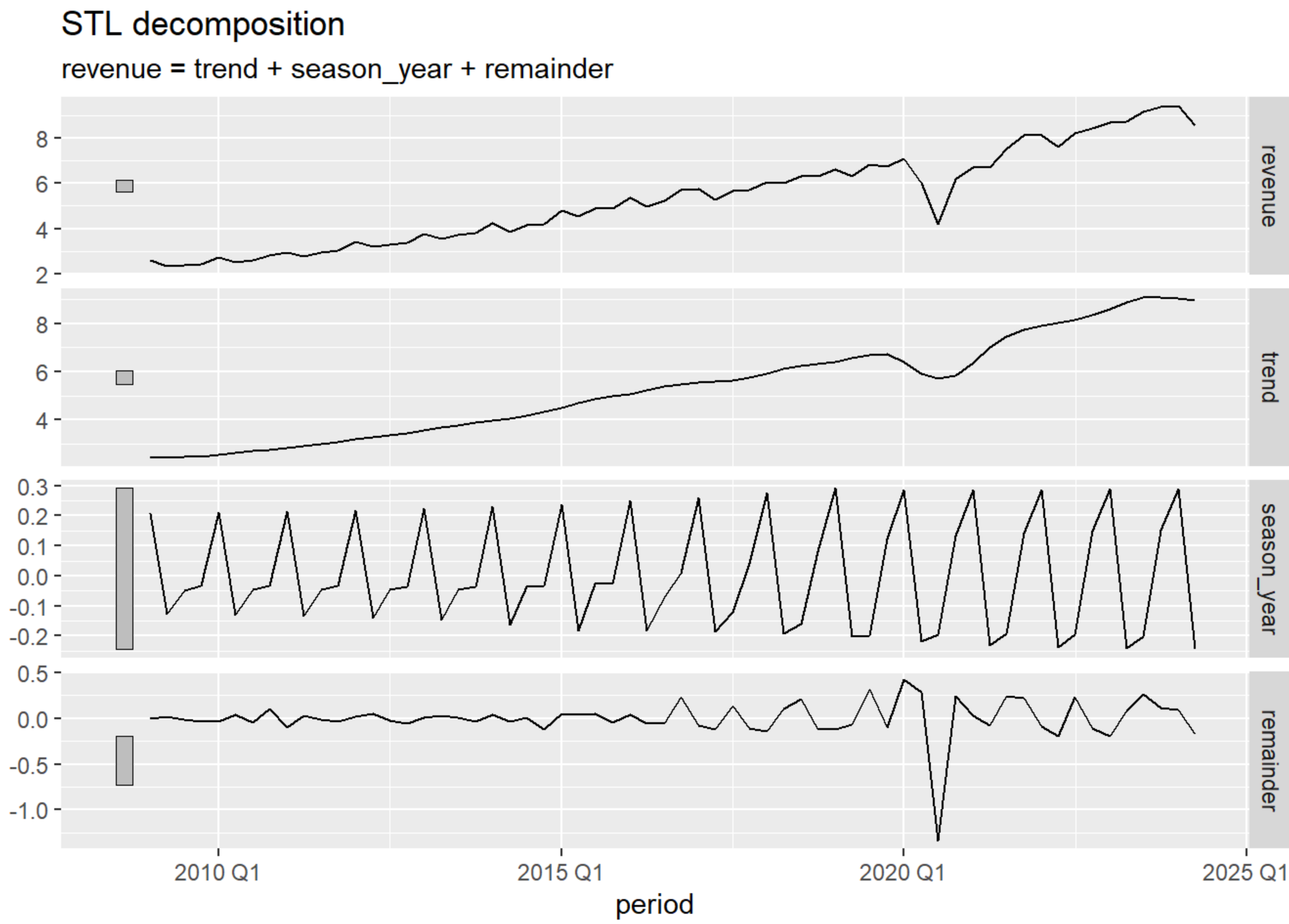
```
Plot variable not specified, automatically selected `y = revenue`
```




```
rev_ts %>% ACF(revenue) %>% autoplot() + theme_clean()
```




```r
rev_ts %>% model(STL(revenue~trend()+season())) %>%
     components() %>% autoplot()
```




```
rev_ts %>% filter_index(.~"2024 Q1") -> train_r
rev_ts %>% filter_index("2024 Q2") -> test_r

train_r %>% model(TSLM=TSLM(revenue~trend()+season()),
                  TSLM2=TSLM(revenue~trend()+ I(trend()^2) + season()),
                  ETS=ETS(revenue),
                  ARIMA=ARIMA(revenue)) -> fit_rev

train_r %>% model(TSLM=TSLM(revenue~trend()+season()),
                  TSLM2=TSLM(revenue~trend()+ I(trend()^2) + season()),
                  ETS=ETS(revenue),
                  ARIMA=ARIMA(revenue),
                  MEAN=MEAN(revenue)) -> fit_rev_mean

fit_rev_mean %>% accuracy() %>% gt()
```

.model	.type	ME	RMSE	MAE	MPE	MAPE	MASE	RM
TSLM	Training	-1.819327e-17	0.4836542	0.2756551	-0.2206900	5.642110	0.4528053	0.5902

.model	.type	ME	RMSE	MAE	MPE	MAPE	MASE	RM
TSLM2	Training	1.456563e-17	0.4494005	0.2467425	-0.6450426	4.764061	0.4053118	0.5484
ETS	Training	7.556052e-02	0.4309528	0.2276928	0.6939597	4.244837	0.3740199	0.5259
ARIMA	Training	-7.246430e-03	0.4379995	0.2889253	-1.3976489	5.930286	0.4746035	0.5345
MEAN	Training	-1.379390e-16	2.0313090	1.7298791	-17.5716549	39.992497	2.8415881	2.4788

```
fit_rev %>%  accuracy() %>% gt()
```

.model	.type	ME	RMSE	MAE	MPE	MAPE	MASE	RMSS
TSLM	Training	-1.819327e-17	0.4836542	0.2756551	-0.2206900	5.642110	0.4528053	0.590224
TSLM2	Training	1.456563e-17	0.4494005	0.2467425	-0.6450426	4.764061	0.4053118	0.548423
ETS	Training	7.556052e-02	0.4309528	0.2276928	0.6939597	4.244837	0.3740199	0.525910
ARIMA	Training	-7.246430e-03	0.4379995	0.2889253	-1.3976489	5.930286	0.4746035	0.534509

```
fit_rev %>% glance() %>%
     select('.model',"AIC","AICc","BIC") %>% gt()
```

.model	AIC	AICc	BIC
TSLM	-76.61897	-75.06341	-63.95373
TSLM2	-83.58058	-81.46737	-68.80446
ETS	130.25884	133.78825	149.25671

.model	AIC	AICc	BIC
ARIMA	80.53540	81.26267	88.91278

```
fit_rev %>% forecast(test_r) %>%
    accuracy(rev_ts, list(winkler = winkler_score)) %>% gt()
```

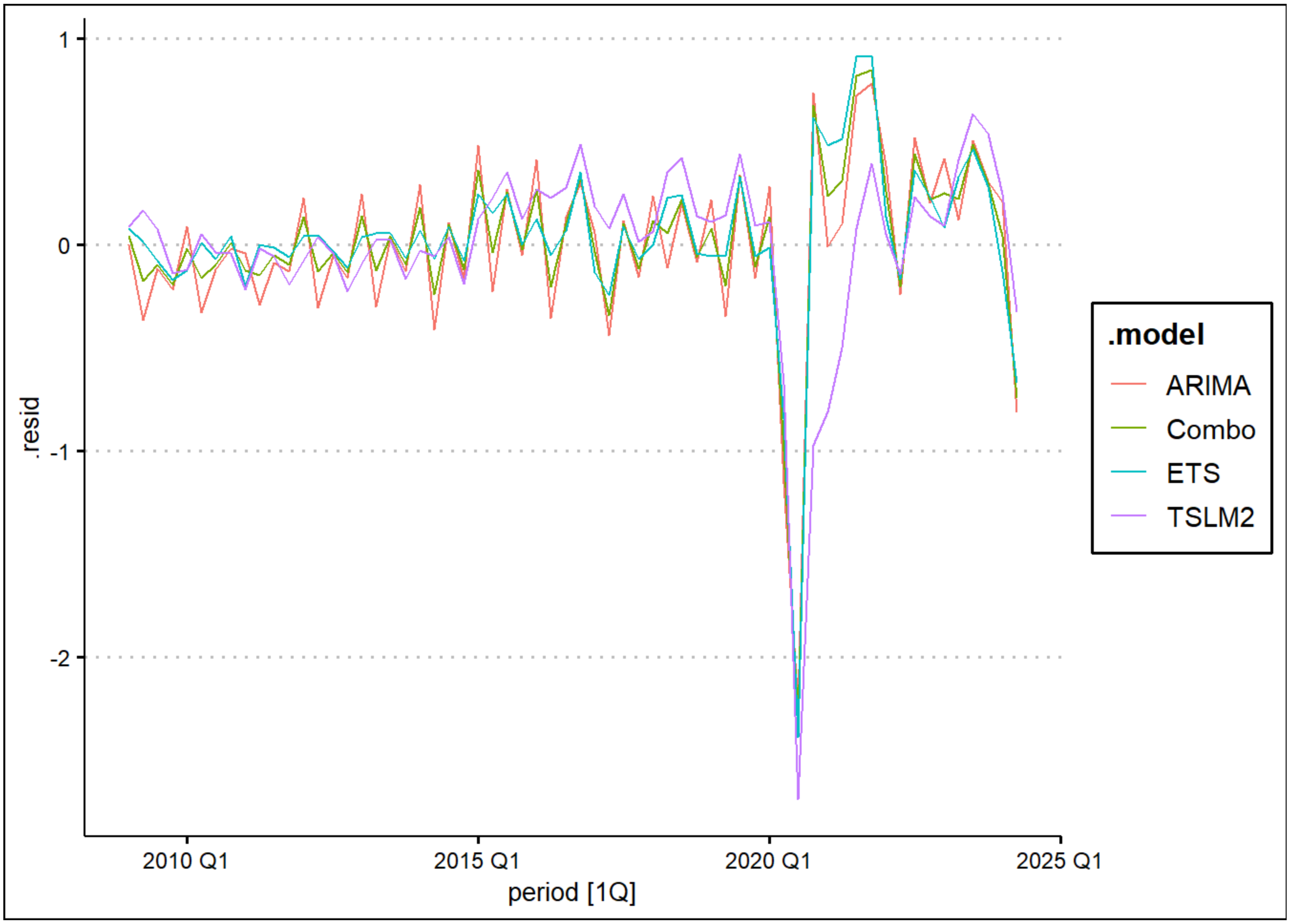
.model	.type	winkler
ARIMA	Test	1.776148
ETS	Test	2.590697
TSLM	Test	2.094924
TSLM2	Test	2.044642

```
rev_ts %>% stretch_tsibble(.init = 20, .step=1) %>%
    model(TSLM=TSLM(revenue~trend()+season()),
          TSLM2=TSLM(revenue~trend()+ I(trend()^2) + season()),
          ARIMA=ARIMA(revenue),
          ETS=ETS(revenue)) %>%
    mutate(Combo=0.5*ARIMA+0.5*ETS) %>%
    forecast(h=1) %>%
    accuracy(rev_ts) %>% gt()
```

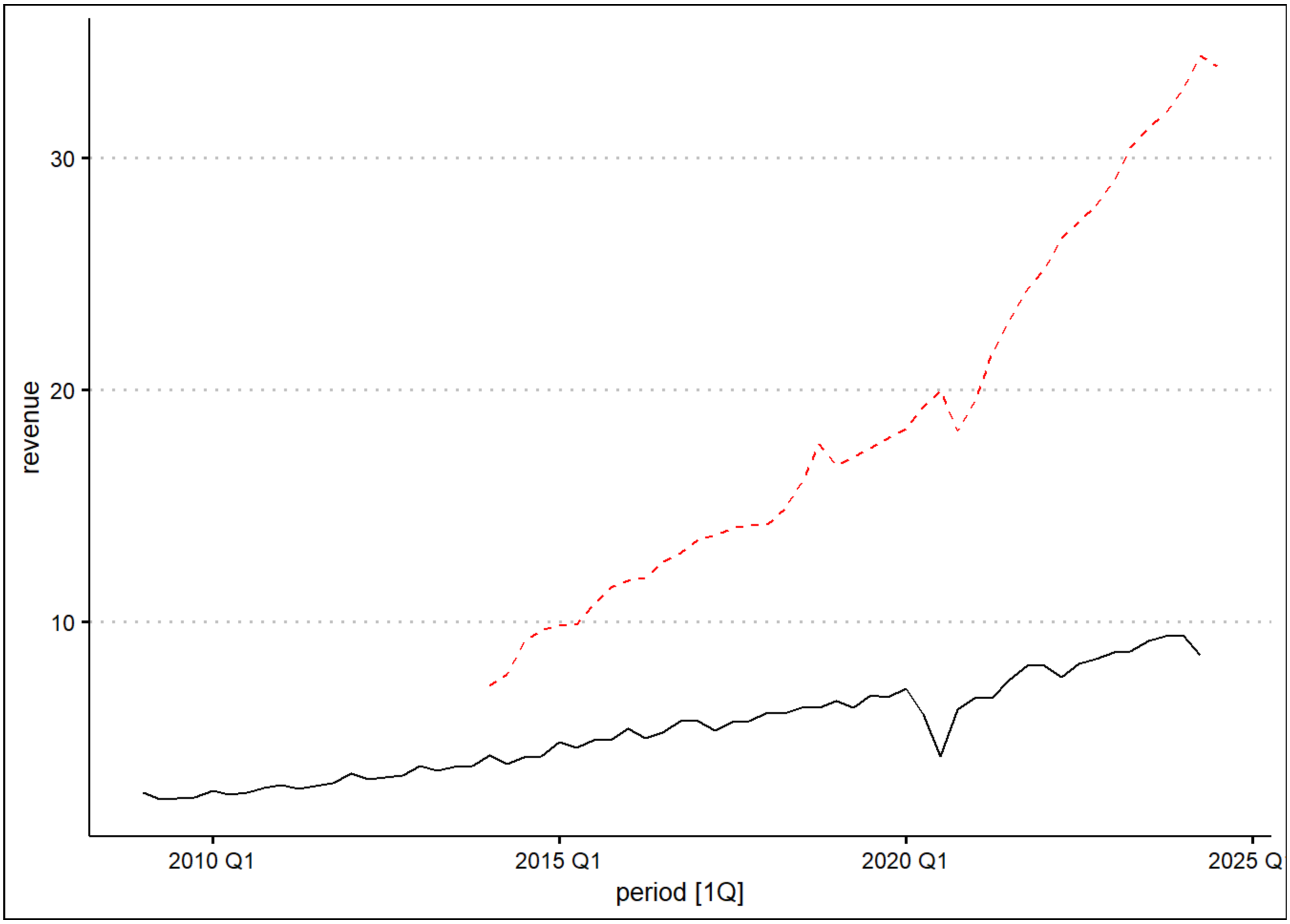
```
Warning: The future dataset is incomplete, incomplete out-of-sample data will be treated as
missing.
1 observation is missing at 2024 Q3
```

.model	.type	ME	RMSE	MAE	MPE	MAPE	MASE	RMSSE
ARIMA	Test	0.07330212	0.7687252	0.4086351	0.3802946	6.750180	0.6798863	0.9459857
Combo	Test	0.08156771	0.7133183	0.3904485	0.5009045	6.485811	0.6496274	0.8778025
ETS	Test	0.08983330	0.6711829	0.3868308	0.6215144	6.406779	0.6436084	0.8259511
TSLM	Test	0.18740076	0.6250657	0.4173001	1.9821680	6.686416	0.6943030	0.7691998
TSLM2	Test	-0.01305022	0.6169259	0.3823214	-1.4485712	6.161671	0.6361056	0.7591830

```
rev_ts %>% model(TSLM2=TSLM(revenue~trend()+ I(trend()^2) + season()),
                  ARIMA=ARIMA(revenue),
                  ETS=ETS(revenue)) %>%
     mutate(Combo=0.5*ARIMA+0.5*ETS) -> fit2_r


fit2_r %>% augment() -> resids2_r

resids2_r %>% autoplot(.resid) + theme_clean()
```



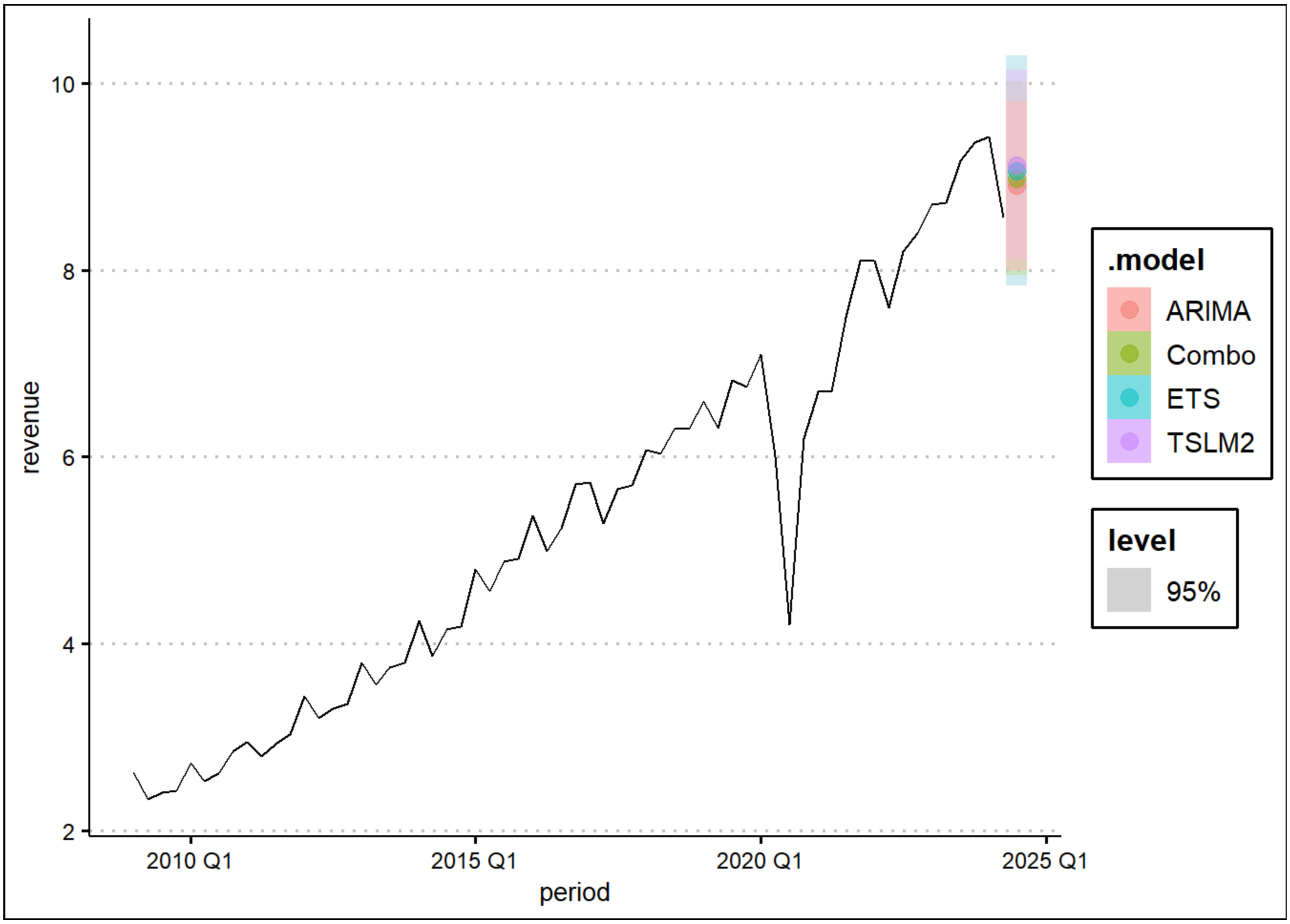

```
rev_ts %>% autoplot(revenue) +
     autolayer(resids2_s %>% filter(.model=="Combo"),.fitted,
               lty=2,col="red") +
     theme_clean()
```




```
fit2_r %>% forecast(h=1) %>% hilo(level=95) %>% gt()
```

.model	period	revenue	.mean	95%
TSLM2	2024 Q3	N(9.1, 0.27)	9.124209	[8.10621720753283, 10.1422005356683]95
ARIMA	2024 Q3	N(8.9, 0.21)	8.901961	[7.9957479602656, 9.80817471418686]95
ETS	2024 Q3	N(9.1, 0.4)	9.060848	[7.82895567033893, 10.2927410920723]95
Combo	2024 Q3	N(9, 0.28)	8.981405	[7.94308724705549, 10.0197224713764]95

```
fit2_r %>% forecast(h=1) %>% autoplot(level=95, alpha=0.5) +
    autolayer(rev_ts, revenue) +
    theme_clean()
```


10
8
6
4
2
revenue
2010 Q1
2015 Q1
2020 Q1
2025 Q1
period
.model
ARIMA
Combo
ETS
TSLM2
level
95%