- Assignment: 8.2 Time Series Modeling
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- Course: DSC630-T301
- Week8: Time Series
- Date: 04/30/2025

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### Load necessary packages

In [37]:
```
# Load libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from sklearn.metrics import mean_squared_error
```

### Load the US Retail Sales dataset

In [2]:
```
retail_df = pd.read_csv('us_retail_sales.csv')
retail_df.head()
```

Out[2]:

| | YEAR | JAN | FEB | MAR | APR | MAY | JUN | JUL | AUG | SEP | OCT | NOV | DEC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1992 | 146925 | 147223 | 146805 | 148032 | 149010 | 149800 | 150761.0 | 151067.0 | 152588.0 | 153521.0 | 153583.0 | 155614.0 |
| **1** | 1993 | 157555 | 156266 | 154752 | 158979 | 160605 | 160127 | 162816.0 | 162506.0 | 163258.0 | 164685.0 | 166594.0 | 168161.0 |
| **2** | 1994 | 167518 | 169649 | 172766 | 173106 | 172329 | 174241 | 174781.0 | 177295.0 | 178787.0 | 180561.0 | 180703.0 | 181524.0 |
| **3** | 1995 | 182413 | 179488 | 181013 | 181686 | 183536 | 186081 | 185431.0 | 186806.0 | 187366.0 | 186565.0 | 189055.0 | 190774.0 |
| **4** | 1996 | 189135 | 192266 | 194029 | 194744 | 196205 | 196136 | 196187.0 | 196218.0 | 198859.0 | 200509.0 | 200174.0 | 201284.0 |

### The original dataset has years in rows and months as columns. We'll melt it to long format for time series analysis

In [3]:
```
# Convert wide to long format
retail_melted = retail_df.melt(id_vars=['YEAR'], var_name='Month', value_name='Sales')
# Map month names to month names
```

```python
month_num = {
    'JAN': 1, 'FEB': 2, 'MAR': 3, 'APR': 4, 'MAY': 5, 'JUN': 6,
    'JUL': 7, 'AUG': 8, 'SEP': 9, 'OCT': 10, 'NOV': 11, 'DEC': 12
}
retail_melted['Month_Num'] = retail_melted['Month'].map(month_num)
# Create a proper datetime column
retail_melted['Date'] = pd.to_datetime(dict(year=retail_melted['YEAR'], month=retail_melted['Month_Num'], day=1))

# Sort the table by date
retail_melted = retail_melted.sort_values('Date')
```

In [4]:
```python
retail_melted.head()
```

Out[4]:

| | YEAR | Month | Sales | Month_Num | Date |
|---|---|---|---|---|---|
| **0** | 1992 | JAN | 146925.0 | 1 | 1992-01-01 |
| **30** | 1992 | FEB | 147223.0 | 2 | 1992-02-01 |
| **60** | 1992 | MAR | 146805.0 | 3 | 1992-03-01 |
| **90** | 1992 | APR | 148032.0 | 4 | 1992-04-01 |
| **120** | 1992 | MAY | 149010.0 | 5 | 1992-05-01 |

Check for NAs and drop them

In [27]:
```python
# Check for NAs
print(retail_melted.columns[retail_melted.isna().any()].tolist())
```

```
['Sales']
```

In [28]:
```python
retail_melted['Sales'].isna().sum()
```

Out[28]:
```
np.int64(6)
```

### Column Sales has 6 rows of NA and has to be dropped

In [30]:
```python
retail_melted = retail_melted.dropna(subset=['Sales'])
```

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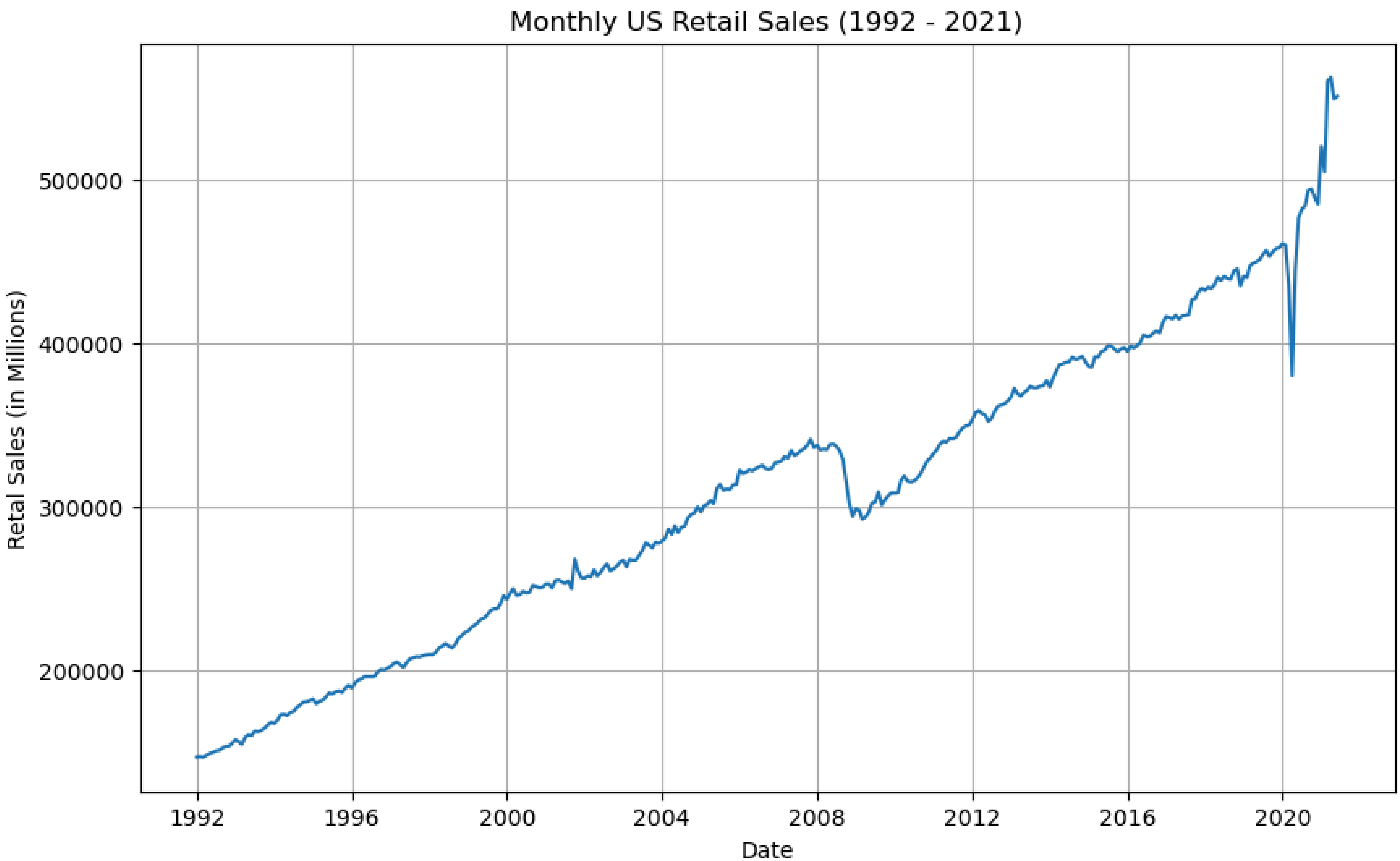
### Step1. Plot the data with proper labeling and make some observations on the graph.

In [32]:
```
plt.figure(figsize=(10,6))
plt.plot(retail_melted['Date'], retail_melted['Sales'])
plt.title('Monthly US Retail Sales (1992 - 2021)')
plt.xlabel('Date')
plt.ylabel('Retal Sales (in Millions)')
plt.grid(True)
plt.show()
```




### Achieved so far:

Loaded the data in dataframe

Reshaped the data from wide format to long format

Dropped NA rows

Plotted monthly retail sales from 1992 to 2021

### Observations from graph

Sales show a dip around 2008 and 2020

- 2008, could be due to the housing crisis

- 2020, could be due to COVid crisis

There is a steady upward trend over the years - retail sales generally increase over time

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### Step2. Split this data into a training and test set. Use the last year of data (July 2020 – June 2021) of data as your test set and the rest as your training set.

In [33]:
```
# Per requirement Define Test set: July 2020 till June 2021
test = retail_melted[(retail_melted['Date'] >= '2020-07-01') & (retail_melted['Date'] <= '2021-06-01')]
# Define Train set as everything else
train = retail_melted[~retail_melted['Date'].isin(test['Date'])]
```

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### Step3. Use the training set to build a predictive model for the monthly retail sales.

In [34]:
```
# Fit model using training data
model = ExponentialSmoothing(train['Sales'],
                             trend = 'add',
                             seasonal='add',
                             seasonal_periods=12).fit()
```

```
/opt/anaconda3/lib/python3.12/site-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: An unsupported index w
as provided. As a result, forecasts cannot be generated. To use the model for forecasting, use one of the supported cla
sses of index.
  self._init_dates(dates, freq)
/opt/anaconda3/lib/python3.12/site-packages/statsmodels/tsa/holtwinters/model.py:918: ConvergenceWarning: Optimization
failed to converge. Check mle_retvals.
  warnings.warn(
```

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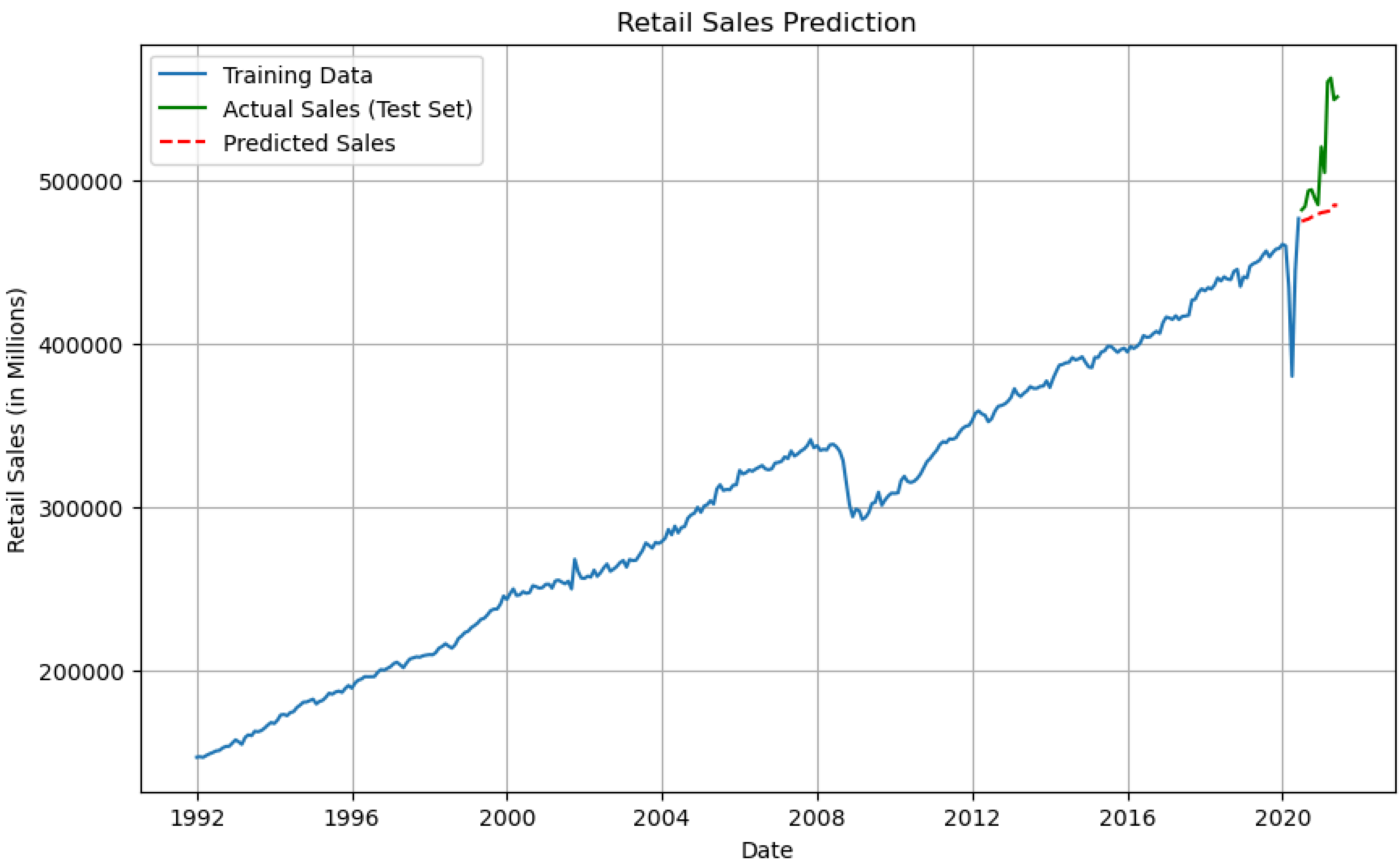
Step4. Use the model to predict the monthly retail sales on the last year of data.

In [35]:
```
# Predict on test period
predictions = model.forecast(steps=12)

# Plot actual vs predicted
plt.figure(figsize=(10,6))
plt.plot(train['Date'], train['Sales'], label = 'Training Data')
plt.plot(test['Date'], test['Sales'], label = 'Actual Sales (Test Set)', color = 'green')
plt.plot(test['Date'], predictions, label = 'Predicted Sales', color = 'red' , linestyle='--')
plt.title('Retail Sales Prediction')
plt.xlabel('Date')
plt.ylabel('Retail Sales (in Millions)')
plt.legend()
plt.grid(True)
plt.show()
```

```
/opt/anaconda3/lib/python3.12/site-packages/statsmodels/tsa/base/tsa_model.py:837: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at `start`.
  return get_prediction_index(
/opt/anaconda3/lib/python3.12/site-packages/statsmodels/tsa/base/tsa_model.py:837: FutureWarning: No supported index is available. In the next version, calling this method in a model without a supported index will result in an exception.
  return get_prediction_index(
```

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Step5. Report the RMSE of the model predictions on the test set.

In [38]:
```
# Calculate RMSE
rmse = np.sqrt(mean_squared_error(test['Sales'], predictions))
rmse
```

Out[38]:
```
np.float64(45156.97171858635)
```

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### Achieved so far:

Model used: Holt-Winters Exponential Smoothing (captures both trend and seasonality)

Prediction Period: July 2020 - June 2021

Root Mean Squared Error on Test Set: 45,156.97, this means the typical prediction error is around $45,157 million

### Final Summary

Training data: January 1992 to June 2020

Test data: July 2020 to June 2021

Observation: The model closely tracks the trend, but some deviation occurs possibly due to COVID-era volatility

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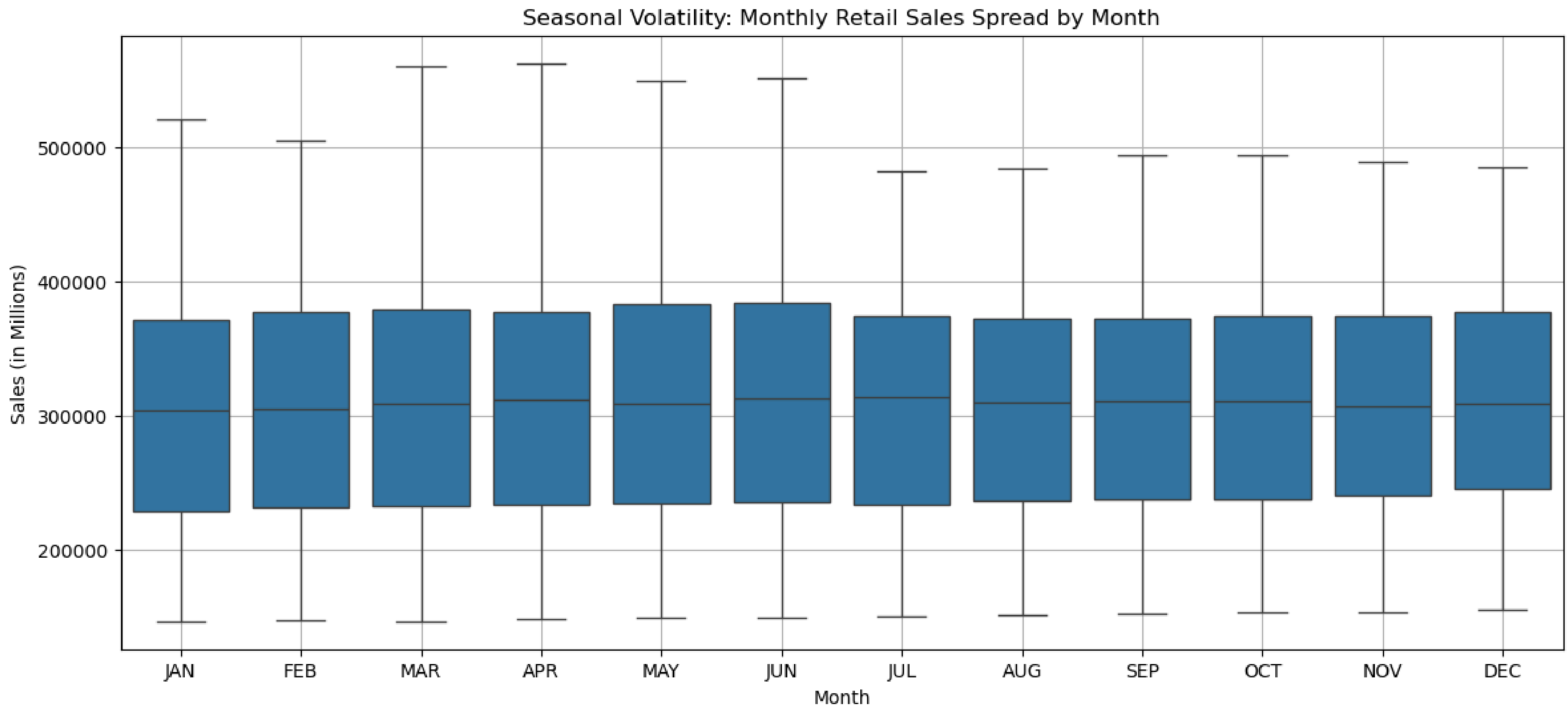
### Additionally check for Seasonal Volatility using Box Plot

In [40]:

```
import seaborn as sns
# Ensure month order
df_melted = retail_melted.copy()
df_melted['Month'] = pd.Categorical(df_melted['Month'],
                                    categories = ['JAN','FEB','MAR','APR','MAY','JUN',
                                                  'JUL','AUG','SEP','OCT','NOV','DEC'],
                                    ordered = True)
plt.figure(figsize=(14,6))
sns.boxplot(x='Month', y='Sales', data = df_melted)
plt.title('Seasonal Volatility: Monthly Retail Sales Spread by Month')
plt.ylabel('Sales (in Millions)')
plt.grid(True)
plt.show()
```




Noticed certain months March, May, June have higher retail sales this could be seasonality

In [ ]: