#### 1: Import Libraries

```
In [2]:
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        from statsmodels.tsa.arima.model import ARIMA
        from statsmodels.tsa.stattools import adfuller
        from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
        from sklearn.model_selection import train_test_split
        from sklearn.preprocessing import MinMaxScaler
        from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_sco
        re
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import LSTM, Dense, Dropout
        from tensorflow.keras.callbacks import EarlyStopping
        from tcn import TCN
        import math
        import sys
        print(sys.executable)
```

b:\Dublin City University\Practicum\Proj\venv\_311\Scripts\python.exe

#### 2: Load and Explore Dataset

#### Out[3]:

	Date	Open	High	Low	Close	Volume	Adj Close
0	2016- 07-01	17924.240234	18002.380859	17916.910156	17949.369141	82160000	17949.369141
1	2016- 06-30	17712.759766	17930.609375	17711.800781	17929.990234	133030000	17929.990234
2	2016- 06-29	17456.019531	17704.509766	17456.019531	17694.679688	106380000	17694.679688
3	2016- 06-28	17190.509766	17409.720703	17190.509766	17409.720703	112190000	17409.720703
4	2016- 06-27	17355.210938	17355.210938	17063.080078	17140.240234	138740000	17140.240234

5 rows × 56 columns

>

```
In [4]: missing_values = multimodal.isnull().sum()
    print("\nMissing values per column:")
    missing_values[missing_values > 0]
```

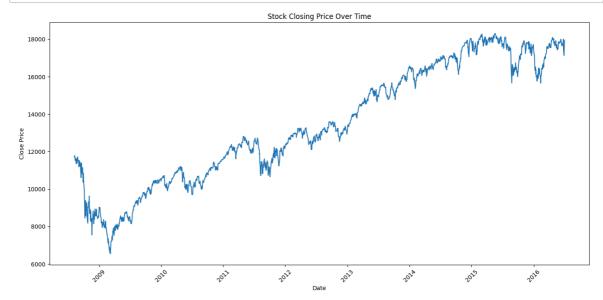
Missing values per column:

Out[4]:	Log_Returns	1
	Volatility_Log_10	10
	<pre>pct_change</pre>	1
	Next_3_Close	3
	Next_7_Close	7
	Next_Close	1
	dtype: int64	

```
In [5]: multimodal.describe()
    multimodal.dtypes
```

Out[5]:	Date	<pre>datetime64[ns]</pre>
	0pen	float64
	High	float64
	Low	float64
	Close	float64
	Volume	int64
	Adj Close	float64
	Log_Returns	float64
	Volatility_Log_10	float64
	cl-op	float64
	hi-lo	float64
	Label	int64
	vader_news_sentiment	float64
	FinBERT_news_sentiment	float64
	Smart_news_sentiment	float64
	news buying intent	float64
	news_selling_intent	float64
	news_uncertainty_intent	float64
	news_urgency_intent	float64
	_ ~ /_	float64
	news_prediction_intent	float64
	news_fear_intent	float64
	news_greed_intent	float64
	news_question_intent	
	news_action_intent	float64
	vader_reddit_sentiment	float64
	FinBERT_reddit_sentiment	float64
	Smart_reddit_sentiment	float64 float64
	reddit_buying_intent	float64
	reddit_selling_intent	float64
	reddit_uncertainty_intent	
	reddit_urgency_intent	float64
	reddit_prediction_intent	float64
	reddit_fear_intent	float64
	reddit_greed_intent	float64
	reddit_question_intent	float64
	reddit_action_intent	float64
	Target	int64
	pct_change	float64
	finbert_final_sentiment	float64
	total_buying_intent	float64
	total_selling_intent	float64
	total_uncertainty_intent	float64
	total_urgency_intent	float64
	total_prediction_intent	float64
	total_fear_intent	float64
	total_greed_intent	float64
	total_question_intent	float64
	total_action_intent	float64
	sentiment_minus_uncertainty	float64
	sentiment_minus_fear	float64
	sentiment_minus_action	float64
	sentiment_minus_urgency	float64
	sentiment_minus_prediction	float64
	Next_3_Close	float64
	Next_7_Close	float64
	Next_Close	float64
	dtype: object	

```
In [6]: plt.figure(figsize=(14, 7))
    plt.plot(pd.to_datetime(multimodal['Date']), multimodal['Close'])
    plt.title('Stock Closing Price Over Time')
    plt.xlabel('Date')
    plt.ylabel('Close Price')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
```



## 3: Data Preprocessing

```
In [7]: # Drop top 10 (rolling NaNs) and bottom 7 (from shift(-7))
multimodal_modelling = multimodal.iloc[10:-7].copy()

# Optional: reset index
# multimodal_modelling.reset_index(drop=True, inplace=True)

# Sanity check
print(f"Shape: {multimodal_modelling.shape}")
print(multimodal_modelling.isnull().sum())
```

Shape: (1972, 56)	
Date	0
0pen	0
High	0
Low	0
Close	0
Volume	0
Adj Close	0
Log_Returns	0
Volatility_Log_10	0
cl-op	0
hi-lo	0
Label	0
vader_news_sentiment	0
FinBERT_news_sentiment	0
Smart_news_sentiment	0
news buying intent	0
news_selling_intent	0
news uncertainty intent	0
_ /-	0
news_urgency_intent news_prediction_intent	0
news_fear_intent	0
news_greed_intent	0
news_question_intent	0
news_action_intent	0
vader_reddit_sentiment	0
FinBERT_reddit_sentiment	0
Smart_reddit_sentiment	0
reddit_buying_intent	0
reddit_selling_intent	0
reddit_uncertainty_intent	0
reddit_urgency_intent	0
reddit_prediction_intent	0
reddit_fear_intent	0
reddit_greed_intent	0
reddit_question_intent	0
reddit_action_intent	0
Target	0
pct_change	0
finbert_final_sentiment	0
total_buying_intent	0
total_selling_intent	0
total_uncertainty_intent	0
total_urgency_intent	0
total_prediction_intent	0
total_fear_intent	0
total_greed_intent	0
total_question_intent	0
total_action_intent	0
sentiment_minus_uncertainty	0
sentiment_minus_fear	0
sentiment_minus_action	0
sentiment_minus_urgency	0
sentiment_minus_prediction	0
Next_3_Close	0
Next_7_Close	0
Next_Close	0
dtype: int64	

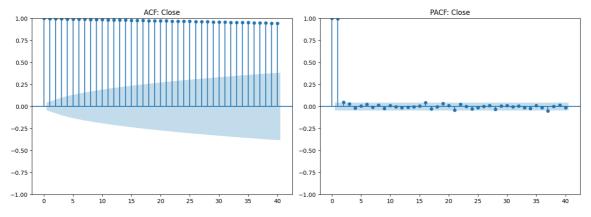
### 4: Time Series Stationarity Analysis for ARIMA

```
In [9]:
          df arima.head()
Out[9]:
                           Close
                                   Next_Close
                Date
           2016-06-17 17675.160156 17733.099609
           2016-06-16 17733.099609 17640.169922
           2016-06-15 17640.169922 17674.820312
           2016-06-14 17674.820312 17732.480469
           2016-06-13 17732.480469 17865.339844
In [10]:
          result = adfuller(df_arima["Close"])
          print(f"ADF Statistic: {result[0]}")
          print(f"p-value: {result[1]}")
          ADF Statistic: -1.210171226984291
          p-value: 0.6692050737972017
```

```
In [11]: plt.figure(figsize=(14, 5))
    plt.subplot(1, 2, 1)
    plot_acf(multimodal_modelling["Close"], lags=40, ax=plt.gca())
    plt.title("ACF: Close")

plt.subplot(1, 2, 2)
    plot_pacf(multimodal_modelling["Close"], lags=40, ax=plt.gca(), method='yw m')
    plt.title("PACF: Close")

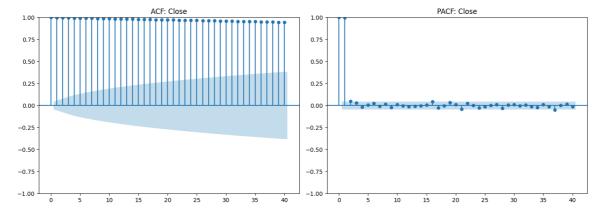
plt.tight_layout()
    plt.show()
```



```
In [12]: plt.figure(figsize=(14, 5))
    plt.subplot(1, 2, 1)
    plot_acf(df_arima["Close"], lags=40, ax=plt.gca())
    plt.title("ACF: Close")

    plt.subplot(1, 2, 2)
    plot_pacf(df_arima["Close"], lags=40, ax=plt.gca(), method='ywm')
    plt.title("PACF: Close")

    plt.tight_layout()
    plt.show()
```



```
In [13]:
         # Fit ARIMA model (you can ADF test and gridsearch later)
         model = ARIMA(df_arima["Close"], order=(1,0,1))
         model_fit = model.fit()
         # Forecast next day
         forecast = model_fit.predict(start=0, end=len(df_arima)-1)
         true = df_arima["Next_Close"]
         # Shift Close forward to align with Next_Close
         forecast = forecast.shift(1) # now forecast[i] ≈ Close[i+1]
         forecast = forecast[:len(true)]
         # Align forecast and true by dropping NaNs introduced by shift
         mask = forecast.notna()
         forecast_clean = forecast[mask]
         true clean = true[mask]
         # Evaluation
         print("R2:", r2_score(true_clean, forecast_clean))
         print("MSE:", mean_squared_error(true_clean, forecast_clean))
```

R<sup>2</sup>: 0.9937197053841297 MSE: 61862.3376472596

b:\Dublin City University\Practicum\Proj\venv\_311\Lib\site-packages\statsm odels\tsa\base\tsa\_model.py:473: ValueWarning: A date index has been provi ded, but it has no associated frequency information and so will be ignored when e.g. forecasting.

self.\_init\_dates(dates, freq)

b:\Dublin City University\Practicum\Proj\venv\_311\Lib\site-packages\statsm odels\tsa\base\tsa\_model.py:473: ValueWarning: A date index has been provi ded, but it is not monotonic and so will be ignored when e.g. forecasting. self.\_init\_dates(dates, freq)

b:\Dublin City University\Practicum\Proj\venv\_311\Lib\site-packages\statsm odels\tsa\base\tsa\_model.py:473: ValueWarning: A date index has been provi ded, but it has no associated frequency information and so will be ignored when e.g. forecasting.

self. init dates(dates, freq)

b:\Dublin City University\Practicum\Proj\venv\_311\Lib\site-packages\statsm odels\tsa\base\tsa\_model.py:473: ValueWarning: A date index has been provi ded, but it is not monotonic and so will be ignored when e.g. forecasting. self.\_init\_dates(dates, freq)

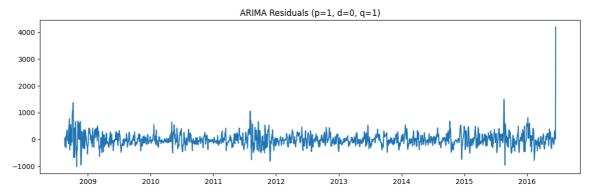
b:\Dublin City University\Practicum\Proj\venv\_311\Lib\site-packages\statsm odels\tsa\base\tsa\_model.py:473: ValueWarning: A date index has been provi ded, but it has no associated frequency information and so will be ignored when e.g. forecasting.

self. init dates(dates, freq)

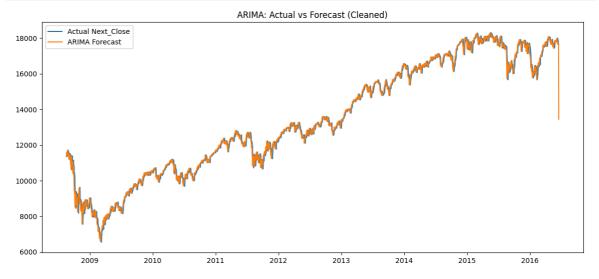
b:\Dublin City University\Practicum\Proj\venv\_311\Lib\site-packages\statsm odels\tsa\base\tsa\_model.py:473: ValueWarning: A date index has been provi ded, but it is not monotonic and so will be ignored when e.g. forecasting.

self.\_init\_dates(dates, freq)

```
In [14]: residuals = true_clean - forecast_clean
    plt.figure(figsize=(14,4))
    plt.plot(residuals)
    plt.title("ARIMA Residuals (p=1, d=0, q=1)")
    plt.show()
```



```
In [15]: plt.figure(figsize=(14,6))
    plt.plot(forecast_clean.index, true_clean, label="Actual Next_Close")
    plt.plot(forecast_clean.index, forecast_clean, label="ARIMA Forecast")
    plt.title("ARIMA: Actual vs Forecast (Cleaned)")
    plt.legend()
    plt.show()
```



## **LSTM Model**

```
In [16]: df_lstm.columns
Out[16]: Index(['Open', 'High', 'Low', 'Close', 'Volume', 'Adj Close', 'Log_Return
                 'Volatility_Log_10', 'cl-op', 'hi-lo', 'vader_news_sentiment',
                 'FinBERT_news_sentiment', 'Smart_news_sentiment', 'news_buying_inte
          nt',
                 'news_selling_intent', 'news_uncertainty_intent', 'news_urgency_int
          ent',
                 'news_prediction_intent', 'news_fear_intent', 'news_greed_intent',
                 'news_question_intent', 'news_action_intent', 'vader_reddit_sentime
          nt',
                 'FinBERT_reddit_sentiment', 'Smart_reddit_sentiment',
                 'reddit_buying_intent', 'reddit_selling_intent',
                 'reddit_uncertainty_intent', 'reddit_urgency_intent',
                 'reddit_prediction_intent', 'reddit_fear_intent', 'reddit_greed_int
         ent',
                 'reddit_question_intent', 'reddit_action_intent', 'pct_change',
'finbert_final_sentiment', 'total_buying_intent',
                 'total_selling_intent', 'total_uncertainty_intent',
                 'total_urgency_intent', 'total_prediction_intent', 'total_fear_inte
          nt',
                 'total_greed_intent', 'total_question_intent', 'total_action_inten
          t',
                 'sentiment_minus_uncertainty', 'sentiment_minus_fear',
                 'sentiment_minus_action', 'sentiment_minus_urgency',
                 'sentiment_minus_prediction'],
                dtype='object')
In [17]: # Separate features and target
          X = df_1stm
          y = df targets["Next Close"]
          # Scale features and target
          X_scaler = MinMaxScaler()
          y_scaler = MinMaxScaler()
          X scaled = X scaler.fit transform(X)
          y scaled = y scaler.fit transform(y.values.reshape(-1, 1))
          # Create sequences
          def create_sequences(X, y, window_size=60):
              Xs, ys = [], []
              for i in range(window_size, len(X)):
                  Xs.append(X[i-window size:i])
                  ys.append(y[i])
              return np.array(Xs), np.array(ys)
          X_seq, y_seq = create_sequences(X_scaled, y_scaled)
          # Return final sequence shapes
          X_seq.shape, y_seq.shape
Out[17]: ((1912, 60, 50), (1912, 1))
```

```
In [18]:
         # simple lstm model
         X_train, X_test, y_train, y_test = train_test_split(X_seq, y_seq, test_size
         =0.2, shuffle=False)
         model = Sequential()
         model.add(LSTM(64, input_shape=(X_train.shape[1], X_train.shape[2])))
         model.add(Dense(1))
         model.compile(optimizer='adam', loss='mse')
         history = model.fit(
             X_train, y_train,
             epochs=20,
             batch_size=32,
             validation_split=0.1,
             verbose=1
         )
         y_pred_scaled = model.predict(X_test)
         y_pred = y_scaler.inverse_transform(y_pred_scaled)
         y_true = y_scaler.inverse_transform(y_test)
         y_pred[:5], y_true[:5]
```

WARNING:tensorflow:From b:\Dublin City University\Practicum\Proj\venv\_311 \Lib\site-packages\keras\src\backend.py:873: The name tf.get\_default\_graph is deprecated. Please use tf.compat.v1.get\_default\_graph instead.

WARNING:tensorflow:From b:\Dublin City University\Practicum\Proj\venv\_311 \Lib\site-packages\keras\src\optimizers\\_\_init\_\_.py:309: The name tf.trai n.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instea d.

#### Epoch 1/20

WARNING:tensorflow:From b:\Dublin City University\Practicum\Proj\venv\_311 \Lib\site-packages\keras\src\utils\tf\_utils.py:492: The name tf.ragged.RaggedTensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.

```
loss: 0.0033
Epoch 2/20
loss: 0.0019
Epoch 3/20
val_loss: 9.6582e-04
Epoch 4/20
43/43 [============= ] - 1s 12ms/step - loss: 6.9453e-04 -
val loss: 7.9687e-04
Epoch 5/20
val_loss: 6.7365e-04
Epoch 6/20
43/43 [============= ] - 1s 13ms/step - loss: 4.4752e-04 -
val_loss: 5.2529e-04
Epoch 7/20
43/43 [=============== ] - 1s 12ms/step - loss: 4.0316e-04 -
val_loss: 4.3235e-04
Epoch 8/20
43/43 [============ - - 1s 12ms/step - loss: 3.5750e-04 -
val loss: 4.3866e-04
Epoch 9/20
43/43 [=============== ] - 1s 12ms/step - loss: 3.2052e-04 -
val loss: 4.3915e-04
Epoch 10/20
43/43 [============ ] - 1s 13ms/step - loss: 3.7284e-04 -
val loss: 3.4279e-04
Epoch 11/20
val_loss: 3.8910e-04
Epoch 12/20
43/43 [============ ] - 1s 14ms/step - loss: 3.0392e-04 -
val loss: 4.2350e-04
Epoch 13/20
val loss: 4.8148e-04
Epoch 14/20
43/43 [=============== ] - 1s 12ms/step - loss: 2.4175e-04 -
val_loss: 2.6846e-04
Epoch 15/20
43/43 [=============== ] - Os 12ms/step - loss: 2.5177e-04 -
val loss: 3.0993e-04
Epoch 16/20
43/43 [============ ] - 1s 13ms/step - loss: 2.1522e-04 -
```

```
val_loss: 2.5791e-04
        Epoch 17/20
        43/43 [============= ] - 1s 13ms/step - loss: 2.1244e-04 -
        val_loss: 3.1360e-04
        Epoch 18/20
        43/43 [=============== ] - 1s 13ms/step - loss: 1.9313e-04 -
        val_loss: 2.8534e-04
        Epoch 19/20
        43/43 [============= ] - 1s 12ms/step - loss: 1.9394e-04 -
        val_loss: 2.8639e-04
        Epoch 20/20
        43/43 [============= ] - 1s 12ms/step - loss: 2.1770e-04 -
        val loss: 5.7899e-04
        12/12 [======== ] - 0s 5ms/step
Out[18]: (array([[10657.491],
               [10429.721],
               [10492.446],
               [10471.94],
               [10583.363]], dtype=float32),
         array([[10374.160156],
               [10282.410156],
               [10383.379883],
               [10402.349609],
               [10392.900391]]))
```

```
In [19]:
         # two Stacked Layers LSTM Model
         model = Sequential()
         model.add(LSTM(64, return_sequences=True, input_shape=(X_train.shape[1], X_
         train.shape[2])))
         model.add(Dropout(0.2))
         model.add(LSTM(32))
         model.add(Dropout(0.2))
         model.add(Dense(1))
         model.compile(optimizer='adam', loss='mse')
         early_stop = EarlyStopping(monitor='val_loss', patience=5, restore_best_wei
         ghts=True)
         history = model.fit(
             X_train, y_train,
             epochs=100,
             batch_size=32,
             validation_split=0.1,
             callbacks=[early_stop],
             verbose=1
         y_pred_scaled = model.predict(X_test)
         y_pred = y_scaler.inverse_transform(y_pred_scaled)
         y_true = y_scaler.inverse_transform(y_test)
         rmse = np.sqrt(mean_squared_error(y_true, y_pred))
         r2 = r2_score(y_true, y_pred)
         print(f"RMSE: {rmse:.2f}")
         print(f"R2: {r2:.4f}")
```

```
Epoch 1/100
43/43 [============= ] - 4s 35ms/step - loss: 0.0587 - val
_loss: 0.0070
Epoch 2/100
loss: 0.0011
Epoch 3/100
loss: 0.0011
Epoch 4/100
_loss: 8.4096e-04
Epoch 5/100
loss: 9.1441e-04
Epoch 6/100
loss: 9.4233e-04
Epoch 7/100
43/43 [============== ] - 1s 23ms/step - loss: 0.0060 - val
_loss: 6.5717e-04
Epoch 8/100
_loss: 6.4488e-04
Epoch 9/100
43/43 [============== ] - 1s 22ms/step - loss: 0.0055 - val
_loss: 7.8311e-04
Epoch 10/100
_loss: 6.2761e-04
Epoch 11/100
loss: 0.0013
Epoch 12/100
_loss: 6.4265e-04
Epoch 13/100
43/43 [============== ] - 1s 21ms/step - loss: 0.0052 - val
_loss: 9.2899e-04
Epoch 14/100
43/43 [============ ] - 1s 21ms/step - loss: 0.0048 - val
_loss: 5.6294e-04
Epoch 15/100
_loss: 6.0678e-04
Epoch 16/100
loss: 5.9768e-04
Epoch 17/100
43/43 [=============== ] - 1s 22ms/step - loss: 0.0045 - val
loss: 7.4557e-04
Epoch 18/100
_loss: 5.0253e-04
Epoch 19/100
loss: 6.1953e-04
Epoch 20/100
43/43 [=============== ] - 1s 23ms/step - loss: 0.0047 - val
_loss: 6.1856e-04
Epoch 21/100
```

# **Temporal Convolutional Networks**

```
In [20]: X = df tcn.values
         y = df_targets['Next_Close'].values.reshape(-1, 1)
         # Scale features and target
         X_scaler = MinMaxScaler()
         y_scaler = MinMaxScaler()
         X_scaled = X_scaler.fit_transform(X)
         y_scaled = y_scaler.fit_transform(y)
In [21]: def create_sequences(X, y, window_size=60):
             X_{seq}, y_{seq} = [], []
             for i in range(window_size, len(X)):
                 X_seq.append(X[i-window_size:i])
                 y_seq.append(y[i])
             return np.array(X_seq), np.array(y_seq)
         X_seq, y_seq = create_sequences(X_scaled, y_scaled)
         print(f"X_seq shape: {X_seq.shape}, y_seq shape: {y_seq.shape}")
         X_seq shape: (1912, 60, 50), y_seq shape: (1912, 1)
In [22]: | split = int(0.8 * len(X_seq)) |
         X_train, X_test = X_seq[:split], X_seq[split:]
         y_train, y_test = y_seq[:split], y_seq[split:]
```

Model: "sequential\_2"

Layer (type)	Output Shape	Param #
tcn (TCN)	(None, 64)	99392
dense_2 (Dense)	(None, 1)	65

\_\_\_\_\_\_

Total params: 99457 (388.50 KB)
Trainable params: 99457 (388.50 KB)
Non-trainable params: 0 (0.00 Byte)

```
Epoch 1/100
43/43 [============= ] - 3s 20ms/step - loss: 1.3935 - val
_loss: 0.0819
Epoch 2/100
loss: 0.0450
Epoch 3/100
43/43 [============= ] - 1s 14ms/step - loss: 0.0899 - val
loss: 0.0290
Epoch 4/100
_loss: 0.0224
Epoch 5/100
loss: 0.0187
Epoch 6/100
loss: 0.0126
Epoch 7/100
43/43 [=============== ] - 1s 14ms/step - loss: 0.0302 - val
_loss: 0.0138
Epoch 8/100
_loss: 0.0098
Epoch 9/100
loss: 0.0094
Epoch 10/100
_loss: 0.0080
Epoch 11/100
loss: 0.0057
Epoch 12/100
_loss: 0.0061
Epoch 13/100
loss: 0.0049
Epoch 14/100
loss: 0.0045
Epoch 15/100
_loss: 0.0043
Epoch 16/100
loss: 0.0044
Epoch 17/100
loss: 0.0037
Epoch 18/100
_loss: 0.0036
Epoch 19/100
loss: 0.0031
Epoch 20/100
43/43 [=============== ] - 1s 14ms/step - loss: 0.0093 - val
_loss: 0.0034
Epoch 21/100
```

```
loss: 0.0035
Epoch 22/100
43/43 [============== ] - 1s 14ms/step - loss: 0.0083 - val
loss: 0.0030
Epoch 23/100
loss: 0.0025
Epoch 24/100
43/43 [============== ] - 1s 14ms/step - loss: 0.0080 - val
loss: 0.0030
Epoch 25/100
43/43 [============= ] - 1s 14ms/step - loss: 0.0079 - val
loss: 0.0031
Epoch 26/100
43/43 [============== ] - 1s 14ms/step - loss: 0.0067 - val
loss: 0.0035
Epoch 27/100
loss: 0.0025
Epoch 28/100
_loss: 0.0022
Epoch 29/100
_loss: 0.0020
Epoch 30/100
43/43 [============== ] - 1s 14ms/step - loss: 0.0057 - val
loss: 0.0020
Epoch 31/100
_loss: 0.0023
Epoch 32/100
loss: 0.0017
Epoch 33/100
loss: 0.0021
Epoch 34/100
loss: 0.0017
Epoch 35/100
43/43 [============= ] - 1s 15ms/step - loss: 0.0046 - val
loss: 0.0017
Epoch 36/100
loss: 0.0015
Epoch 37/100
43/43 [============ ] - 1s 14ms/step - loss: 0.0042 - val
loss: 0.0013
Epoch 38/100
loss: 0.0018
Epoch 39/100
43/43 [=============== ] - 1s 14ms/step - loss: 0.0042 - val
_loss: 0.0017
Epoch 40/100
43/43 [============= ] - 1s 14ms/step - loss: 0.0040 - val
loss: 0.0016
Epoch 41/100
```

```
_loss: 0.0011
Epoch 42/100
loss: 0.0014
Epoch 43/100
43/43 [============== ] - 1s 14ms/step - loss: 0.0038 - val
loss: 0.0012
Epoch 44/100
loss: 0.0012
Epoch 45/100
loss: 0.0012
Epoch 46/100
loss: 0.0010
Epoch 47/100
_loss: 0.0010
Epoch 48/100
loss: 0.0012
Epoch 49/100
_loss: 9.9372e-04
Epoch 50/100
loss: 0.0011
Epoch 51/100
loss: 0.0010
Epoch 52/100
loss: 0.0010
Epoch 53/100
loss: 9.1456e-04
Epoch 54/100
43/43 [============= ] - 1s 14ms/step - loss: 0.0025 - val
loss: 9.2352e-04
Epoch 55/100
_loss: 8.1137e-04
Epoch 56/100
43/43 [============= ] - 1s 15ms/step - loss: 0.0025 - val
loss: 8.0810e-04
Epoch 57/100
loss: 8.7996e-04
Epoch 58/100
loss: 8.2694e-04
Epoch 59/100
loss: 9.2751e-04
Epoch 60/100
loss: 8.3767e-04
Epoch 61/100
loss: 7.7993e-04
```

```
Epoch 62/100
loss: 6.8478e-04
Epoch 63/100
_loss: 7.8318e-04
Epoch 64/100
_loss: 6.3919e-04
Epoch 65/100
_loss: 6.6885e-04
Epoch 66/100
loss: 7.0671e-04
Epoch 67/100
43/43 [================ ] - 1s 14ms/step - loss: 0.0019 - val
loss: 6.1753e-04
Epoch 68/100
_loss: 5.9483e-04
Epoch 69/100
loss: 6.0356e-04
Epoch 70/100
_loss: 5.6949e-04
Epoch 71/100
loss: 5.4879e-04
Epoch 72/100
_loss: 6.7285e-04
Epoch 73/100
43/43 [=============== ] - 1s 15ms/step - loss: 0.0016 - val
loss: 6.6422e-04
Epoch 74/100
_loss: 5.6020e-04
Epoch 75/100
loss: 6.0786e-04
Epoch 76/100
_loss: 5.0926e-04
Epoch 77/100
_loss: 6.1035e-04
Epoch 78/100
_loss: 5.5441e-04
Epoch 79/100
_loss: 5.5164e-04
Epoch 80/100
loss: 5.5822e-04
Epoch 81/100
loss: 4.8048e-04
Epoch 82/100
```

```
_loss: 5.1199e-04
     Epoch 83/100
     _loss: 5.1879e-04
     Epoch 84/100
     _loss: 5.6091e-04
     Epoch 85/100
     43/43 [============= ] - 1s 16ms/step - loss: 0.0012 - val
      loss: 4.9482e-04
     Epoch 86/100
     _loss: 4.8312e-04
In [25]: | y_pred_scaled = model.predict(X_test)
     y_pred = y_scaler.inverse_transform(y_pred_scaled)
     y_true = y_scaler.inverse_transform(y_test)
     mse = mean_squared_error(y_true, y_pred)
     r2 = r2_score(y_true, y_pred)
     print(f" ✓ MSE: {mse:.4f}")
     print(f" ✓ R²: {r2:.4f}")
     12/12 [======= ] - 0s 5ms/step
      ✓ MSE: 895016.4955

✓ R²: 0.3049
```

```
In [26]: plt.figure(figsize=(14,6))
    plt.plot(y_true, label='Actual')
    plt.plot(y_pred, label='TCN Prediction')
    plt.title("TCN: Actual vs Predicted Next_Close")
    plt.legend()
    plt.show()

# Residuals
    residuals = y_true - y_pred
    plt.figure(figsize=(14,4))
    plt.plot(residuals)
    plt.axhline(0, color='gray', linestyle='--')
    plt.title("Residuals")
    plt.show()
```

