1: Import Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from scipy.stats import skew, kurtosis

from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_sco
re

from statsmodels.tools.sm_exceptions import ValueWarning

from tensorflow.keras import backend as K
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout, GroupNormalizatio
n
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.models import load_model
from tensorflow.keras.regularizers import l2
from tensorflow.keras.losses import Huber
from tcn import TCN

import shap
import gc
import joblib
import warnings
warnings.filterwarnings("ignore", category=UserWarning)
warnings.filterwarnings("ignore", category=FutureWarning)
warnings.filterwarnings("ignore", category=ValueWarning)

import os
import sys
print(sys.executable)
```

```
b:\DCU\Practicum\Proj\App\venv_3_11\Scripts\python.exe

b:\DCU\Practicum\Proj\App\venv_3_11\Lib\site-packages\tqdm\auto.py:21: Tqd
mWarning: IProgress not found. Please update jupyter and ipywidgets. See h
ttps://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

2: Load and Explore Dataset

In [2]:
```
multimodal = pd.read_csv("train_dataset.csv", parse_dates=["Date"])
multimodal.drop(columns=['Next_Close', 'Next_3_Close', 'Next_7_Close'], inp
lace=True)
multimodal.head()
```

Out[2]:

	Date	Open	High	Low	Close	Volume	Adj Close	l
0	2008-08-08	11432.089844	11759.959961	11388.040039	11734.320312	212830000	11734.320312	
1	2008-08-11	11729.669922	11867.110352	11675.530273	11782.349609	183190000	11782.349609	
2	2008-08-12	11781.700195	11782.349609	11601.519531	11642.469727	173590000	11642.469727	
3	2008-08-13	11632.809570	11633.780273	11453.339844	11532.959961	182550000	11532.959961	
4	2008-08-14	11532.070312	11718.280273	11450.889648	11615.929688	159790000	11615.929688	

5 rows × 53 columns

In [3]:
```
multimodal.shape
```

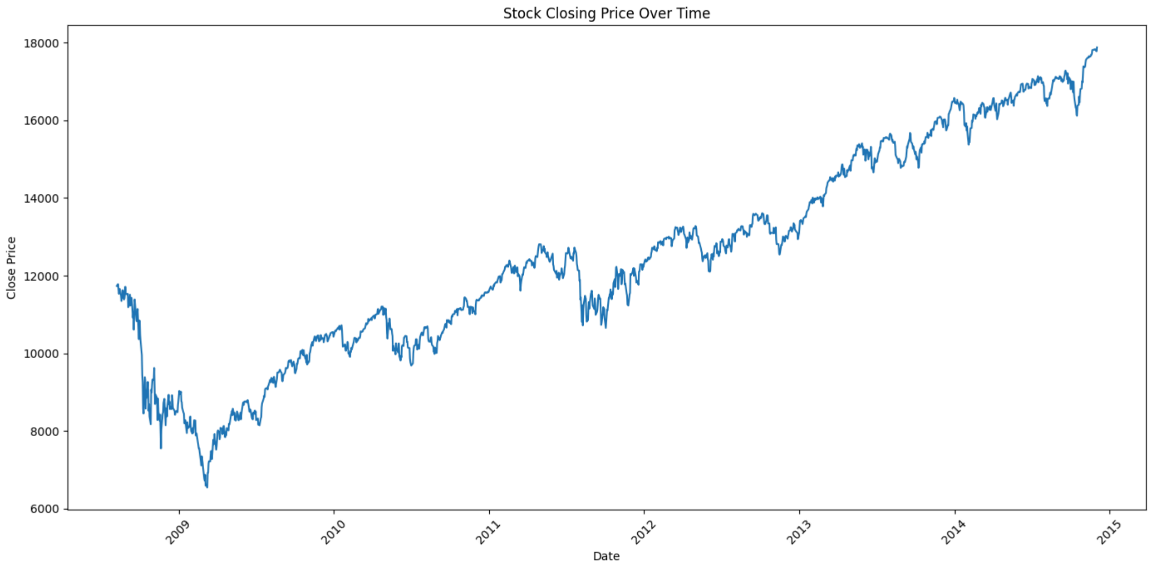
Out[3]: (1591, 53)

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

```
Missing values per column:
```

Out[4]: Series([], dtype: int64)

In [5]:
```
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.savefig("B:/DCU/Practicum/Proj/Outputs/closing_price_plot.png")
plt.show()
```



3: Data Preprocessing

In [6]:
```
df_targets = multimodal[["Date", "Target", "Label", "Close"]].copy()

df_arima = multimodal[["Date", "Close"]].copy()
df_arima.set_index("Date", inplace=True)

drop_cols_lstm = ["Date", "Label", "Target"]
df_lstm = multimodal.drop(columns=drop_cols_lstm).copy()

drop_cols_tcn = ["Date", "Label", "Target"]
df_tcn = multimodal.drop(columns=drop_cols_tcn).copy()
```

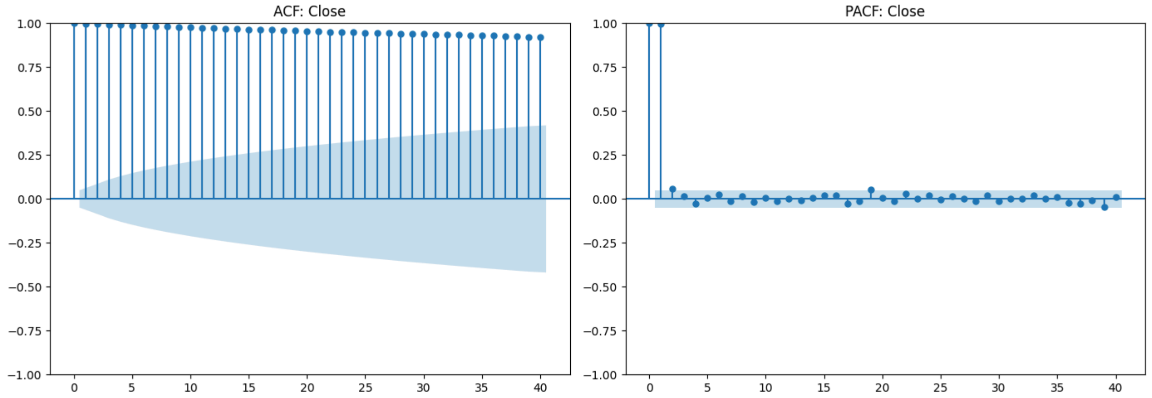
In [7]:
```
# Function to clear TensorFlow memory before running any model so that the
model doesnt predict on cached data
def clear_tf_memory():
    K.clear_session()
    gc.collect()
```

4: ARIMA Model

In [8]:
```
result = adfuller(df_arima["Close"])
print(f"ADF Statistic: {result[0]}")
print(f"p-value: {result[1]}")
```

```
ADF Statistic: 0.49003049114940356
p-value: 0.9845669104126585
```

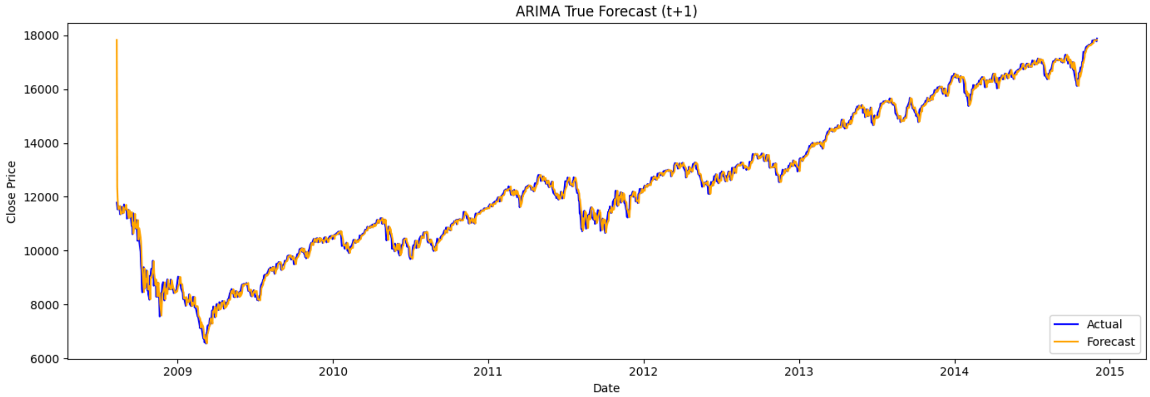
In [9]:
```
plt.figure(figsize=(14, 5))
plt.subplot(1, 2, 1)
plot_acf(df_arima["Close"], lags=40, ax=plt.gca())
plt.title("ACF: Close")

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.savefig("B:/DCU/Practicum/Proj/Outputs/arima_acf_pacf.png")
plt.show()
```



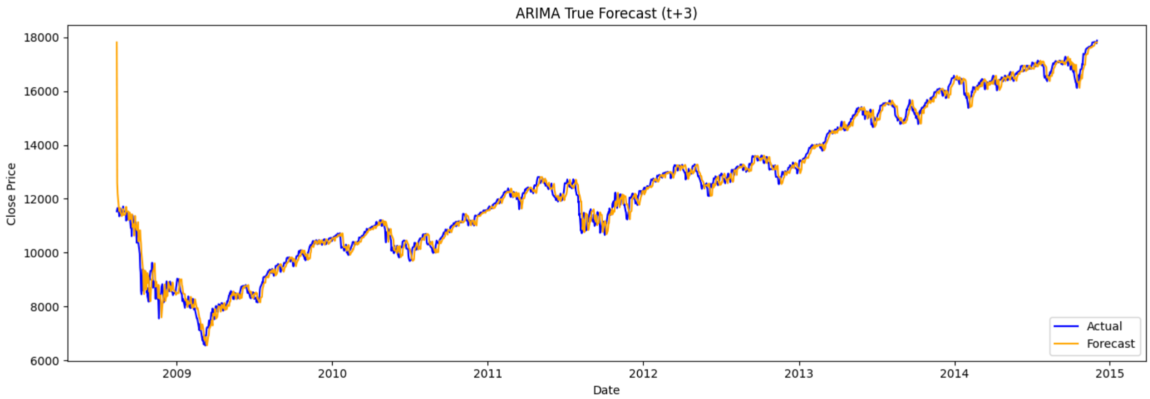
In [10]:
```
def arima_true_forecast(df_arima, forecast_horizon=1, order=(1, 1, 1), save
_dir=None, plot=True):
    print(df_arima.columns)
    close_series = df_arima['Close'].values
    history = close_series[:-(forecast_horizon + 1)].tolist()
    y_true = []
    y_pred = []

    for t in range(len(close_series) - forecast_horizon):
        try:
            model = ARIMA(history, order=order).fit()
            forecast = model.forecast(steps=forecast_horizon)
            y_pred.append(forecast[-1])
            y_true.append(close_series[t + forecast_horizon])
        except:
            y_pred.append(np.nan)
            y_true.append(np.nan)
        history.append(close_series[t])

    y_true = np.array(y_true)
    y_pred = np.array(y_pred)
    mask = ~np.isnan(y_pred)
    y_true = y_true[mask]
    y_pred = y_pred[mask]

    date_series = df_arima.index[forecast_horizon : forecast_horizon + len
(y_true)]

    # Metrics
    r2 = r2_score(y_true, y_pred)
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    mae = mean_absolute_error(y_true, y_pred)

    print(f"ARIMA Forecast Horizon = {forecast_horizon}")
    print(f"R² = {r2:.4f}, RMSE = {rmse:.2f}, MAE = {mae:.2f}")

    if plot:
        plt.figure(figsize=(14, 5))
        plt.plot(date_series, y_true, label='Actual', color='blue')
        plt.plot(date_series ,y_pred, label='Forecast', color='orange')
        plt.title(f"ARIMA True Forecast (t+{forecast_horizon})")
        plt.xlabel("Date")
        plt.ylabel("Close Price")
        plt.legend()
        plt.tight_layout()
        plt.savefig(f"B:/DCU/Practicum/Proj/Outputs/arima_train_t_plus_{for
ecast_horizon}.png")
        plt.show()

    if save_dir:
        os.makedirs(save_dir, exist_ok=True)
        model = ARIMA(close_series.tolist(), order=order).fit()
        save_path = os.path.join(save_dir, f'arima_t_plus_{forecast_horizo
n}.pkl')
        joblib.dump(model, save_path)
        print(f"Model saved to {save_path}")

    return {
        "horizon": forecast_horizon,
        "r2": r2,
```

```
        "rmse": rmse,
        "mae": mae
    }

results = []
for h in [1, 3, 7]:
    clear_tf_memory()
    res = arima_true_forecast(df_arima, forecast_horizon=h, order=(1,1,1),
save_dir="B:/DCU/Practicum/Proj/Models")
    results.append(res)
```

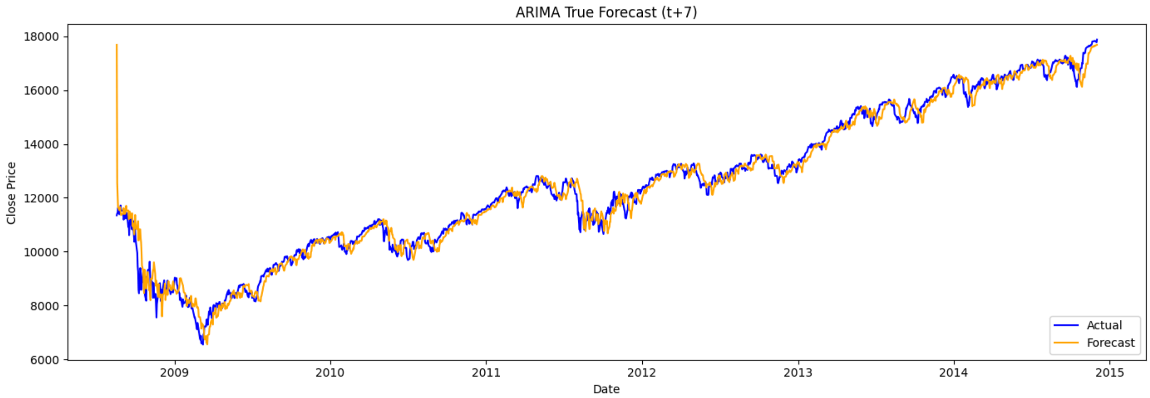
```
WARNING:tensorflow:From b:\DCU\Practicum\Proj\App\venv_3_11\Lib\site-packa
ges\keras\src\backend\common\global_state.py:82: The name tf.reset_default
_graph is deprecated. Please use tf.compat.v1.reset_default_graph instead.

Index(['Close'], dtype='object')
ARIMA Forecast Horizon = 1
R² = 0.9921, RMSE = 238.87, MAE = 136.61
```




```
Model saved to B:/DCU/Practicum/Proj/Models\arima_t_plus_1.pkl
Index(['Close'], dtype='object')
ARIMA Forecast Horizon = 3
R² = 0.9877, RMSE = 297.54, MAE = 190.21
```




```
Model saved to B:/DCU/Practicum/Proj/Models\arima_t_plus_3.pkl
Index(['Close'], dtype='object')
ARIMA Forecast Horizon = 7
R² = 0.9800, RMSE = 380.06, MAE = 260.24
```



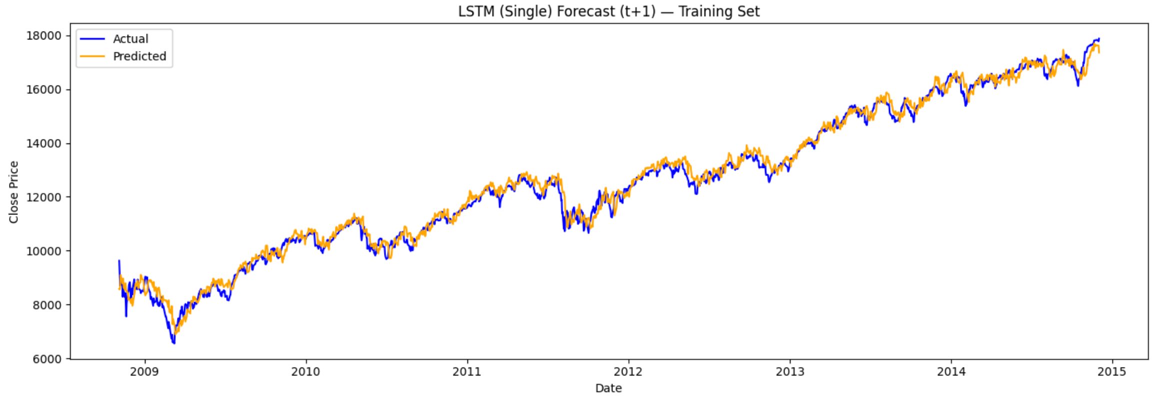

```
Model saved to B:/DCU/Practicum/Proj/Models\arima_t_plus_7.pkl
```

LSTM Model

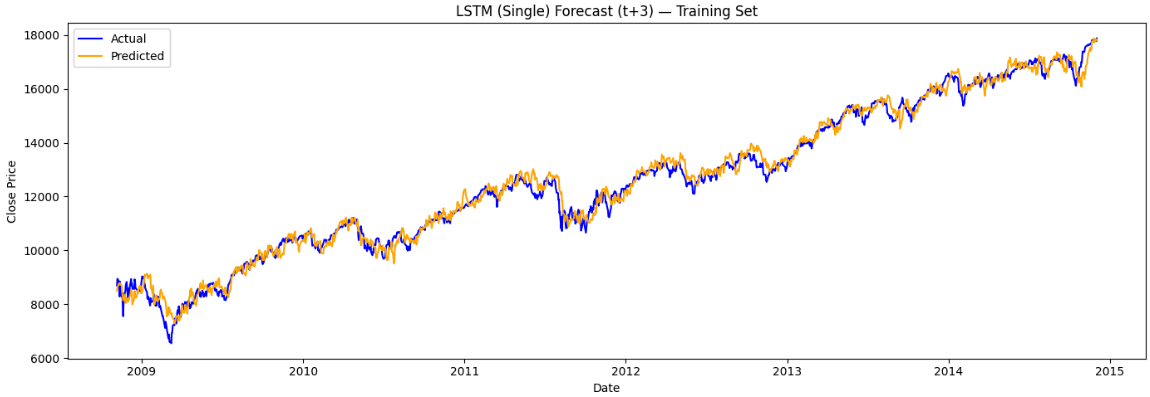
In [13]:
```
def train_lstm_multistep(df_lstm, forecast_horizon=1, window_size=60, epoch
s=50, batch_size=32, stacked=False):
    print(f"\nTraining LSTM ({'Stacked' if stacked else 'Single'}) model fo
r horizon t+{forecast_horizon}")

    close_values = df_lstm['Close'].values

    # Scale input and output
    X_scaler = MinMaxScaler()
    y_scaler = MinMaxScaler()
    X_scaled = X_scaler.fit_transform(df_lstm.values)
    y_scaled = y_scaler.fit_transform(close_values.reshape(-1, 1))

    # Create sequences
    X_seq, y_seq = [], []
    for i in range(window_size, len(X_scaled) - forecast_horizon):
        X_seq.append(X_scaled[i - window_size:i])
        y_seq.append(y_scaled[i + forecast_horizon])
    X_seq, y_seq = np.array(X_seq), np.array(y_seq)

    X_train, y_train = X_seq, y_seq

    # Build model
    model = Sequential()

    if stacked:
        reg = l2(1e-5)
        model.add(LSTM(64, return_sequences=True, input_shape=(X_train.shap
e[1], X_train.shape[2]),
                       kernel_regularizer=reg, recurrent_regularizer=reg))
        model.add(Dropout(0.3))
        model.add(LSTM(32, kernel_regularizer=reg, recurrent_regularizer=re
g))
        model.add(Dropout(0.3))
    else:
        model.add(LSTM(64, input_shape=(X_train.shape[1], X_train.shape
[2])))
        model.add(Dropout(0.1))
    model.add(Dense(1))

    optimizer = Adam(learning_rate=1e-4)
    model.compile(optimizer=optimizer, loss='mse')
    early_stop = EarlyStopping(monitor='val_loss', patience=5, restore_best
_weights=True)

    model.fit(
        X_train, y_train,
        epochs=epochs,
        batch_size=batch_size,
        validation_split=0.1,
        callbacks=[early_stop],
        verbose=1
    )

    # Save model and scalers
    model_name = f"lstm_tplus{forecast_horizon}{'_stacked' if stacked else
```

```
'_simple'}"
    base_path = "B:/DCU/Practicum/Proj/Models"
    os.makedirs(base_path, exist_ok=True)

    model.save(f"{base_path}/{model_name}.keras")
    joblib.dump(X_scaler, f"{base_path}/{model_name}_scalerX.pkl")
    joblib.dump(y_scaler, f"{base_path}/{model_name}_scalerY.pkl")

    # Save feature list
    feature_columns = df_lstm.columns.tolist()
    joblib.dump(feature_columns, f"{base_path}/{model_name}_features.pkl")
    print(f"Saved model and scalers: {model_name}")

    # Predict on train set to evaluate
    y_pred_scaled = model.predict(X_train)
    y_pred = y_scaler.inverse_transform(y_pred_scaled)
    y_true = y_scaler.inverse_transform(y_train.reshape(-1, 1))

    date_series = multimodal['Date'].iloc[window_size + forecast_horizon :
window_size + forecast_horizon + len(y_pred)]

    # Metrics
    r2 = r2_score(y_true, y_pred)
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    mae = mean_absolute_error(y_true, y_pred)
    print(f"Train R²: {r2:.4f}, RMSE: {rmse:.2f}, MAE: {mae:.2f}")

    # Plot
    plt.figure(figsize=(14, 5))
    plt.plot(date_series, y_true, label='Actual', color='blue')
    plt.plot(date_series, y_pred, label='Predicted', color='orange')
    plt.title(f"LSTM ({'Stacked' if stacked else 'Single'}) Forecast (t+{fo
recast_horizon}) – Training Set")
    plt.xlabel("Date")
    plt.ylabel("Close Price")
    plt.legend()
    plt.tight_layout()
    plt.savefig(f"B:/DCU/Practicum/Proj/Outputs/lstm_train_t_plus_{forecast
_horizon}{'_stacked' if stacked else '_simple'}.png")
    plt.show()

    return model, {"r2": r2, "rmse": rmse, "mae": mae}


for horizon in [1, 3, 7]:
    clear_tf_memory()
    train_lstm_multistep(df_lstm, forecast_horizon=horizon, stacked=False)

for horizon in [1, 3, 7]:
    clear_tf_memory()
    train_lstm_multistep(df_lstm, forecast_horizon=horizon, stacked=True)
```

```
Training LSTM (Single) model for horizon t+1
Epoch 1/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 2s 20ms/step - loss: 0.0427 - val_loss: 0.0370
Epoch 2/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - loss: 0.0146 - val_loss: 0.0056
Epoch 3/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0089 - val_loss: 0.0039
Epoch 4/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 16ms/step - loss: 0.0084 - val_loss: 0.0033
Epoch 5/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - loss: 0.0061 - val_loss: 0.0031
Epoch 6/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - loss: 0.0058 - val_loss: 0.0016
Epoch 7/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - loss: 0.0053 - val_loss: 0.0014
Epoch 8/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - loss: 0.0048 - val_loss: 0.0016
Epoch 9/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0039 - val_loss: 0.0013
Epoch 10/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0039 - val_loss: 0.0017
Epoch 11/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - loss: 0.0037 - val_loss: 0.0017
Epoch 12/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 18ms/step - loss: 0.0037 - val_loss: 0.0016
Epoch 13/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - loss: 0.0031 - val_loss: 0.0010
Epoch 14/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 19ms/step - loss: 0.0028 - val_loss: 0.0016
Epoch 15/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0029 - val_loss: 0.0022
Epoch 16/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - loss: 0.0029 - val_loss: 0.0020
Epoch 17/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 16ms/step - loss: 0.0026 - val_loss: 9.3109e
-04
Epoch 18/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 16ms/step - loss: 0.0026 - val_loss: 0.0011
Epoch 19/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 16ms/step - loss: 0.0022 - val_loss: 6.5980e
-04
Epoch 20/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 17ms/step - loss: 0.0021 - val_loss: 0.0015
Epoch 21/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 16ms/step - loss: 0.0020 - val_loss: 8.1791e
-04
Epoch 22/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0019 - val_loss: 8.4484e
-04
Epoch 23/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - loss: 0.0020 - val_loss: 0.0012
Epoch 24/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - loss: 0.0019 - val_loss: 8.5470e
-04
Saved model and scalers: lstm_tplus1_simple
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
Train R²: 0.9881, RMSE: 294.14, MAE: 225.36
```

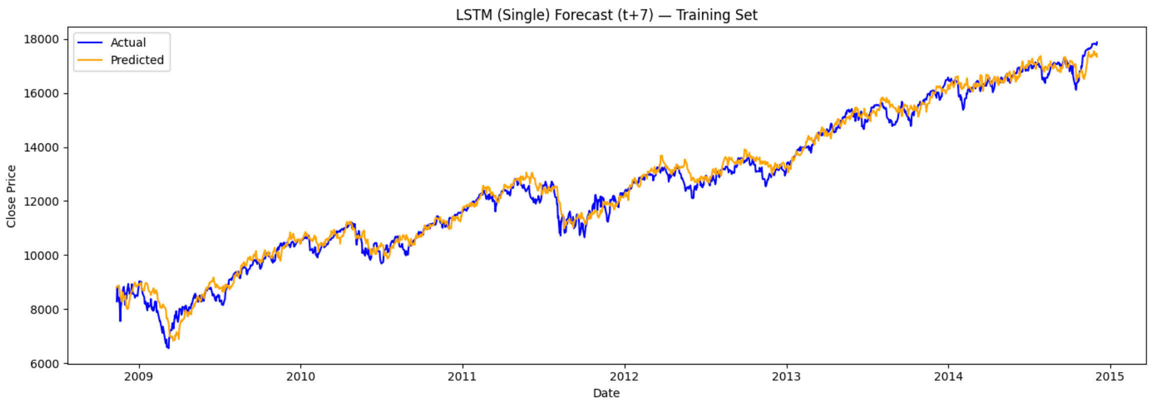



```
Training LSTM (Single) model for horizon t+3
Epoch 1/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 2s 21ms/step - loss: 0.0490 - val_loss: 0.0317
Epoch 2/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0130 - val_loss: 0.0048
Epoch 3/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0119 - val_loss: 0.0041
Epoch 4/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0100 - val_loss: 0.0033
Epoch 5/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0080 - val_loss: 0.0035
Epoch 6/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0071 - val_loss: 0.0040
Epoch 7/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0066 - val_loss: 0.0021
Epoch 8/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0056 - val_loss: 0.0011
Epoch 9/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0052 - val_loss: 9.8040e
-04
Epoch 10/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0046 - val_loss: 9.2705e
-04
Epoch 11/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0042 - val_loss: 9.5220e
-04
Epoch 12/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0039 - val_loss: 0.0013
Epoch 13/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 16ms/step - loss: 0.0040 - val_loss: 9.4911e
-04
Epoch 14/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 16ms/step - loss: 0.0037 - val_loss: 0.0011
Epoch 15/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 15ms/step - loss: 0.0033 - val_loss: 0.0012
Saved model and scalers: lstm_tplus3_simple
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
Train R²: 0.9863, RMSE: 315.44, MAE: 241.68
```

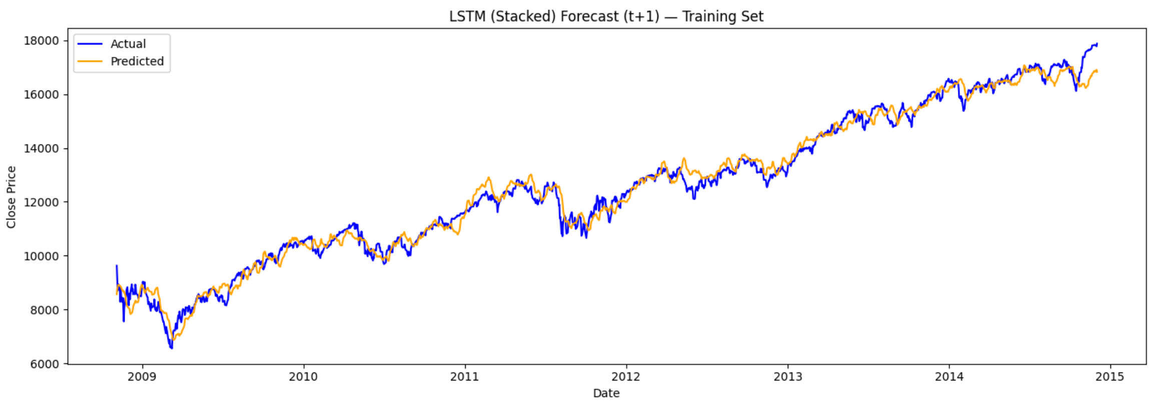

LSTM (Single) Forecast (t+3) — Training Set
Actual
Predicted
Close Price
18000
16000
14000
12000
10000
8000
6000
2009
2010
2011
2012
2013
2014
2015
Date

```
Training LSTM (Single) model for horizon t+7
Epoch 1/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 2s 17ms/step - loss: 0.0637 - val_loss: 0.0921
Epoch 2/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - loss: 0.0210 - val_loss: 0.0226
Epoch 3/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0087 - val_loss: 0.0042
Epoch 4/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0072 - val_loss: 0.0046
Epoch 5/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0060 - val_loss: 0.0033
Epoch 6/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0058 - val_loss: 0.0034
Epoch 7/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0048 - val_loss: 0.0053
Epoch 8/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0045 - val_loss: 0.0034
Epoch 9/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0041 - val_loss: 0.0031
Epoch 10/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0044 - val_loss: 0.0028
Epoch 11/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0037 - val_loss: 0.0031
Epoch 12/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0037 - val_loss: 0.0022
Epoch 13/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0034 - val_loss: 0.0016
Epoch 14/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0031 - val_loss: 0.0012
Epoch 15/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0030 - val_loss: 0.0015
Epoch 16/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0029 - val_loss: 0.0012
Epoch 17/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0029 - val_loss: 0.0011
Epoch 18/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0027 - val_loss: 0.0013
Epoch 19/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0026 - val_loss: 0.0017
Epoch 20/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0027 - val_loss: 0.0014
Epoch 21/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0024 - val_loss: 0.0011
Epoch 22/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0023 - val_loss: 9.6655e
-04
Epoch 23/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0024 - val_loss: 8.4553e
-04
Epoch 24/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - loss: 0.0022 - val_loss: 0.0013
Epoch 25/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0022 - val_loss: 8.9481e
-04
Epoch 26/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0022 - val_loss: 8.6509e
-04
Epoch 27/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0018 - val_loss: 0.0012
Epoch 28/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0020 - val_loss: 8.1267e
```

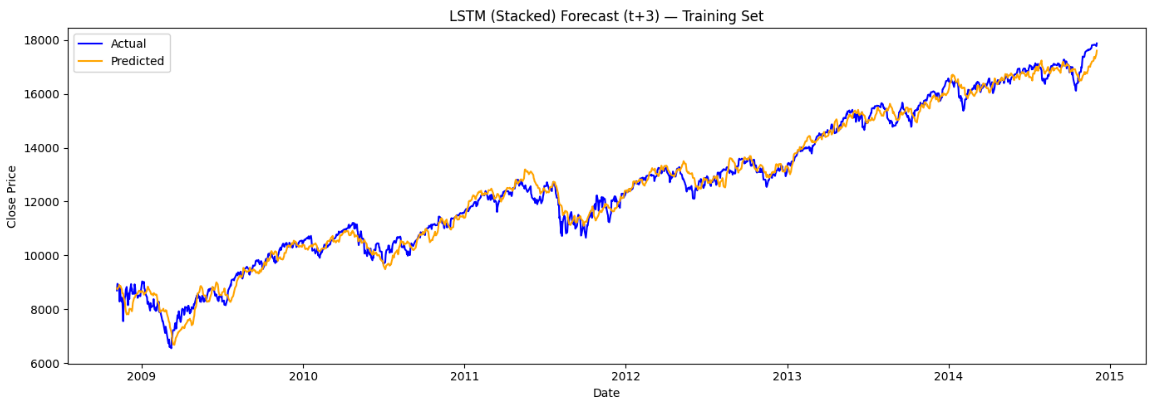
```
-04
Epoch 29/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0019 - val_loss: 7.1048e
-04
Epoch 30/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0020 - val_loss: 7.2605e
-04
Epoch 31/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0020 - val_loss: 0.0011
Epoch 32/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0021 - val_loss: 8.5533e
-04
Epoch 33/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0019 - val_loss: 7.5960e
-04
Epoch 34/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0019 - val_loss: 0.0016
Saved model and scalers: lstm_tplus7_simple
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
Train R²: 0.9855, RMSE: 323.81, MAE: 246.69
```



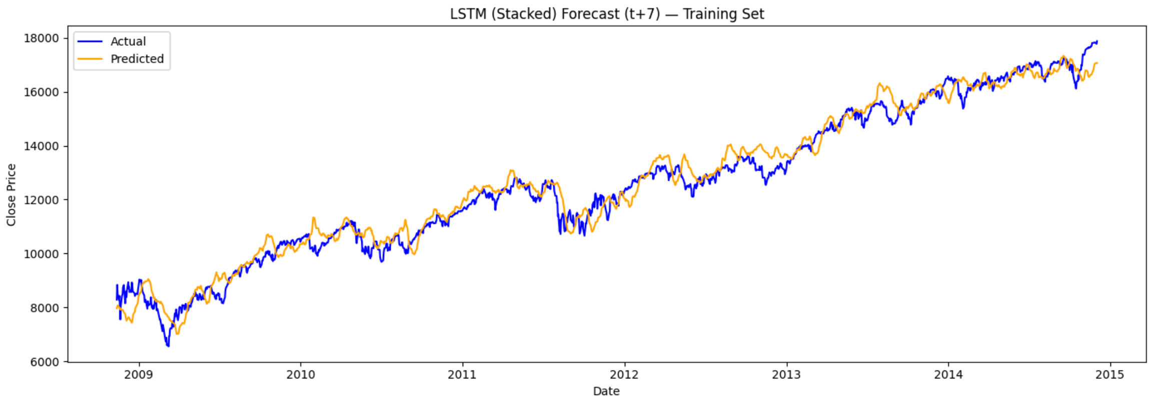
```
Training LSTM (Stacked) model for horizon t+1
Epoch 1/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 3s 28ms/step - loss: 0.1739 - val_loss: 0.0531
Epoch 2/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0360 - val_loss: 0.0362
Epoch 3/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0209 - val_loss: 0.0116
Epoch 4/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 22ms/step - loss: 0.0158 - val_loss: 0.0086
Epoch 5/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 22ms/step - loss: 0.0150 - val_loss: 0.0080
Epoch 6/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 22ms/step - loss: 0.0134 - val_loss: 0.0057
Epoch 7/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0130 - val_loss: 0.0074
Epoch 8/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 22ms/step - loss: 0.0113 - val_loss: 0.0058
Epoch 9/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 22ms/step - loss: 0.0118 - val_loss: 0.0052
Epoch 10/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0118 - val_loss: 0.0067
Epoch 11/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 22ms/step - loss: 0.0106 - val_loss: 0.0085
Epoch 12/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0114 - val_loss: 0.0054
Epoch 13/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0104 - val_loss: 0.0049
Epoch 14/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0111 - val_loss: 0.0051
Epoch 15/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0102 - val_loss: 0.0046
Epoch 16/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0097 - val_loss: 0.0055
Epoch 17/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 22ms/step - loss: 0.0096 - val_loss: 0.0051
Epoch 18/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0094 - val_loss: 0.0065
Epoch 19/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0095 - val_loss: 0.0052
Epoch 20/50
44/44 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0091 - val_loss: 0.0059
Saved model and scalers: lstm_tplus1_stacked
48/48 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step
Train R²: 0.9826, RMSE: 355.83, MAE: 272.09
```



```
Training LSTM (Stacked) model for horizon t+3
Epoch 1/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 29ms/step - loss: 0.0749 - val_loss: 0.0647
Epoch 2/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0342 - val_loss: 0.0112
Epoch 3/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0212 - val_loss: 0.0064
Epoch 4/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0176 - val_loss: 0.0072
Epoch 5/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0149 - val_loss: 0.0052
Epoch 6/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0135 - val_loss: 0.0051
Epoch 7/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0125 - val_loss: 0.0038
Epoch 8/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0132 - val_loss: 0.0035
Epoch 9/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0118 - val_loss: 0.0047
Epoch 10/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0108 - val_loss: 0.0038
Epoch 11/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0112 - val_loss: 0.0048
Epoch 12/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0107 - val_loss: 0.0038
Epoch 13/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0097 - val_loss: 0.0037
Saved model and scalers: lstm_tplus3_stacked
48/48 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step
Train R²: 0.9858, RMSE: 320.75, MAE: 251.53
```



```
Training LSTM (Stacked) model for horizon t+7
Epoch 1/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 3s 29ms/step - loss: 0.0723 - val_loss: 0.0758
Epoch 2/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0271 - val_loss: 0.0129
Epoch 3/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0178 - val_loss: 0.0084
Epoch 4/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0166 - val_loss: 0.0050
Epoch 5/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0141 - val_loss: 0.0062
Epoch 6/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0149 - val_loss: 0.0042
Epoch 7/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0126 - val_loss: 0.0066
Epoch 8/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0132 - val_loss: 0.0043
Epoch 9/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0122 - val_loss: 0.0043
Epoch 10/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 24ms/step - loss: 0.0118 - val_loss: 0.0059
Epoch 11/50
43/43 ━━━━━━━━━━━━━━━━━━━━ 1s 23ms/step - loss: 0.0116 - val_loss: 0.0069
Saved model and scalers: lstm_tplus7_stacked
48/48 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step
Train R²: 0.9700, RMSE: 466.63, MAE: 365.38
```



Temporal Convolutional Networks

In [15]:
```python
Dropped_tcn_cols = [
    'Open', 'High', 'Low', 'Volume', 'Adj Close',
    'Volatility_Log_10', 'cl-op', 'hi-lo', 'pct_change',
    'total_buying_intent', 'total_prediction_intent'
]
df_tcn_filtered = df_tcn.drop(columns=Dropped_tcn_cols).copy()
```

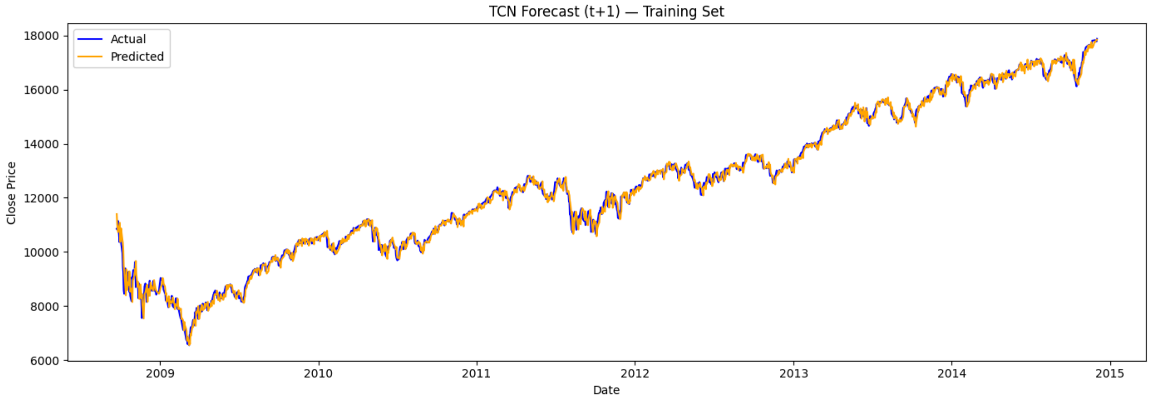
In [24]:
```
def train_tcn_logreturn_model(df_tcn_filtered, df_targets, forecast_horizon
=1, window_size=30, epochs=50, batch_size=32):
    print(f"\nTraining TCN model to predict Log Returns at t+{forecast_hori
zon}")

    target_series = df_tcn_filtered['Log_Returns'].shift(-forecast_horizo
n).dropna()
    df_inputs = df_tcn_filtered.iloc[:len(target_series)]

    # Scaling
    X_scaler = MinMaxScaler()
    y_scaler = MinMaxScaler()
    X_scaled = X_scaler.fit_transform(df_inputs)
    y_scaled = y_scaler.fit_transform(target_series.values.reshape(-1, 1))

    # Sequences
    X_seq, y_seq = [], []
    for i in range(window_size, len(X_scaled)):
        X_seq.append(X_scaled[i - window_size:i])
        y_seq.append(y_scaled[i])
    X_seq, y_seq = np.array(X_seq), np.array(y_seq)

    assert len(X_seq) == len(y_seq), "Sequence and target length mismatch"

    # Build model
    model = Sequential()
    model.add(TCN(
        input_shape=(X_seq.shape[1], X_seq.shape[2]),
        nb_filters=32,
        kernel_size=2,
        dropout_rate=0.1,
    ))
    model.add(GroupNormalization(groups=8))
    model.add(Dropout(0.2))
    model.add(Dense(1))  # Linear output
    model.compile(optimizer=Adam(learning_rate=1e-4), loss=Huber())

    early_stop = EarlyStopping(monitor='val_loss', patience=5, restore_best
_weights=True)

    # Fit model
    print("Starting model.fit()")
    model.fit(
        X_seq, y_seq,
        epochs=epochs,
        batch_size=batch_size,
        validation_split=0.1,
        callbacks=[early_stop],
        verbose=2
    )
    print("model.fit() complete")

    # Save model & scalers
    model_name = f"tcn_logret_tplus{forecast_horizon}"
    base_path = "B:/DCU/Practicum/Proj/Models"
    os.makedirs(base_path, exist_ok=True)
    model.save(f"{base_path}/{model_name}.keras")
    joblib.dump(X_scaler, f"{base_path}/{model_name}_scalerX.pkl")
    joblib.dump(y_scaler, f"{base_path}/{model_name}_scalerY.pkl")
    joblib.dump(df_tcn_filtered.columns.tolist(), f"{base_path}/{model_nam
```

```
e}_features.pkl")
    print(f"Saved model, scalers, and features for {model_name}")

    # Predict
    y_pred_scaled = model.predict(X_seq)
    y_pred_log = y_scaler.inverse_transform(y_pred_scaled).flatten()

    # clip predicted log returns to avoid exponential blowups
    y_pred_log = np.clip(y_pred_log, -0.15, 0.15)

    # Reconstruct close price
    close_start_idx = window_size - 1
    close_end_idx = close_start_idx + len(y_pred_log)
    close_t = df_targets['Close'].iloc[close_start_idx:close_end_idx].value
s

    assert len(close_t) == len(y_pred_log), "Mismatch: Close_t vs Predicted
log returns"
    y_pred_close = close_t * np.exp(y_pred_log)

    # Actual Close at t+h
    y_true_close = df_targets['Close'].shift(-forecast_horizon).dropna().il
oc[window_size:]
    y_true_close = y_true_close[:len(y_pred_close)].values

    date_series = multimodal['Date'].iloc[window_size + forecast_horizon: w
indow_size + forecast_horizon + len(y_pred_close)]

    # Evaluation
    r2 = r2_score(y_true_close, y_pred_close)
    rmse = np.sqrt(mean_squared_error(y_true_close, y_pred_close))
    mae = mean_absolute_error(y_true_close, y_pred_close)
    print(f"TCN Train R²: {r2:.4f}, RMSE: {rmse:.2f}, MAE: {mae:.2f}")

    # Save metrics
    metrics_path = os.path.join(base_path, f"{model_name}_metrics.txt")
    with open(metrics_path, "w") as f:
        f.write(f"Forecast Horizon = t+{forecast_horizon}\n")
        f.write(f"Train R²   = {r2:.4f}\n")
        f.write(f"Train RMSE = {rmse:.2f}\n")
        f.write(f"Train MAE  = {mae:.2f}\n")
    print(f"Saved training metrics to {metrics_path}")

    # Plot
    plt.figure(figsize=(14, 5))
    plt.plot(date_series, y_true_close, label='Actual', color='blue')
    plt.plot(date_series, y_pred_close, label='Predicted', color='orange')
    plt.title(f"TCN Forecast (t+{forecast_horizon}) — Training Set")
    plt.xlabel("Date")
    plt.ylabel("Close Price")
    plt.legend()
    plt.tight_layout()
    plt.savefig(f"B:/DCU/Practicum/Proj/Outputs/tcn_train_t_plus_{forecast_
horizon}.png")
    plt.show()

    return model, {"r2": r2, "rmse": rmse, "mae": mae}

for h in [1, 3, 7]:
    clear_tf_memory()
```

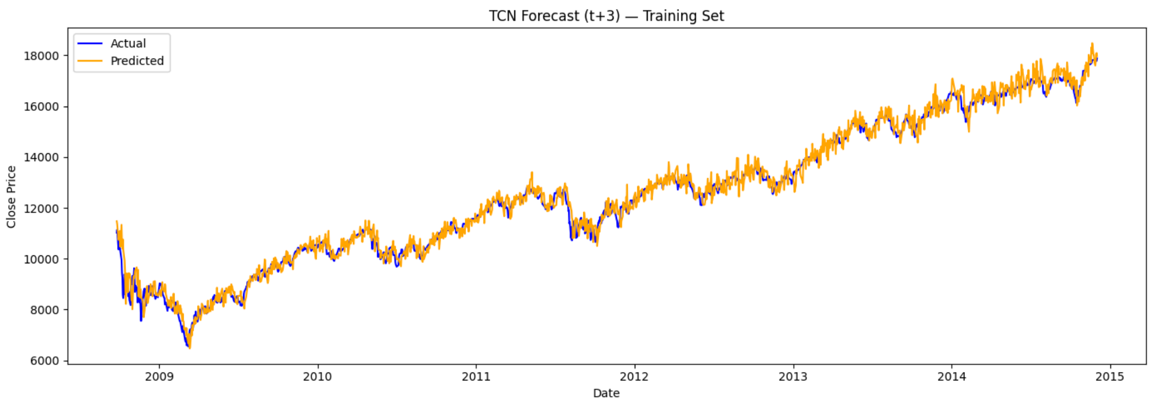
```
    train_tcn_logreturn_model(df_tcn_filtered, df_targets, forecast_horizon
=h)
```

```
Training TCN model to predict Log Returns at t+1
Starting model.fit()
Epoch 1/50
44/44 - 4s - 102ms/step - loss: 0.4008 - val_loss: 0.0530
Epoch 2/50
44/44 - 0s - 11ms/step - loss: 0.3013 - val_loss: 0.0229
Epoch 3/50
44/44 - 0s - 11ms/step - loss: 0.2594 - val_loss: 0.0144
Epoch 4/50
44/44 - 0s - 11ms/step - loss: 0.2413 - val_loss: 0.0122
Epoch 5/50
44/44 - 0s - 11ms/step - loss: 0.2120 - val_loss: 0.0110
Epoch 6/50
44/44 - 0s - 11ms/step - loss: 0.2001 - val_loss: 0.0075
Epoch 7/50
44/44 - 0s - 11ms/step - loss: 0.1776 - val_loss: 0.0055
Epoch 8/50
44/44 - 0s - 11ms/step - loss: 0.1722 - val_loss: 0.0054
Epoch 9/50
44/44 - 0s - 10ms/step - loss: 0.1519 - val_loss: 0.0056
Epoch 10/50
44/44 - 0s - 11ms/step - loss: 0.1408 - val_loss: 0.0034
Epoch 11/50
44/44 - 0s - 11ms/step - loss: 0.1413 - val_loss: 0.0021
Epoch 12/50
44/44 - 0s - 11ms/step - loss: 0.1349 - val_loss: 0.0019
Epoch 13/50
44/44 - 0s - 10ms/step - loss: 0.1249 - val_loss: 0.0018
Epoch 14/50
44/44 - 0s - 10ms/step - loss: 0.1233 - val_loss: 0.0016
Epoch 15/50
44/44 - 0s - 10ms/step - loss: 0.1097 - val_loss: 0.0017
Epoch 16/50
44/44 - 0s - 10ms/step - loss: 0.1098 - val_loss: 0.0014
Epoch 17/50
44/44 - 0s - 10ms/step - loss: 0.1096 - val_loss: 0.0014
Epoch 18/50
44/44 - 0s - 10ms/step - loss: 0.1030 - val_loss: 0.0017
Epoch 19/50
44/44 - 0s - 10ms/step - loss: 0.1002 - val_loss: 0.0015
Epoch 20/50
44/44 - 0s - 10ms/step - loss: 0.0982 - val_loss: 0.0013
Epoch 21/50
44/44 - 0s - 10ms/step - loss: 0.0967 - val_loss: 0.0015
Epoch 22/50
44/44 - 0s - 10ms/step - loss: 0.0982 - val_loss: 0.0011
Epoch 23/50
44/44 - 0s - 10ms/step - loss: 0.0958 - val_loss: 0.0011
Epoch 24/50
44/44 - 0s - 11ms/step - loss: 0.0873 - val_loss: 0.0011
Epoch 25/50
44/44 - 0s - 11ms/step - loss: 0.0869 - val_loss: 0.0011
Epoch 26/50
44/44 - 0s - 10ms/step - loss: 0.0836 - val_loss: 0.0010
Epoch 27/50
44/44 - 0s - 10ms/step - loss: 0.0814 - val_loss: 0.0011
Epoch 28/50
44/44 - 0s - 10ms/step - loss: 0.0813 - val_loss: 0.0011
Epoch 29/50
44/44 - 0s - 10ms/step - loss: 0.0747 - val_loss: 9.8430e-04
Epoch 30/50
```

```
44/44 - 0s - 10ms/step - loss: 0.0721 - val_loss: 9.4004e-04
Epoch 31/50
44/44 - 0s - 10ms/step - loss: 0.0729 - val_loss: 0.0011
Epoch 32/50
44/44 - 0s - 10ms/step - loss: 0.0704 - val_loss: 0.0011
Epoch 33/50
44/44 - 0s - 10ms/step - loss: 0.0657 - val_loss: 0.0013
Epoch 34/50
44/44 - 0s - 10ms/step - loss: 0.0632 - val_loss: 9.6007e-04
Epoch 35/50
44/44 - 0s - 10ms/step - loss: 0.0591 - val_loss: 0.0010
model.fit() complete
Saved model, scalers, and features for tcn_logret_tplus1
49/49 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step
TCN Train R²: 0.9950, RMSE: 192.23, MAE: 141.85
Saved training metrics to B:/DCU/Practicum/Proj/Models\tcn_logret_tplus1_m
etrics.txt
```

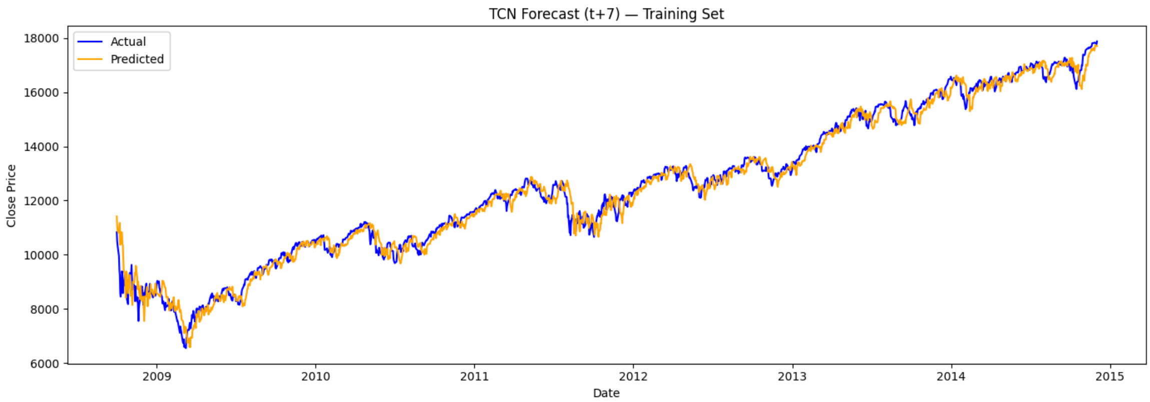


```
Training TCN model to predict Log Returns at t+3
Starting model.fit()
Epoch 1/50
44/44 - 4s - 98ms/step - loss: 0.5472 - val_loss: 0.0603
Epoch 2/50
44/44 - 0s - 10ms/step - loss: 0.4133 - val_loss: 0.0359
Epoch 3/50
44/44 - 0s - 10ms/step - loss: 0.3419 - val_loss: 0.0247
Epoch 4/50
44/44 - 0s - 10ms/step - loss: 0.2831 - val_loss: 0.0216
Epoch 5/50
44/44 - 0s - 10ms/step - loss: 0.2726 - val_loss: 0.0148
Epoch 6/50
44/44 - 0s - 10ms/step - loss: 0.2460 - val_loss: 0.0125
Epoch 7/50
44/44 - 0s - 10ms/step - loss: 0.2292 - val_loss: 0.0067
Epoch 8/50
44/44 - 0s - 10ms/step - loss: 0.2091 - val_loss: 0.0078
Epoch 9/50
44/44 - 0s - 10ms/step - loss: 0.2032 - val_loss: 0.0077
Epoch 10/50
44/44 - 0s - 10ms/step - loss: 0.1896 - val_loss: 0.0093
Epoch 11/50
44/44 - 0s - 10ms/step - loss: 0.1929 - val_loss: 0.0102
Epoch 12/50
44/44 - 0s - 10ms/step - loss: 0.1851 - val_loss: 0.0091
model.fit() complete
Saved model, scalers, and features for tcn_logret_tplus3
49/49 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step
TCN Train R²: 0.9845, RMSE: 337.50, MAE: 261.15
Saved training metrics to B:/DCU/Practicum/Proj/Models\tcn_logret_tplus3_m
etrics.txt
```



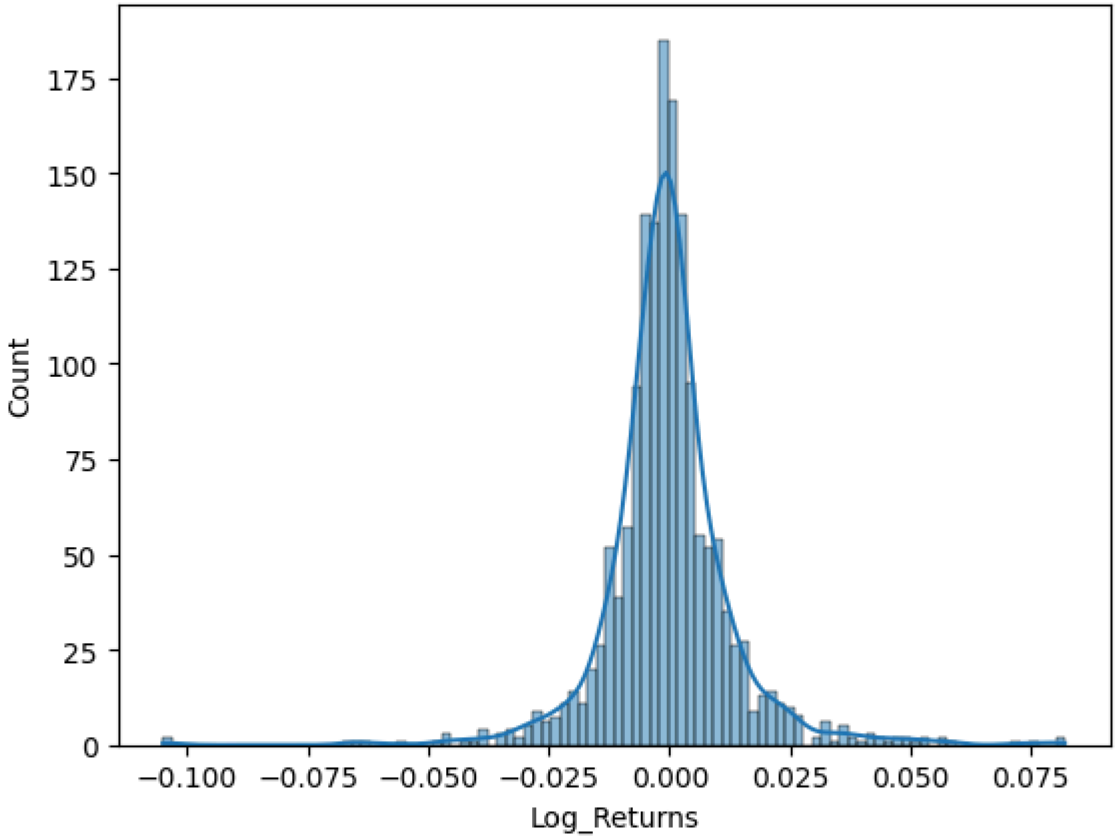
```
Training TCN model to predict Log Returns at t+7
Starting model.fit()
Epoch 1/50
44/44 - 4s - 99ms/step - loss: 0.4403 - val_loss: 0.1279
Epoch 2/50
44/44 - 0s - 10ms/step - loss: 0.3425 - val_loss: 0.0485
Epoch 3/50
44/44 - 0s - 10ms/step - loss: 0.3295 - val_loss: 0.0324
Epoch 4/50
44/44 - 0s - 11ms/step - loss: 0.2898 - val_loss: 0.0197
Epoch 5/50
44/44 - 0s - 10ms/step - loss: 0.2644 - val_loss: 0.0158
Epoch 6/50
44/44 - 0s - 10ms/step - loss: 0.2356 - val_loss: 0.0181
Epoch 7/50
44/44 - 0s - 10ms/step - loss: 0.2451 - val_loss: 0.0156
Epoch 8/50
44/44 - 0s - 10ms/step - loss: 0.2230 - val_loss: 0.0088
Epoch 9/50
44/44 - 0s - 10ms/step - loss: 0.2096 - val_loss: 0.0107
Epoch 10/50
44/44 - 0s - 11ms/step - loss: 0.1912 - val_loss: 0.0031
Epoch 11/50
44/44 - 0s - 10ms/step - loss: 0.1820 - val_loss: 0.0033
Epoch 12/50
44/44 - 0s - 10ms/step - loss: 0.1708 - val_loss: 0.0033
Epoch 13/50
44/44 - 0s - 10ms/step - loss: 0.1656 - val_loss: 0.0019
Epoch 14/50
44/44 - 0s - 11ms/step - loss: 0.1651 - val_loss: 0.0019
Epoch 15/50
44/44 - 0s - 10ms/step - loss: 0.1495 - val_loss: 0.0016
Epoch 16/50
44/44 - 0s - 10ms/step - loss: 0.1520 - val_loss: 0.0014
Epoch 17/50
44/44 - 1s - 12ms/step - loss: 0.1432 - val_loss: 0.0020
Epoch 18/50
44/44 - 1s - 13ms/step - loss: 0.1260 - val_loss: 0.0014
Epoch 19/50
44/44 - 0s - 11ms/step - loss: 0.1200 - val_loss: 0.0012
Epoch 20/50
44/44 - 0s - 10ms/step - loss: 0.1265 - val_loss: 0.0012
Epoch 21/50
44/44 - 1s - 12ms/step - loss: 0.1196 - val_loss: 0.0026
Epoch 22/50
44/44 - 1s - 12ms/step - loss: 0.1076 - val_loss: 9.2440e-04
Epoch 23/50
44/44 - 0s - 10ms/step - loss: 0.1013 - val_loss: 9.5243e-04
Epoch 24/50
44/44 - 0s - 11ms/step - loss: 0.1033 - val_loss: 8.7182e-04
Epoch 25/50
44/44 - 0s - 11ms/step - loss: 0.0967 - val_loss: 0.0014
Epoch 26/50
44/44 - 0s - 11ms/step - loss: 0.0955 - val_loss: 0.0015
Epoch 27/50
44/44 - 1s - 13ms/step - loss: 0.0878 - val_loss: 0.0015
Epoch 28/50
44/44 - 1s - 12ms/step - loss: 0.0882 - val_loss: 8.0366e-04
Epoch 29/50
44/44 - 1s - 11ms/step - loss: 0.0872 - val_loss: 9.2579e-04
Epoch 30/50
```

```
44/44 - 1s - 13ms/step - loss: 0.0888 - val_loss: 7.8006e-04
Epoch 31/50
44/44 - 1s - 13ms/step - loss: 0.0786 - val_loss: 8.0489e-04
Epoch 32/50
44/44 - 0s - 11ms/step - loss: 0.0810 - val_loss: 7.1540e-04
Epoch 33/50
44/44 - 0s - 11ms/step - loss: 0.0760 - val_loss: 6.7770e-04
Epoch 34/50
44/44 - 0s - 11ms/step - loss: 0.0715 - val_loss: 6.5881e-04
Epoch 35/50
44/44 - 0s - 10ms/step - loss: 0.0740 - val_loss: 6.8288e-04
Epoch 36/50
44/44 - 1s - 14ms/step - loss: 0.0650 - val_loss: 6.4124e-04
Epoch 37/50
44/44 - 1s - 14ms/step - loss: 0.0655 - val_loss: 6.3827e-04
Epoch 38/50
44/44 - 1s - 13ms/step - loss: 0.0652 - val_loss: 6.7055e-04
Epoch 39/50
44/44 - 1s - 13ms/step - loss: 0.0609 - val_loss: 6.8099e-04
Epoch 40/50
44/44 - 1s - 14ms/step - loss: 0.0651 - val_loss: 7.0217e-04
Epoch 41/50
44/44 - 1s - 13ms/step - loss: 0.0552 - val_loss: 6.5736e-04
Epoch 42/50
44/44 - 1s - 12ms/step - loss: 0.0542 - val_loss: 7.7907e-04
model.fit() complete
Saved model, scalers, and features for tcn_logret_tplus7
49/49 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step
TCN Train R²: 0.9835, RMSE: 348.33, MAE: 260.38
Saved training metrics to B:/DCU/Practicum/Proj/Models\tcn_logret_tplus7_m
etrics.txt
```



In [17]:
```
sns.histplot(df_tcn_filtered['Log_Returns'], bins=100, kde=True)
```

Out[17]:
```
<Axes: xlabel='Log_Returns', ylabel='Count'>
```



In [18]:
```
print("Skew:", skew(df_tcn_filtered['Log_Returns']))
print("Kurtosis:", kurtosis(df_tcn_filtered['Log_Returns']))
```

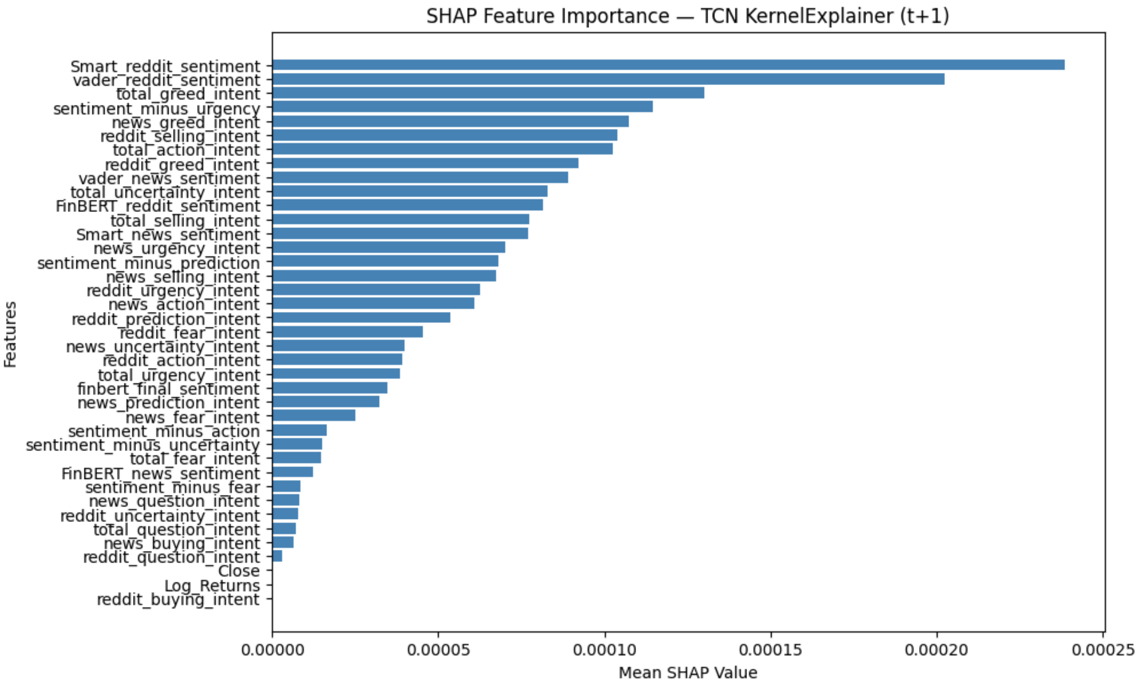
```
Skew: 0.06939321499881877
Kurtosis: 10.324332846429078
```

In [19]:
```
def run_shap_kernel_on_tcn(model_dir, df_input, forecast_horizon, window_si
ze=30, num_samples=25):
    model_name = f"tcn_logret_tplus{forecast_horizon}"
    model_path = os.path.join(model_dir, f"{model_name}.keras")
    scalerX_path = os.path.join(model_dir, f"{model_name}_scalerX.pkl")

    # Load model and scaler
    model = load_model(model_path, compile=False)
    X_scaler = joblib.load(scalerX_path)

    # Scale and sequence input
    df_scaled = X_scaler.transform(df_input)
    X_seq = []
    for i in range(window_size, len(df_scaled)):
        X_seq.append(df_scaled[i - window_size:i])
    X_seq = np.array(X_seq)

    # Sample last N sequences
    X_sampled = X_seq[-num_samples:]

    # Track shape dimensions
    num_samples_actual = X_sampled.shape[0]
    num_timesteps = X_sampled.shape[1]
    num_features = X_sampled.shape[2]

    # Flatten input for KernelExplainer
    X_flat = X_sampled.reshape((num_samples_actual, num_timesteps * num_fea
tures))

    # Define prediction wrapper
    def predict_fn(x_flat):
        x_reshaped = x_flat.reshape((-1, num_timesteps, num_features))
        preds = model.predict(x_reshaped)
        return np.array(preds).astype(np.float64).reshape(-1, 1)

    # Run SHAP KernelExplainer
    explainer = shap.KernelExplainer(predict_fn, X_flat)
    try:
        shap_values = explainer(X_flat)
        with open(f"{model_name}_shap_dump.pkl", "wb") as f:
            joblib.dump(shap_values, f)
    except Exception as e:
        print(f"SHAP failed: {e}")
        return

    shap_array = np.abs(shap_values.values)  # shape: [samples, window_size
* features]
    shap_array_3d = shap_array.reshape(shap_array.shape[0], window_size, nu
m_features)
    shap_feature_mean = np.mean(shap_array_3d, axis=(0, 1))  # average acro
ss time and samples

    feature_names = df_input.columns.tolist()

    # Rank + plot
    shap_df = list(zip(feature_names, shap_feature_mean))
    shap_df.sort(key=lambda x: x[1], reverse=True)
    sorted_features, sorted_importance = zip(*shap_df)

    plt.figure(figsize=(10, 6))
```

```
    plt.barh(sorted_features[::-1], sorted_importance[::-1], color='steelbl
ue')
    plt.title(f"SHAP Feature Importance — TCN KernelExplainer (t+{forecast_
horizon})")
    plt.tight_layout()
    plt.xlabel("Mean SHAP Value")
    plt.ylabel("Features")
    plt.savefig(f"B:/DCU/Practicum/Proj/Outputs/{model_name}_shap_kernel.pn
g")
    plt.show()

model_dir = "B:/DCU/Practicum/Proj/Models"

# for h in [1, 3, 7]:
#     print(f"\n Running SHAP KernelExplainer for TCN t+{h}")
#     run_shap_kernel_on_tcn(model_dir, df_tcn, forecast_horizon=h, num_sam
ples=100)

run_shap_kernel_on_tcn(model_dir, df_tcn_filtered, forecast_horizon=1, num_
samples=25)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 271ms/step
  0%|          | 0/25 [00:00<?, ?it/s]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 288ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
  4%|▍         | 1/25 [00:13<05:18, 13.26s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
  8%|▊         | 2/25 [00:25<04:57, 12.94s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 12%|█▏        | 3/25 [00:38<04:42, 12.84s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 16%|█▌        | 4/25 [00:51<04:31, 12.95s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 20%|██        | 5/25 [01:04<04:17, 12.85s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 24%|██▍       | 6/25 [01:17<04:02, 12.79s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 28%|██▊       | 7/25 [01:29<03:48, 12.70s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 32%|███▏      | 8/25 [01:42<03:35, 12.66s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 36%|███▌      | 9/25 [01:54<03:21, 12.57s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 40%|████      | 10/25 [02:07<03:08, 12.59s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step
 44%|████▍     | 11/25 [02:22<03:08, 13.44s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 48%|████▊     | 12/25 [02:35<02:53, 13.35s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
```

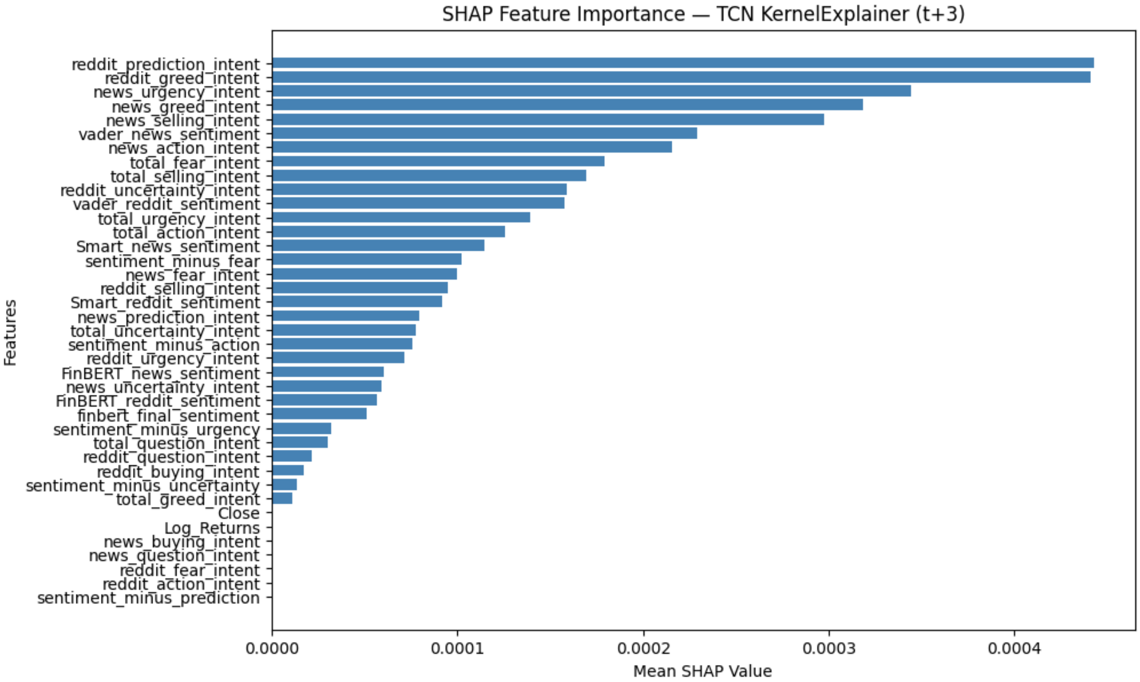
```
 52%|█████     | 13/25 [02:48<02:38, 13.22s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 56%|█████▌    | 14/25 [03:01<02:24, 13.15s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 60%|██████    | 15/25 [03:14<02:10, 13.06s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 64%|██████▍   | 16/25 [03:27<01:56, 12.98s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 68%|██████▊   | 17/25 [03:40<01:43, 12.93s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 72%|███████▏  | 18/25 [03:52<01:30, 12.87s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 76%|███████▌  | 19/25 [04:05<01:17, 12.89s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 80%|████████  | 20/25 [04:18<01:04, 12.88s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 84%|████████▍ | 21/25 [04:31<00:51, 12.84s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 88%|████████▊ | 22/25 [04:44<00:38, 12.79s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 92%|█████████▏| 23/25 [04:56<00:25, 12.80s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 96%|█████████▌| 24/25 [05:10<00:13, 13.02s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
100%|██████████| 25/25 [05:23<00:00, 12.94s/it]
```


SHAP Feature Importance — TCN KernelExplainer (t+1)
Features
Smart_reddit_sentiment
vader_reddit_sentiment
total_greed_intent
sentiment_minus_urgency
news_greed_intent
reddit_selling_intent
total_action_intent
reddit_greed_intent
vader_news_sentiment
total_uncertainty_intent
FinBERT_reddit_sentiment
total_selling_intent
Smart_news_sentiment
news_urgency_intent
sentiment_minus_prediction
news_selling_intent
reddit_urgency_intent
news_action_intent
reddit_prediction_intent
reddit_fear_intent
news_uncertainty_intent
reddit_action_intent
total_urgency_intent
finbert_final_sentiment
news_prediction_intent
news_fear_intent
sentiment_minus_action
sentiment_minus_uncertainty
total_fear_intent
FinBERT_news_sentiment
sentiment_minus_fear
news_question_intent
reddit_uncertainty_intent
total_question_intent
news_buying_intent
reddit_question_intent
Close
Log_Returns
reddit_buying_intent
0.00000
0.00005
0.00010
0.00015
0.00020
0.00025
Mean SHAP Value

In [25]:
```
run_shap_kernel_on_tcn(model_dir, df_tcn_filtered, forecast_horizon=3, num_
samples=25)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 293ms/step

  0%|          | 0/25 [00:00<?, ?it/s]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 280ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step

  4%|▍         | 1/25 [00:15<06:05, 15.21s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step

  8%|▊         | 2/25 [00:29<05:32, 14.47s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step

 12%|█▏        | 3/25 [00:42<05:09, 14.05s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step

 16%|█▌        | 4/25 [00:56<04:51, 13.90s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step

 20%|██        | 5/25 [01:09<04:34, 13.74s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step

 24%|██▍       | 6/25 [01:23<04:19, 13.65s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step

 28%|██▊       | 7/25 [01:36<04:04, 13.57s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step

 32%|███▏      | 8/25 [01:50<03:49, 13.50s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step

 36%|███▌      | 9/25 [02:03<03:35, 13.45s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step

 40%|████      | 10/25 [02:16<03:20, 13.36s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step

 44%|████▍     | 11/25 [02:29<03:06, 13.31s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step

 48%|████▊     | 12/25 [02:43<02:53, 13.31s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
```

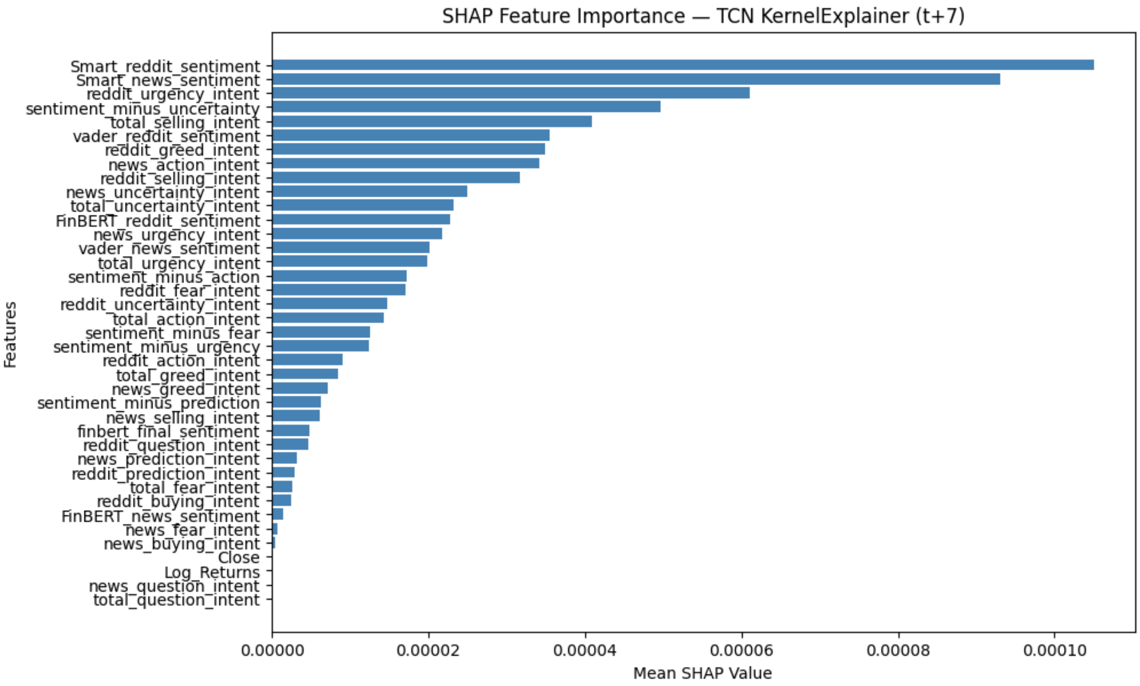
```
 52%|█████▏    | 13/25 [02:56<02:39, 13.30s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 56%|█████▌    | 14/25 [03:09<02:25, 13.26s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step
 60%|██████    | 15/25 [03:22<02:12, 13.29s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step
 64%|██████▍   | 16/25 [03:36<02:00, 13.37s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 68%|██████▊   | 17/25 [03:49<01:46, 13.33s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step
 72%|███████▏  | 18/25 [04:03<01:33, 13.39s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 76%|███████▌  | 19/25 [04:16<01:20, 13.38s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step
 80%|████████  | 20/25 [04:30<01:07, 13.40s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 84%|████████▍ | 21/25 [04:43<00:53, 13.37s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 3ms/step
 88%|████████▊ | 22/25 [04:56<00:40, 13.44s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step
 92%|█████████▏| 23/25 [05:11<00:27, 13.78s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step
 96%|█████████▌| 24/25 [05:26<00:14, 14.04s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 40ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step
100%|██████████| 25/25 [05:41<00:00, 13.64s/it]
```


SHAP Feature Importance — TCN KernelExplainer (t+3)
Features
Mean SHAP Value
reddit_prediction_intent
reddit_greed_intent
news_urgency_intent
news_greed_intent
news_selling_intent
vader_news_sentiment
news_action_intent
total_fear_intent
total_selling_intent
reddit_uncertainty_intent
vader_reddit_sentiment
total_urgency_intent
total_action_intent
Smart_news_sentiment
sentiment_minus_fear
news_fear_intent
reddit_selling_intent
Smart_reddit_sentiment
news_prediction_intent
total_uncertainty_intent
sentiment_minus_action
reddit_urgency_intent
FinBERT_news_sentiment
news_uncertainty_intent
FinBERT_reddit_sentiment
finbert_final_sentiment
sentiment_minus_urgency
total_question_intent
reddit_question_intent
reddit_buying_intent
sentiment_minus_uncertainty
total_greed_intent
Close
Log_Returns
news_buying_intent
news_question_intent
reddit_fear_intent
reddit_action_intent
sentiment_minus_prediction
0.0000
0.0001
0.0002
0.0003
0.0004

In [26]:
```
run_shap_kernel_on_tcn(model_dir, df_tcn_filtered, forecast_horizon=7, num_
samples=25)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 277ms/step

  0%|          | 0/25 [00:00<?, ?it/s]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 294ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step

  4%|▍         | 1/25 [00:14<05:54, 14.75s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 38ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step

  8%|▊         | 2/25 [00:29<05:37, 14.70s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step

 12%|█▏        | 3/25 [00:43<05:20, 14.58s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step

 16%|█▌        | 4/25 [00:58<05:05, 14.52s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step

 20%|██        | 5/25 [01:12<04:49, 14.49s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step

 24%|██▍       | 6/25 [01:27<04:34, 14.45s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 60ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step

 28%|██▊       | 7/25 [01:41<04:20, 14.45s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step

 32%|███▏      | 8/25 [01:55<04:05, 14.42s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 12s 4ms/step

 36%|███▌      | 9/25 [02:10<03:50, 14.38s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 38ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step

 40%|████      | 10/25 [02:24<03:35, 14.38s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step

 44%|████▍     | 11/25 [02:38<03:21, 14.36s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step

 48%|████▊     | 12/25 [02:53<03:07, 14.45s/it]

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step
```

```
 52%|█████     | 13/25 [03:07<02:53, 14.44s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step
 56%|█████▌    | 14/25 [03:22<02:39, 14.49s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step
 60%|██████    | 15/25 [03:37<02:25, 14.51s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 13s 4ms/step
 64%|██████▍   | 16/25 [03:52<02:12, 14.74s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 68%|██████▊   | 17/25 [04:05<01:53, 14.19s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 72%|███████▏  | 18/25 [04:18<01:36, 13.82s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 76%|███████▌  | 19/25 [04:31<01:21, 13.53s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 80%|████████  | 20/25 [04:44<01:06, 13.37s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 84%|████████▍ | 21/25 [04:57<00:52, 13.24s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 88%|████████▊ | 22/25 [05:09<00:39, 13.14s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 92%|█████████▏| 23/25 [05:22<00:26, 13.08s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
 96%|█████████▌| 24/25 [05:35<00:13, 13.02s/it]
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
3429/3429 ━━━━━━━━━━━━━━━━━━━━ 11s 3ms/step
100%|██████████| 25/25 [05:48<00:00, 13.95s/it]
```


SHAP Feature Importance — TCN KernelExplainer (t+7)
Features
Smart_reddit_sentiment
Smart_news_sentiment
reddit_urgency_intent
sentiment_minus_uncertainty
total_selling_intent
vader_reddit_sentiment
reddit_greed_intent
news_action_intent
reddit_selling_intent
news_uncertainty_intent
total_uncertainty_intent
FinBERT_reddit_sentiment
news_urgency_intent
vader_news_sentiment
total_urgency_intent
sentiment_minus_action
reddit_fear_intent
reddit_uncertainty_intent
total_action_intent
sentiment_minus_fear
sentiment_minus_urgency
reddit_action_intent
total_greed_intent
news_greed_intent
sentiment_minus_prediction
news_selling_intent
finbert_final_sentiment
reddit_question_intent
news_prediction_intent
reddit_prediction_intent
total_fear_intent
reddit_buying_intent
FinBERT_news_sentiment
news_fear_intent
news_buying_intent
Close
Log_Returns
news_question_intent
total_question_intent
0.00000
0.00002
0.00004
0.00006
0.00008
0.00010
Mean SHAP Value