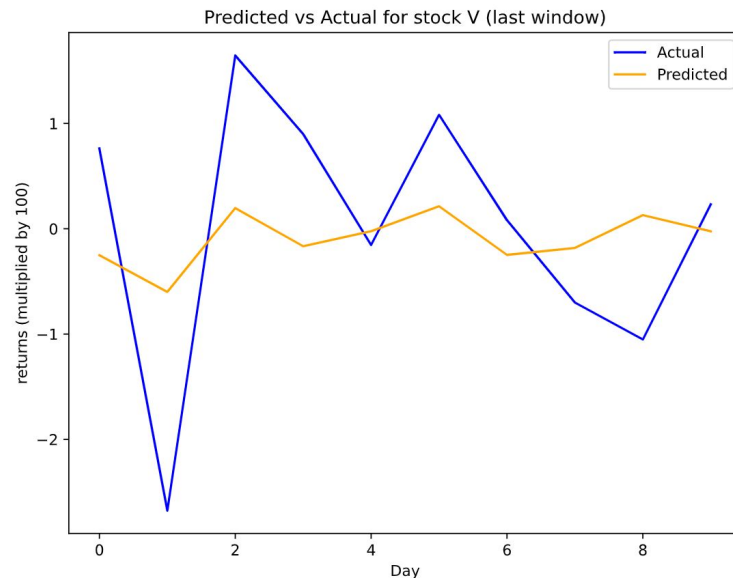
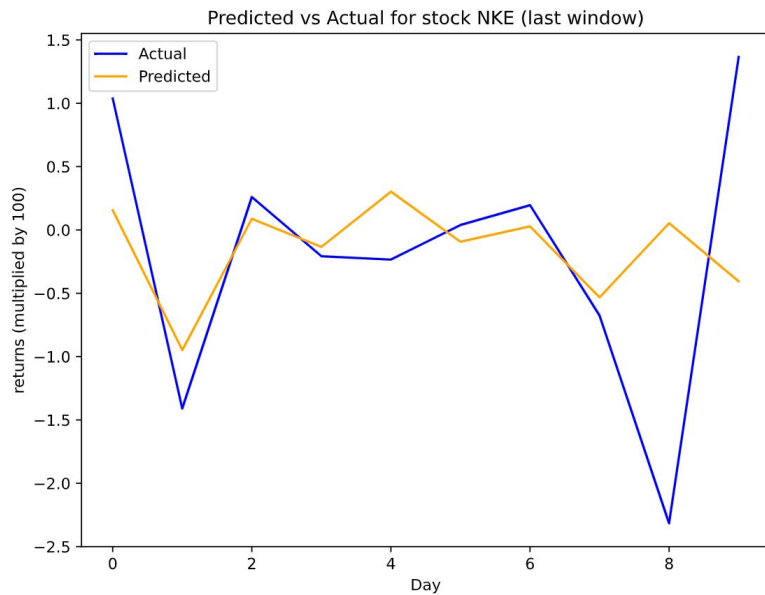


# CSCD94 Week 2 Update

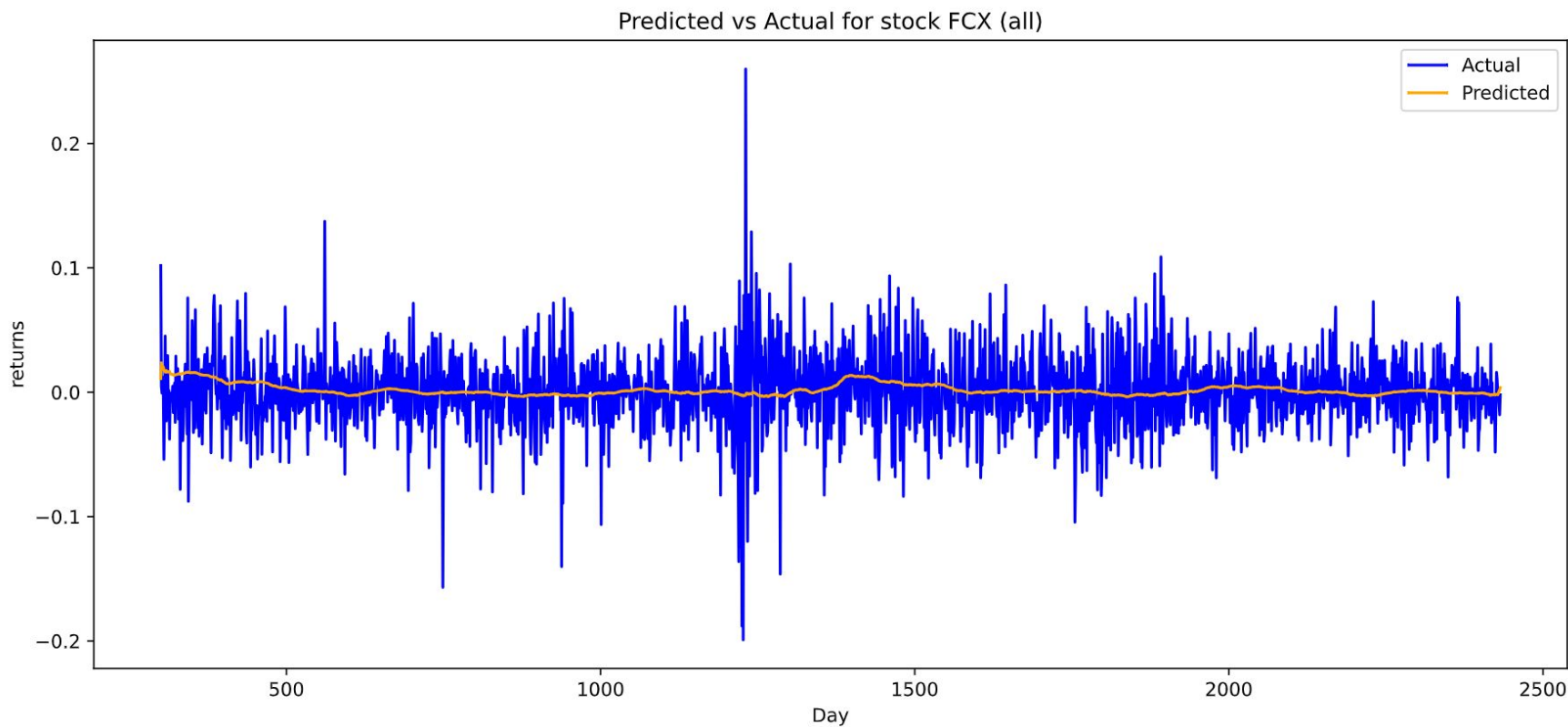
Dominik Luszczyński

# Week 2 Progress

- Training to predict returns



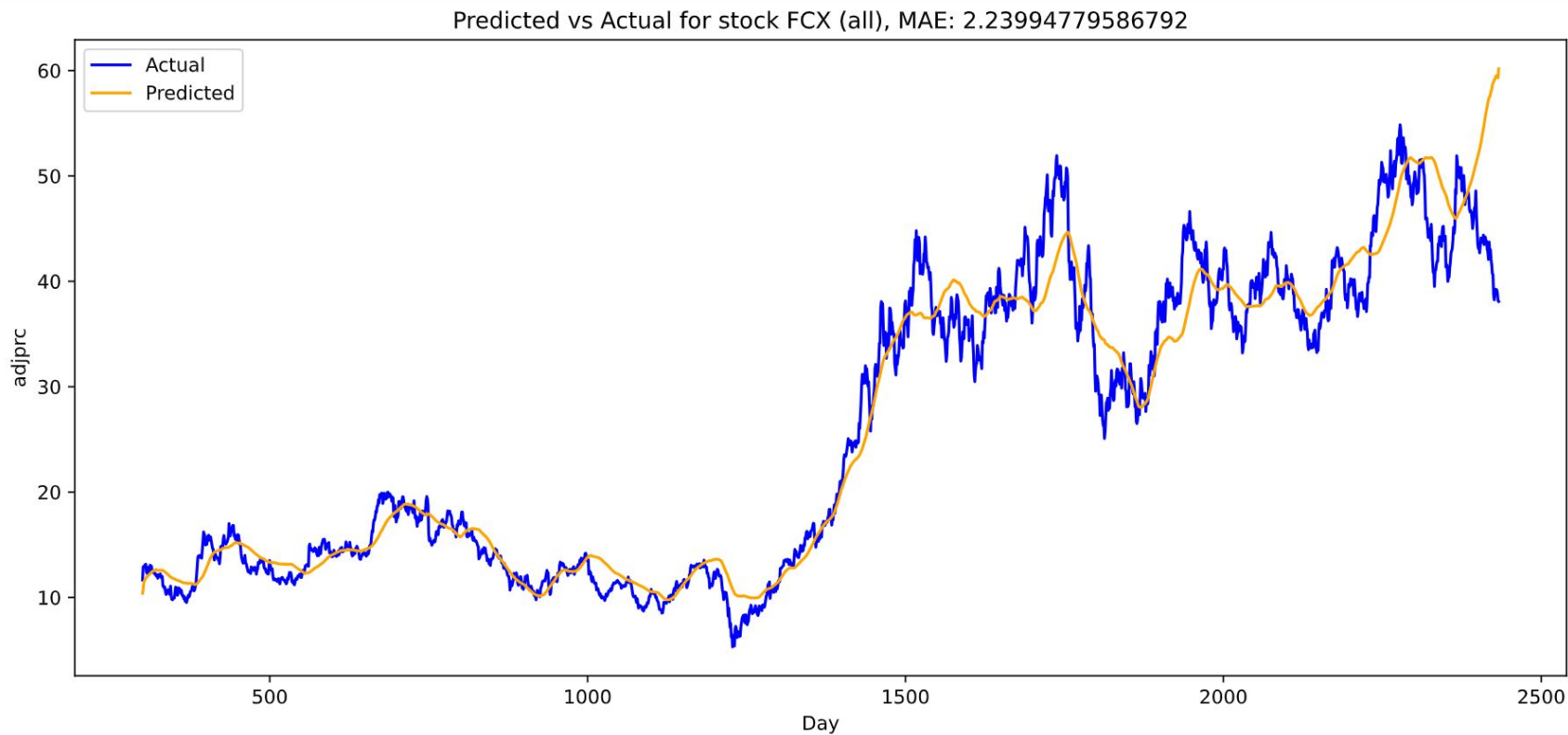
# Full Recording - ret



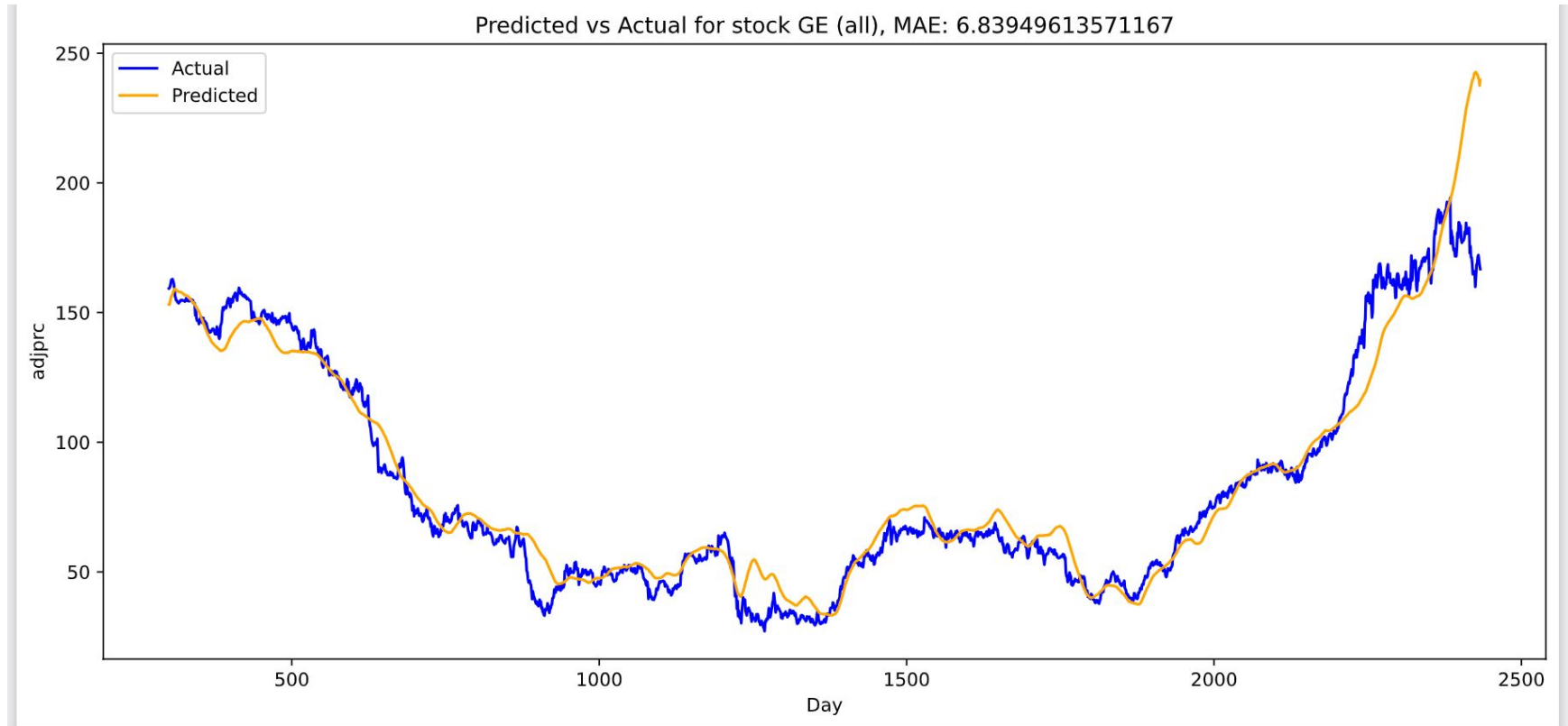
# Week 2 Progress

- Focused on adjprc again
  - Experimented with different loss functions (MSE, MASE (Mean Absolute Scaled Error), SMAPE (Symmetric Mean Absolute Percentage Error))
    - Best loss: Quantile loss (QuantileLoss(quantiles=[0.001, 0.01, 0.05, 0.5, 0.95, 0.99, 0.999]))
  - Extended the max encoder length (max lookback time) to 300, and now we predict 50 days in the future.
    - Filtered data to remove companies with less than 1000 days of data
  - Derived new features from adjprc
    - Log returns ( $\log(\text{adjprc}_t / \text{adjprc}_{(t-1)})$ ), Exponential Moving Averages, Rate of Change (percent change from the previous 5 days)
    - Removed the rolling means and stdev over 3 days
  - Used a Pytorch Lightning Tuner to find the optimal learning rate.

# Sample forecasts

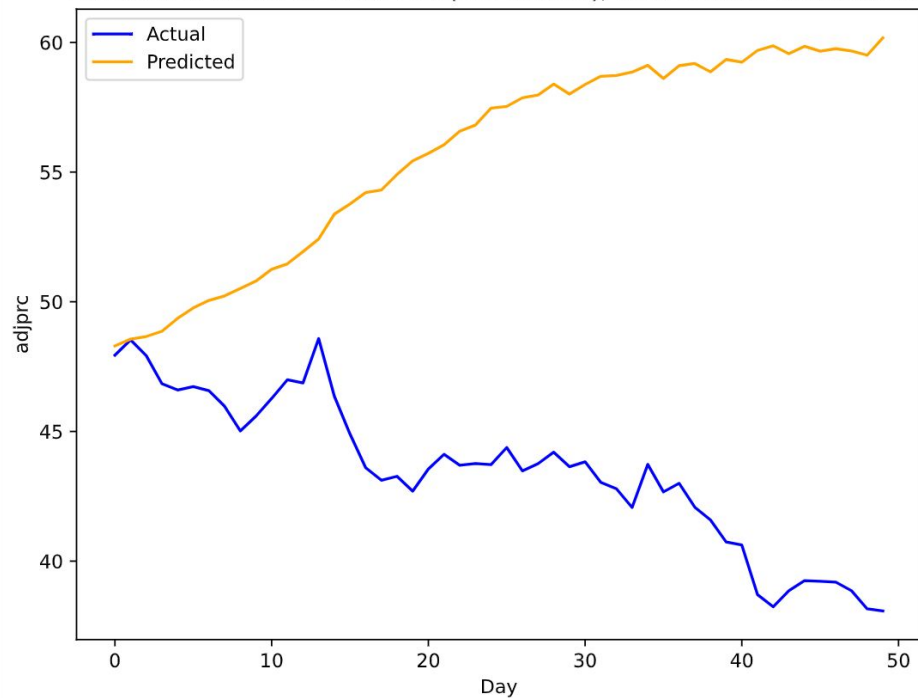


# Sample Forecasts

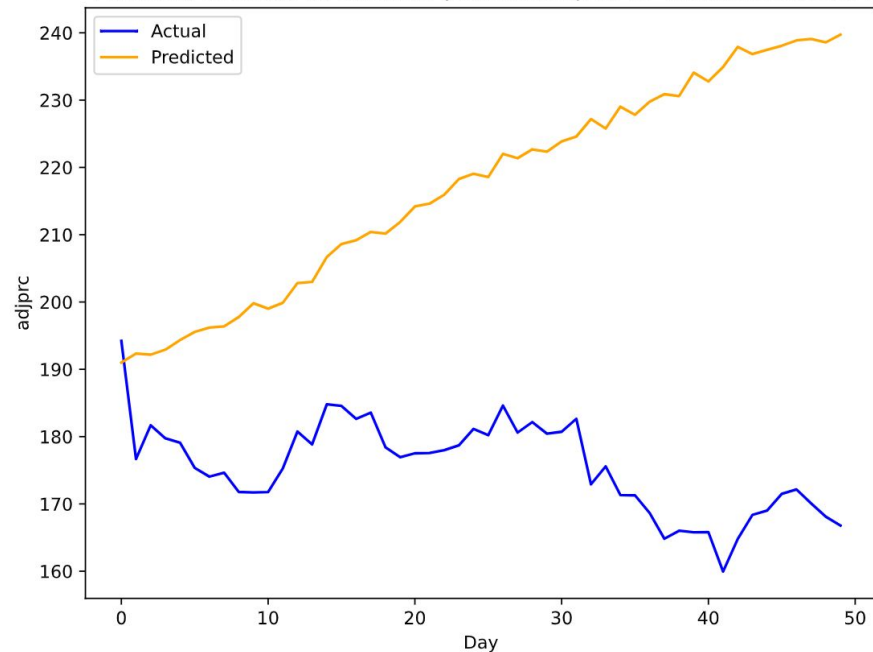


# Forecasts on Last Window

Predicted vs Actual for stock FCX (last window), MAE: 12.259756088256836



Predicted vs Actual for stock GE (last window), MAE: 41.7968635559082

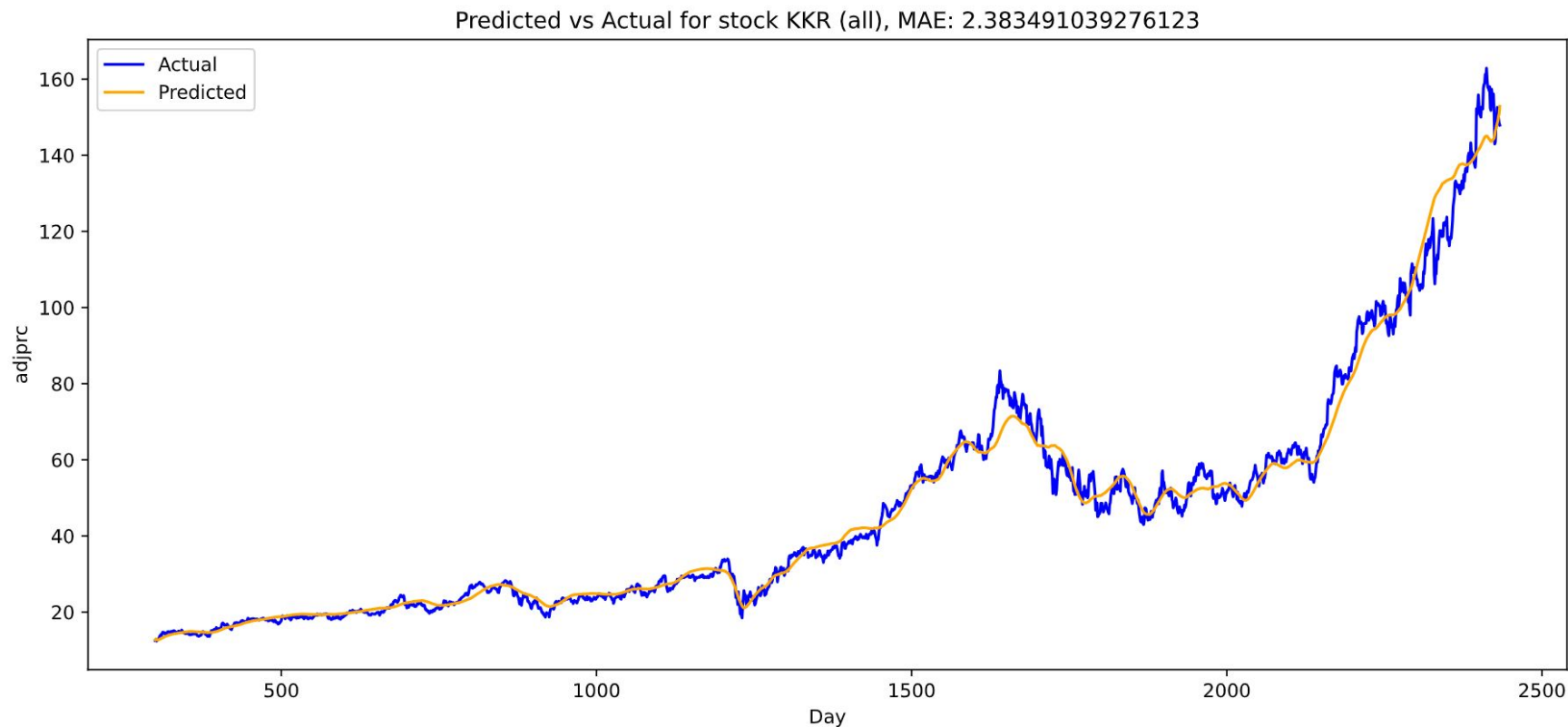


# MAE Over Full Recording vs Last Window (Test Set)

- Full Recording: 7.21
- Last Window: 19.27
- Reason:
  - NHiTs performs predictions in rolling windows of the max encoder length (look-back period). As a result, the full recording predictions are averaged over each window allowing for smoother and more accurate forecasts.



# Would it be an issue? - I don't think so



# Next Steps...

- Now that the forecasting model outputs good results I can:
  - Implement existing gradient methods to get a baseline attack level.
  - Develop a working GAN model.