

Automatic Change-Point Detection

Using Piecewise Support Vector Quantile Regression

Authors: Jing-Rung Yu, Sheng-Yu Tsai, Chun-Yen Tsai, Donald Lien

Speaker: Sheng-Yu Tsai (Justin)



National Chi Nan University, Taiwan

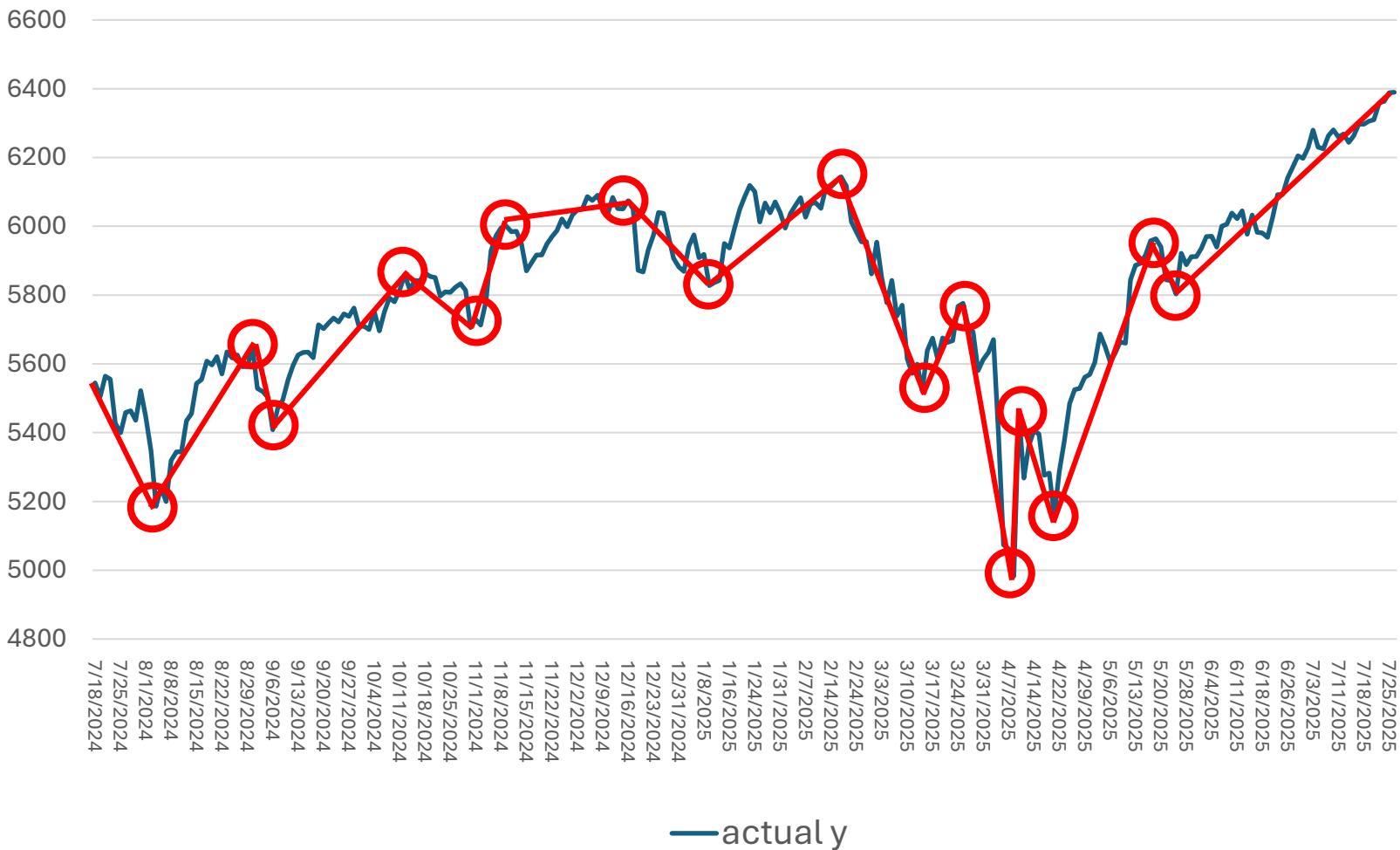
Outline

- Motivations
- Framework
- Experiments
- Conclusions



Pattern Change Detection (PCD)

S&P 500 (07/18/2025 – 07/22/2025)



PCD Statistical Methods (Gupta, Wadhvani, & Rasool, 2024)

1. Statistical Methods	CUSUM, PLR
2. Bayesian Methods	BCPA, BOCD
3. Time-Frequency Methods	WCPD、SDCPD
4. Machine Learning Methods	OC-SVM、LSTM
5. Hybrid Methods	LSCUSUM、Dual-LSTM

PCD Statistical Methods (Gupta, Wadhvani, & Rasool, 2024)

1. Statistical Methods
2. Bayesian Methods
3. Time-Frequency Methods
4. Machine Learning Methods
5. Hybrid Methods

**The performance depends on
the characteristics of datasets**

PCD Statistical Methods (Gupta, Wadhvani, & Rasool, 2024)

1. Statistical Methods
2. Bayesian Methods
3. Time-Frequency Methods
4. Machine Learning Methods
5. Hybrid Methods



Often outperform others!

Key Challenges (Gupta, Wadhvani, & Rasool, 2024)

Detecting multiple change-points

Handling high-dimensional or missing data

Processing large datasets efficiently

Prediction bands can provide valuable, actionable information

Key Challenges (Gupta, Wadhvani, & Rasool, 2024)

Detecting multiple change-points

Handling high-dimensional or missing data

Processing large datasets efficiently

Prediction bands

PSVQR Framework

1

Support Vector Regression

l₁ – norm

kernel free

2

Piecewise Linear Model

Piecewise regression

Detect multiple CP

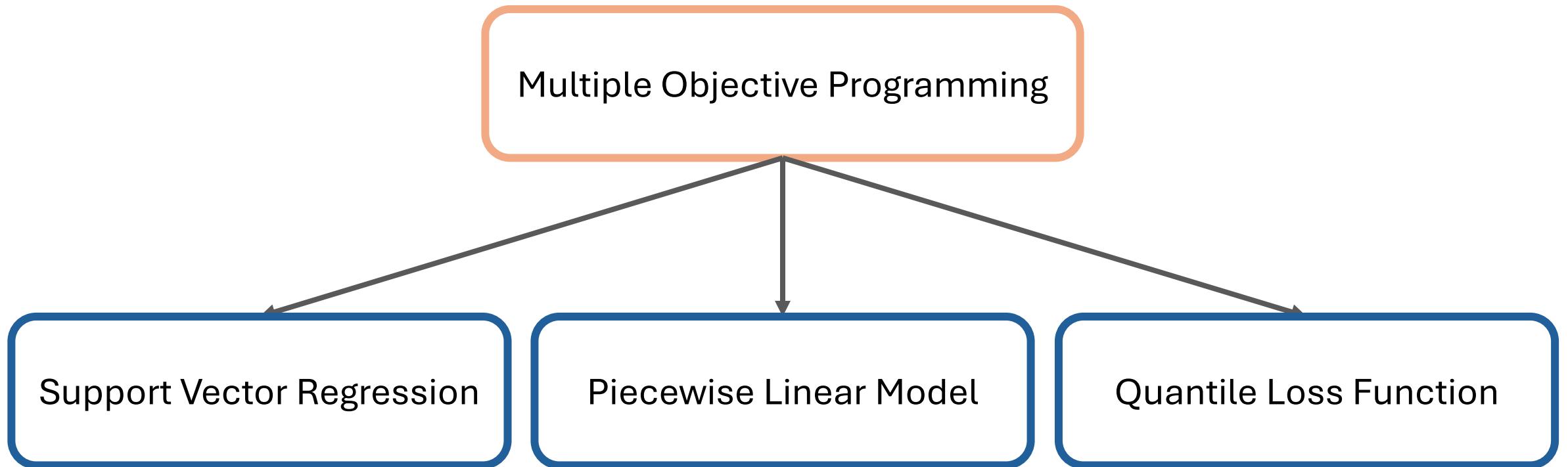
3

Quantile Loss Function

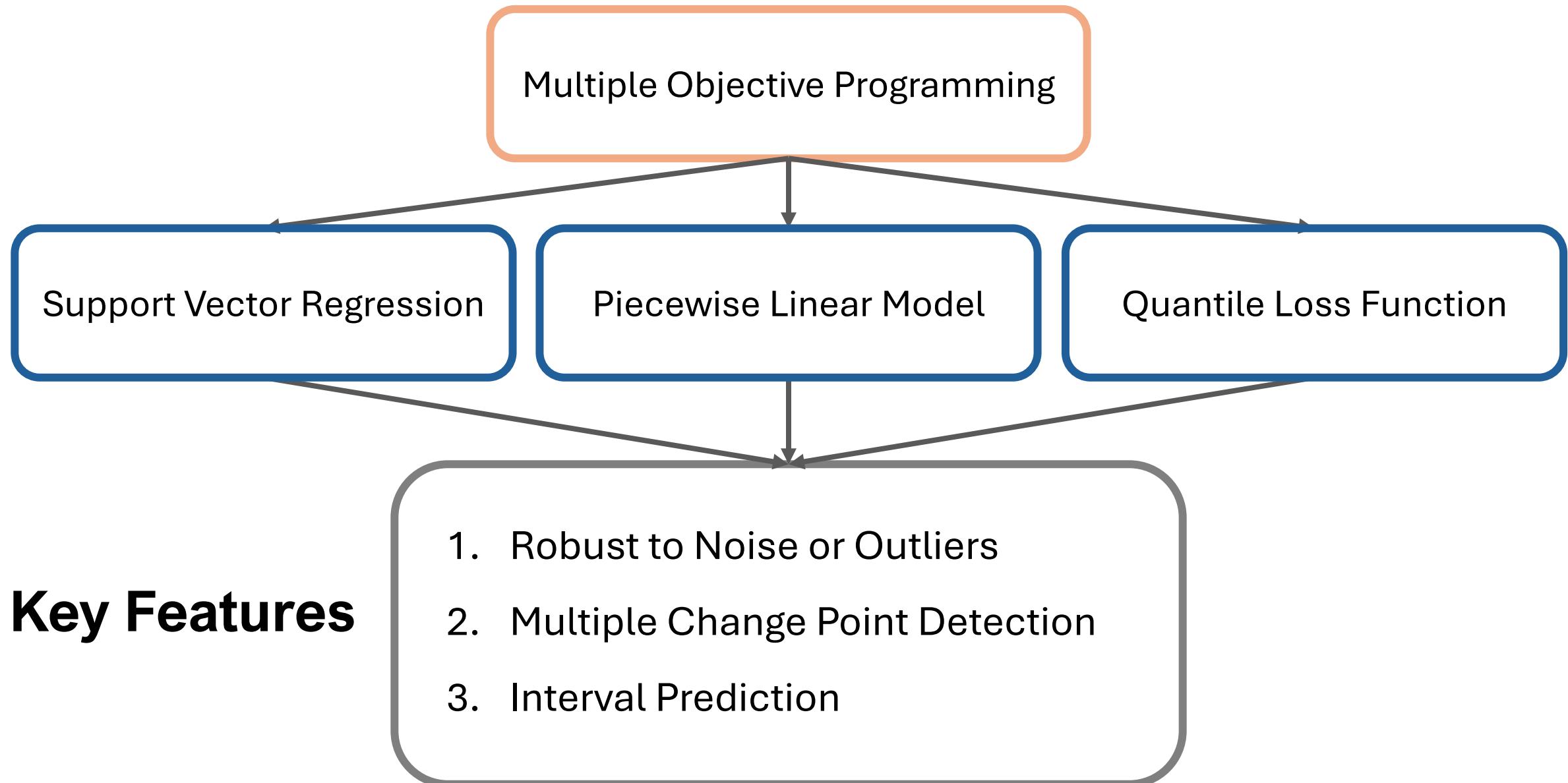
Different quantile tau

Provide prediction intervals

PSVQR Framework



Key Features



The Proposed Model

$$\begin{aligned}
 & \min_{w_j^+, w_j^-, \xi, \rho} && \text{11-norm} \quad \text{Quantile loss} \quad \text{Change Point} \\
 & && (w^+ + w^-) + C_1 \sum_{i=1}^m ((1 - \tau)\xi_i^- + \tau\xi_i^+) + C_2\rho \\
 & \text{s. t.} && \text{Derived from SVR} \\
 & && y_i - (a + \sum_{i=1}^m (w^+ + w^-)x_i + \sum_{t=1}^m (b_t^+ - b_t^-)(|x_i - p_t| + x_i - p_t)/2) \leq \varepsilon + \xi_i^+ \\
 & && (a + \sum_{i=1}^m (w^+ + w^-)x_i + \sum_{t=1}^m (b_t^+ - b_t^-)(|x_i - p_t| + x_i - p_t)/2) - y_i \leq \varepsilon + \xi_i^- \\
 & && \text{Piecewise Terms}
 \end{aligned}$$

w : the hyperplane weight vector

m : the size of sliding window

ε : the ε -insensitive tube width

C_1, C_2 : the penalties

a : intercept term

ρ : numbers of change points of x_i

b_t : coefficient of change p_t

ξ_i : residuals outside the ε -insensitive tube

Experiment Design

Dataset: S&P 500 From 2024/07/18 to 2025/07/22

Features:

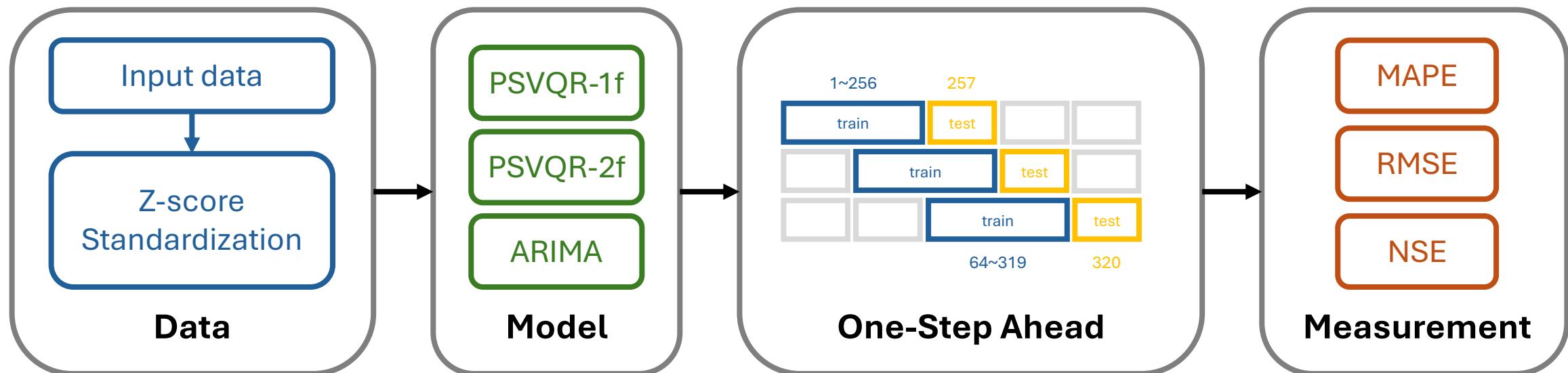
- Sequential Index
- VIX (Volatility Index)

Prediction y:

- price

PSVQR-f1: use 1 feature (index)

PSVQR-f2: use 2 features (index, VIX)



Prediction Results (Using Index)

Model	MAPE	RMSE	NSE
ARIMA	0.6023	0.1815	0.8093
PSVQR-1f, tau=0.1	1.9936	0.3265	0.5620
PSVQR-1f, tau=0.3	0.8064	0.2530	0.7098
PSVQR-1f, tau=0.5	1.7960	0.2454	0.7255
PSVQR-1f, tau=0.7	0.4981	0.2524	0.7300
PSVQR-1f, tau=0.9	0.4769	0.3039	0.8183

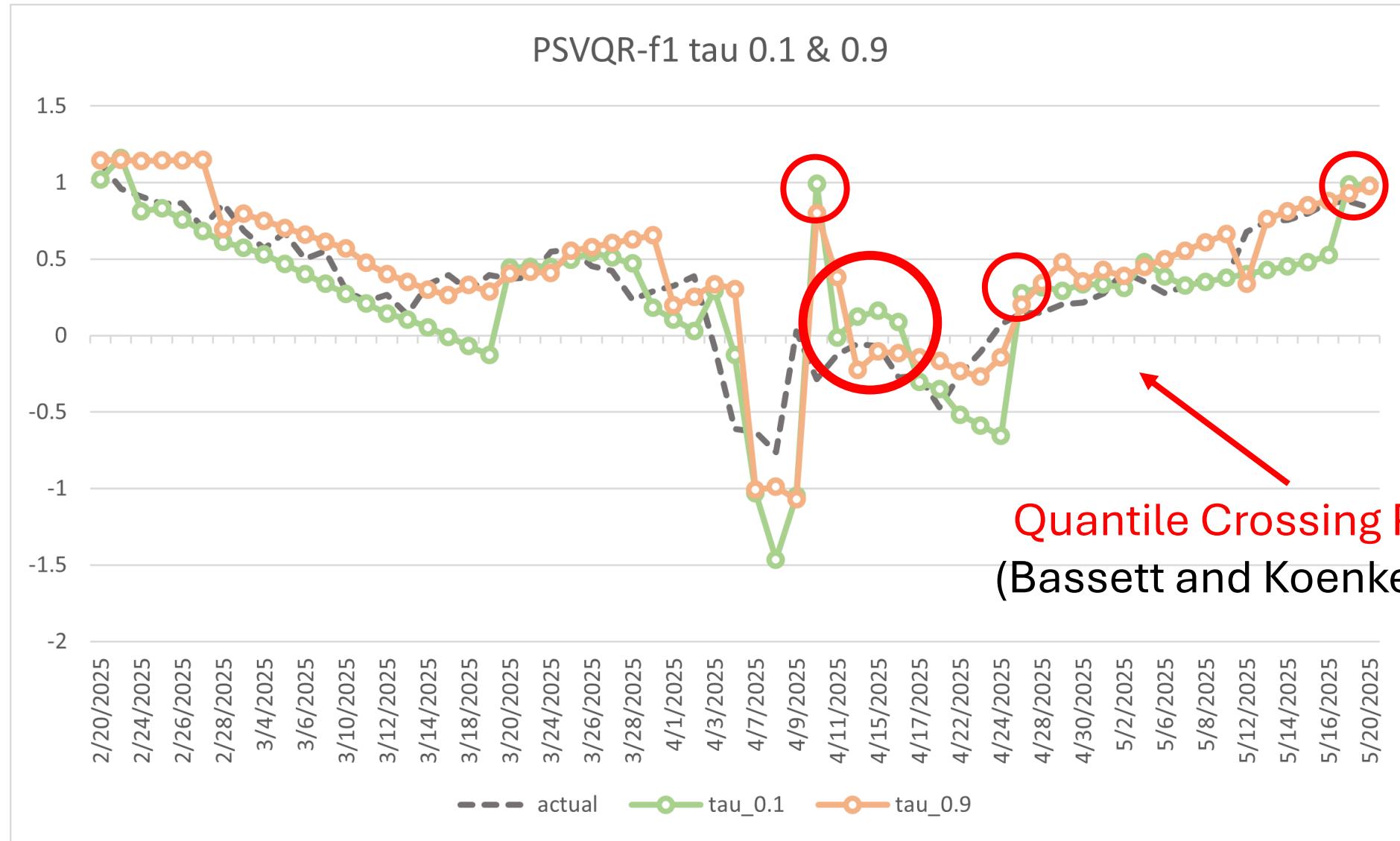
Features:

- sequential index

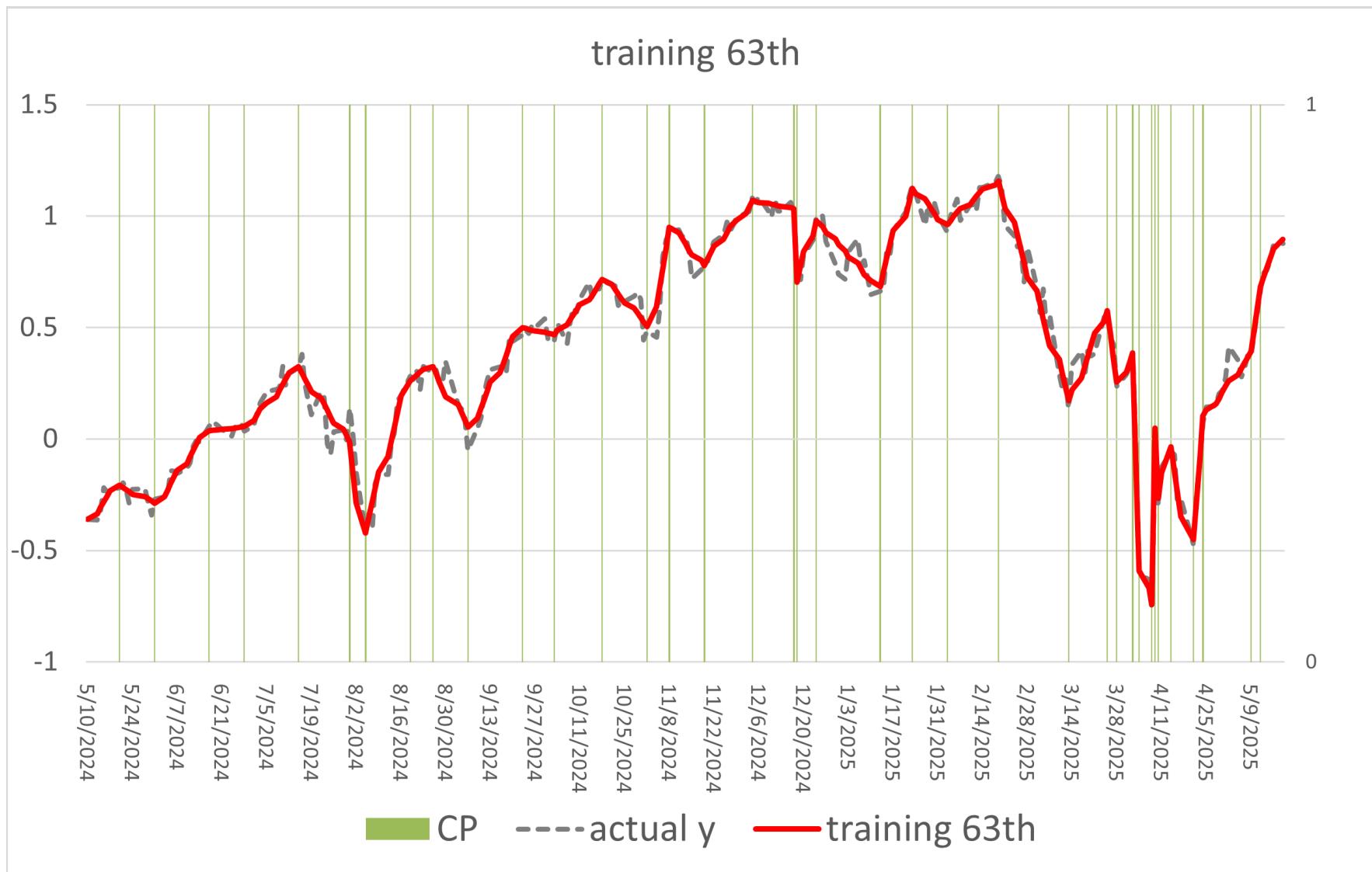
Prediction y:

- price

Prediction Intervals (PSVQR-f1 tau=0.1, 0.9)



CPD Results (PSVQR-f1 tau=0.5)



Prediction Results (Using Index and VIX)

Model	MAPE	RMSE	NSE
ARIMA	0.6023	0.1815	0.8093
PSVQR-2f, tau=0.1	0.9996	0.1399	0.8981
PSVQR-2f, tau=0.3	0.3770	0.1419	0.8994
PSVQR-2f, tau=0.5	0.9267	0.1520	0.8786
PSVQR-2f, tau=0.7	0.3982	0.1549	0.8667
PSVQR-2f, tau=0.9	1.059	0.1786	0.8450

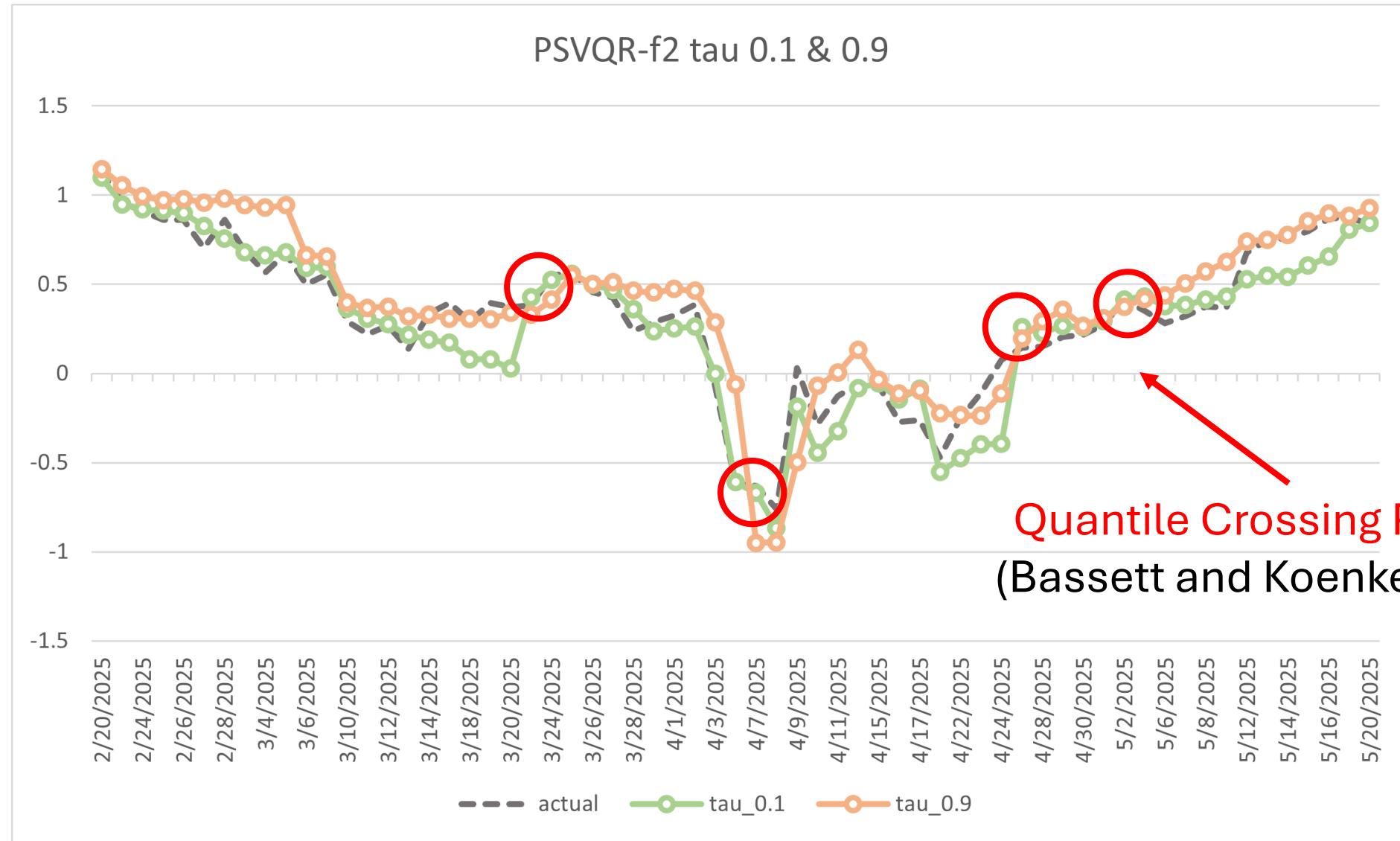
Features:

- sequential index
- VIX (Volatility Index)

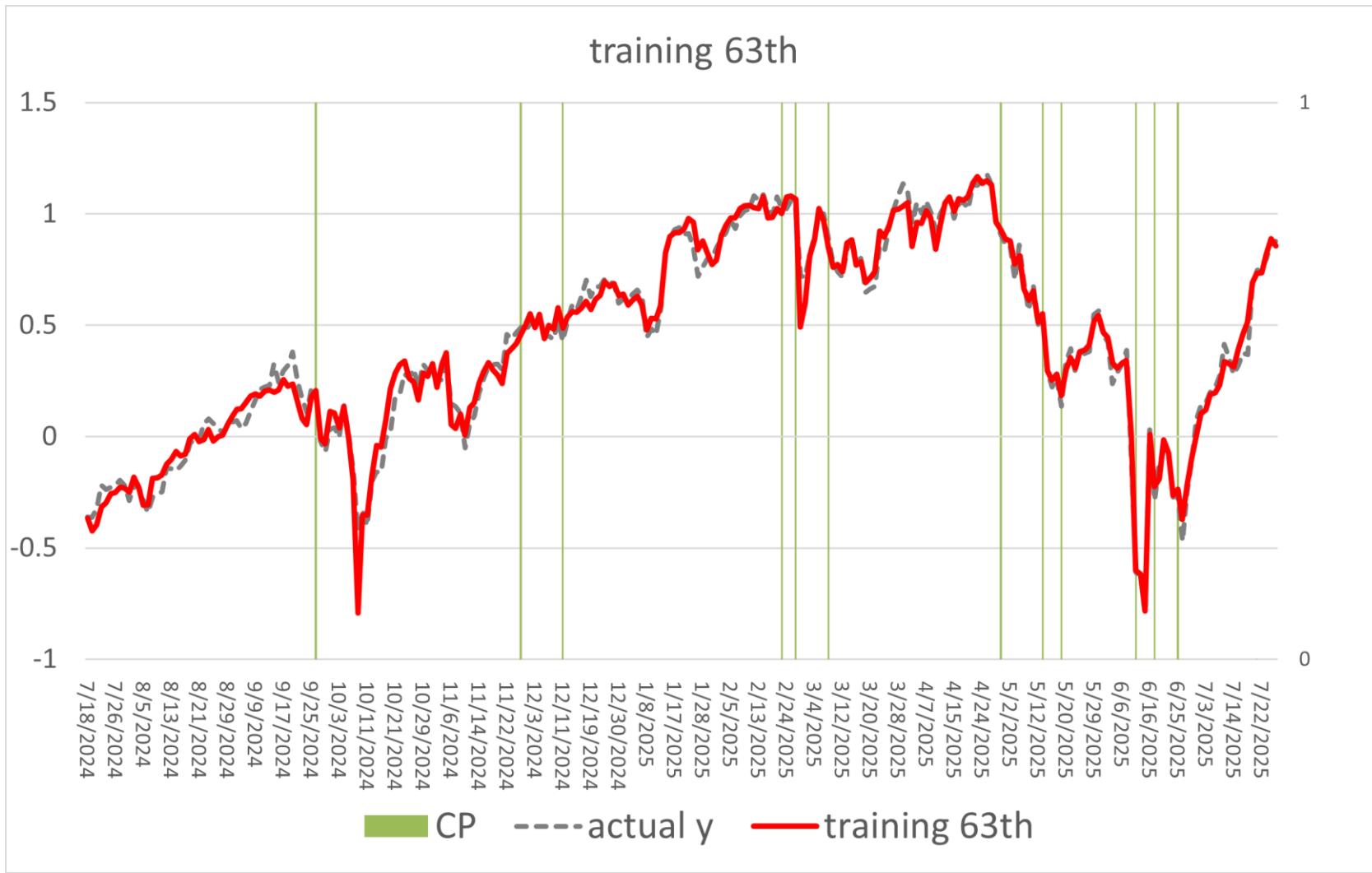
Prediction y:

- price

Prediction Intervals (PSVQR-f2 tau=0.1, 0.9)



CPD Results (PSVQR-f2 tau=0.5)



Experiment Results (PSVQR-f2 vs PSVQR-f1)

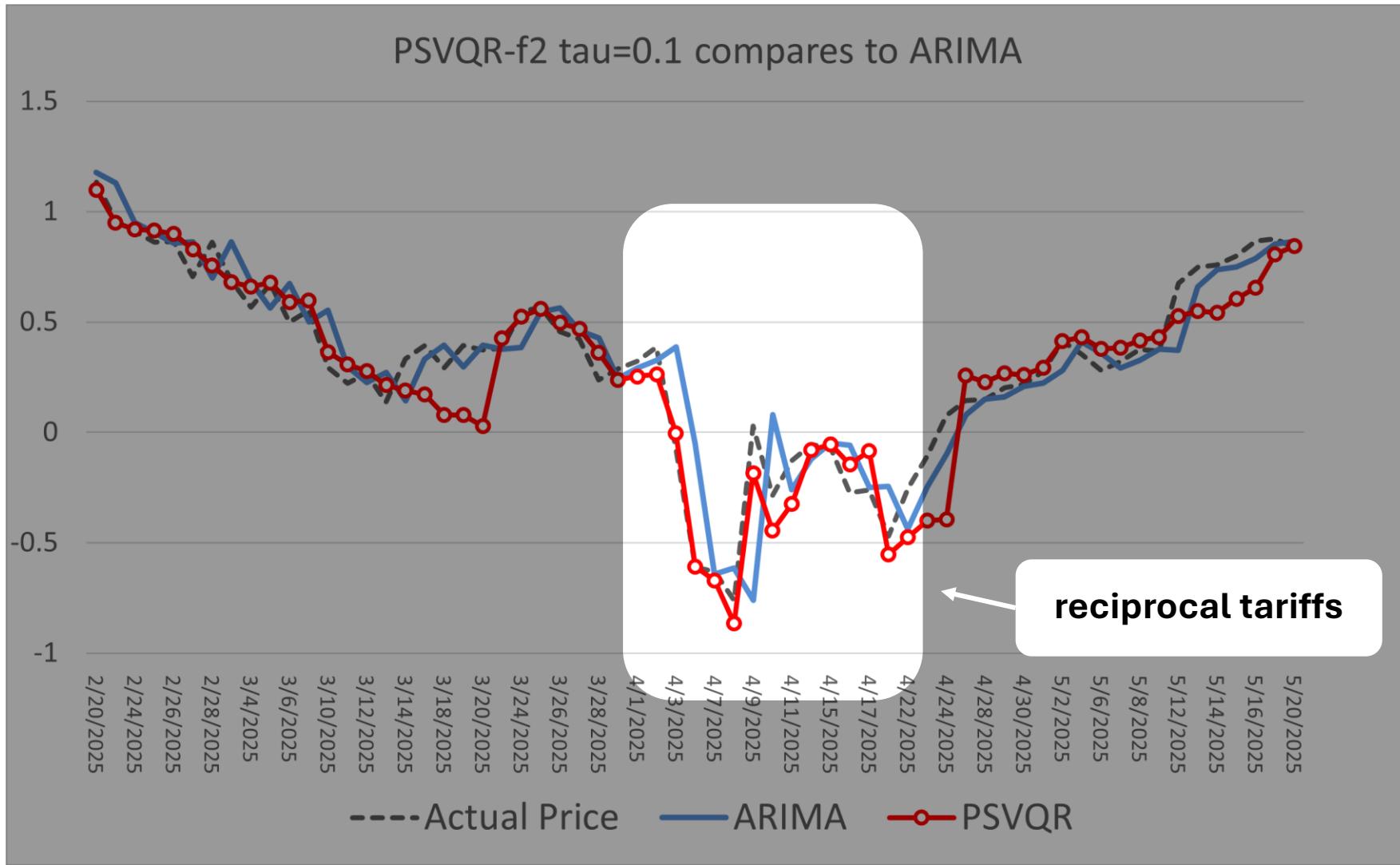


Use 2 features



Use 1 features

Compare to Benchmark



Conclusion

- PSVQR-f2 outperforms ARIMA model in stock price predictions.
- PSVQR-f1 is better for CPD, while PSVQR-f2 is better for prediction.
- PSVQR has crossing quantile problem.

Future Work

- Find a proper method to decide the penalty of CP amounts.
- Solve quantile crossing problem. (Dai, Kuosmanen, & Zhou, 2023)
- Transfer CPU-based solver to GPU solutions.
- Add more features and compare to other PCD method.

References

- Gupta, M., Wadhvani, R., & Rasool, A. (2024). Comprehensive analysis of change-point dynamics detection in time series data: A review. *Expert Systems with Applications*, 123342.
- Bassett Jr, G., & Koenker, R. (1982). An empirical quantile function for linear models with iid errors. *Journal of the American Statistical Association*, 77(378), 407-415.
- Dai, S., Kuosmanen, T., & Zhou, X. (2023). Non-crossing convex quantile regression. *Economics letters*, 233, 111396.



Thanks!

Contact:



Sheng-Yu Tsai (Justin Tsai)



justintsai77@gmail.com



六、相關文獻參考 (Supporting Literature)

以下是一些關於「分位數交叉」問題的經典及相關文獻，可以在您報告的 Q&A 環節或未來研究中提供支持。

1. Koenker, R. (2005). **Quantile Regression**. Cambridge University Press.

1. 重要性：這是分位數迴歸領域最權威的「聖經」。書中詳細討論了分位數交叉的現象及其理論基礎。引用這本書代表您對該領域有著根本性的理解。

2. Bondell, H. D., Reich, B. J., & Wang, H. (2010). **Noncrossing quantile regression curve estimation**. *Biometrika*, 97(4), 825-838.

1. 重要性：這是一篇處理非交叉問題的關鍵論文。它提出了一種在模型估計過程中就加入限制的方法，來確保不同分位數的預測線不會交叉。這篇是您提出「未來工作」方向時最有力的參考。

3. Takeuchi, I., & Furuhashi, T. (2005). **Non-crossing quantile regression with support vector machines**. *2005 SICE Annual Conference*.

1. 重要性：這篇論文與您的研究方法高度相關。它專門探討如何在支持向量機 (SVM) 的框架下解決分位數交叉問題。在 Q&A 時若被問到您的模型該如何改進，引用這篇文獻會非常精準且具說服力。

祝您報告順利！