

# Deep Hedging – Learning to Trade

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URP Summer Presentation, June 24

# Table of Contents

- 1 Introduction
- 2 Research methods
- 3 Result
- 4 Limitation of Deep Hedging

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# Motivation

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Equation: Optimal hedging

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- $C_T(\underline{\delta})$  is transaction cost.

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- Consider different  $\alpha$  impact deep hedging.
- Consider different epoch impact deep hedging.
- Consider different transaction costs impact weight and PnL of deep hedging.
- Use real historical data into my hedging strategy and discuss whether this hedging strategy's effectiveness is significantly improved.

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# BS-model Setting

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# Deep hedging(CVaR) with different $\alpha$

Our utility functions are

$$CVaR_\alpha(X) := \mathbb{E}[X | X \leq VaR_\alpha(X)]$$

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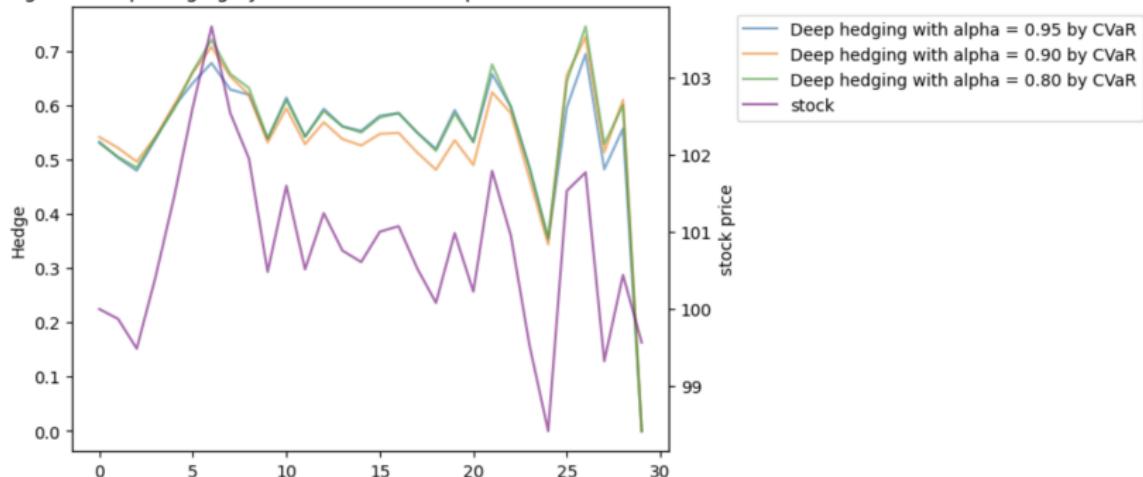
$$CVaR_\alpha(X) := \mathbb{E}[X | X \leq VaR_\alpha(X)]$$

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We compare with variable  $\alpha = 0.95, 0.90, 0.80$

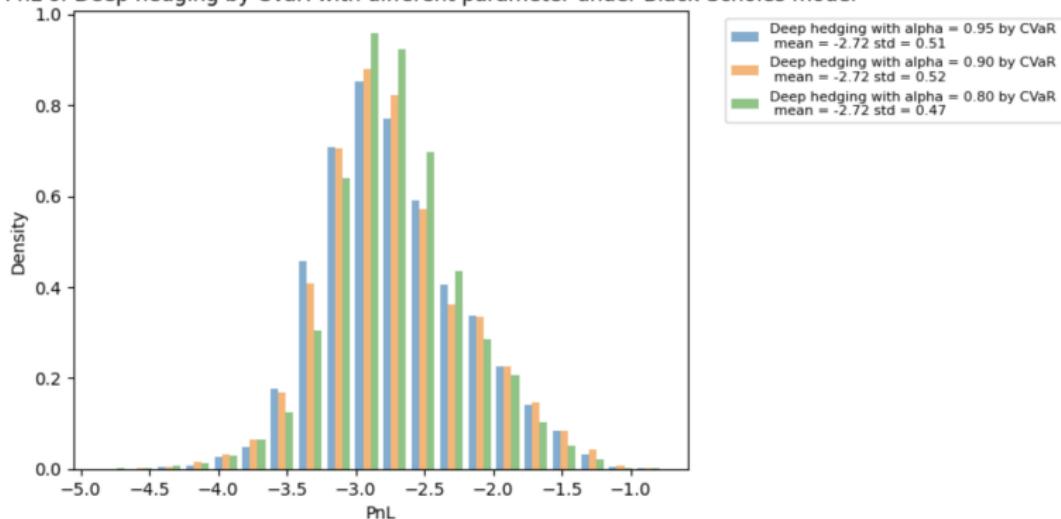
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Compare weight of Deep hedging by CVaR with different parameter under Black-Scholes model



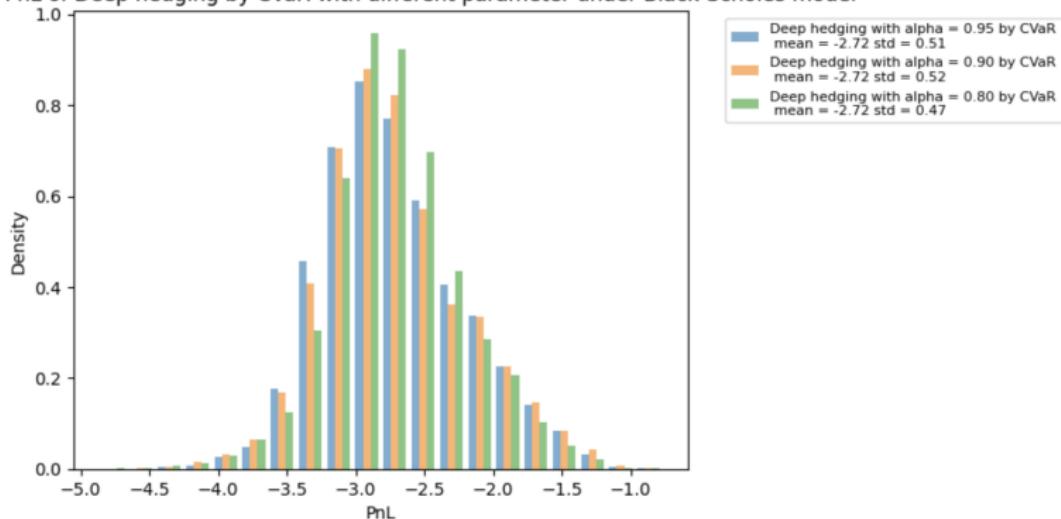
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We will use  $\alpha = 0.95$  on the following experiment.

## Deep hedging with different epoch

We know some function converge very slowly, so we need to insure they have enough training epoch to converge the best solution.

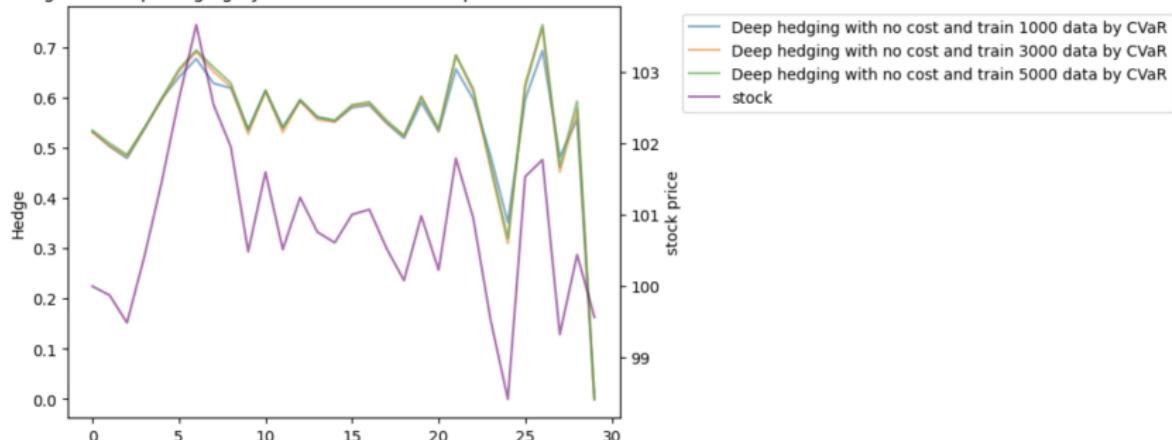
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We compare with training epoch 1000, 3000, 5000, 10000

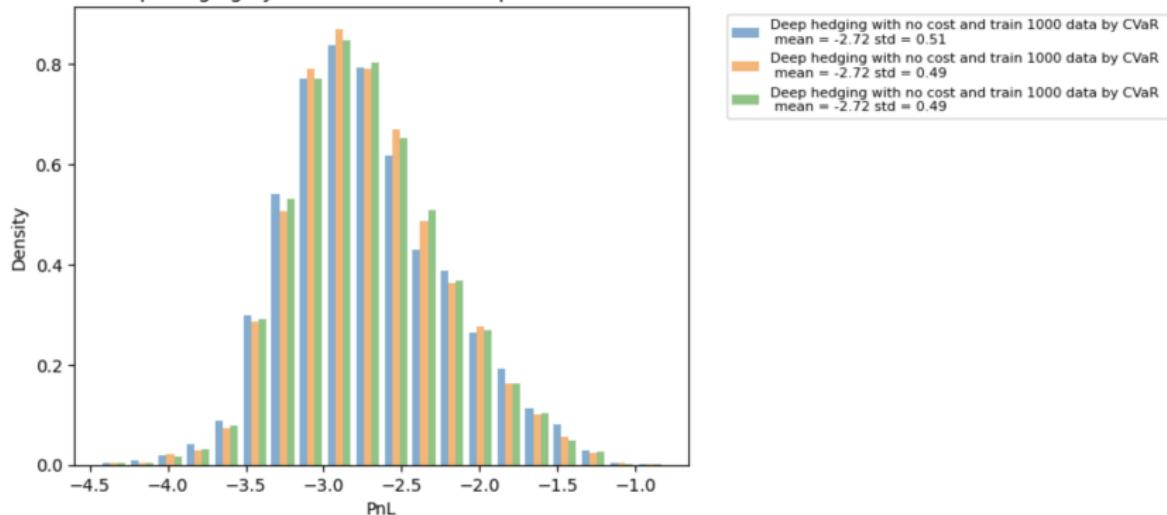
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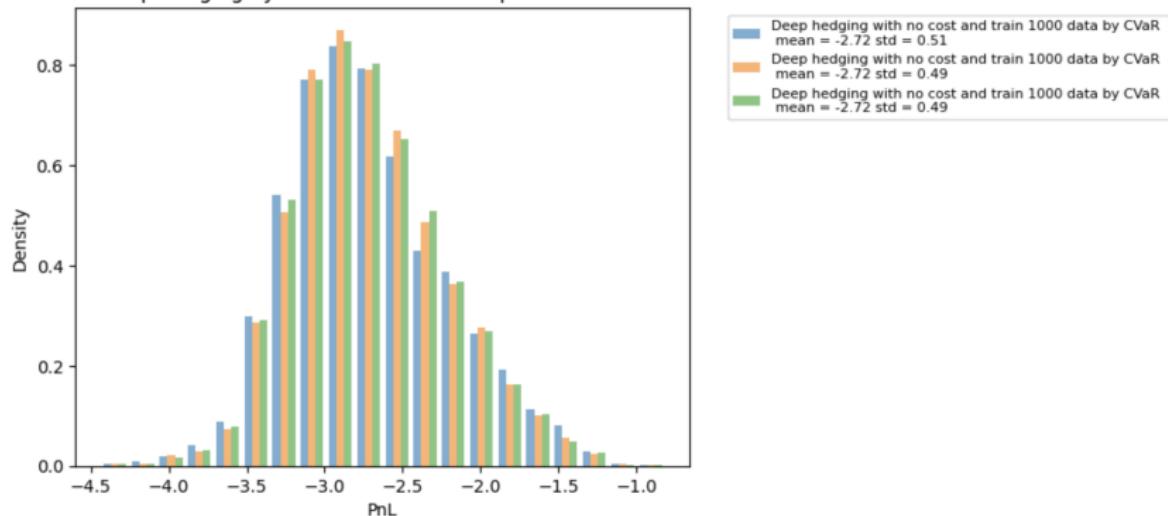
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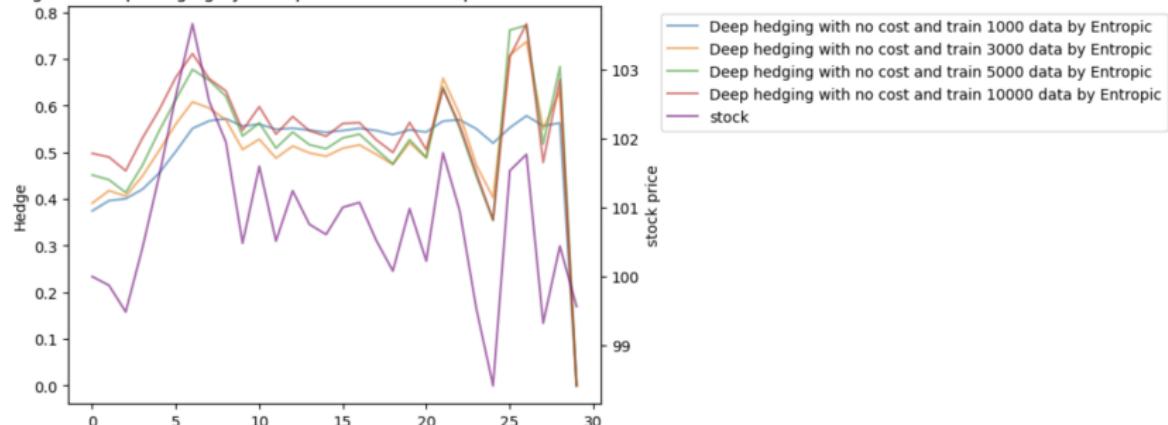
Compare PnL of Deep hedging by CVaR with different epoch under Black-Scholes model



We will use training epoch 1000 on the following experiment for CVaR.

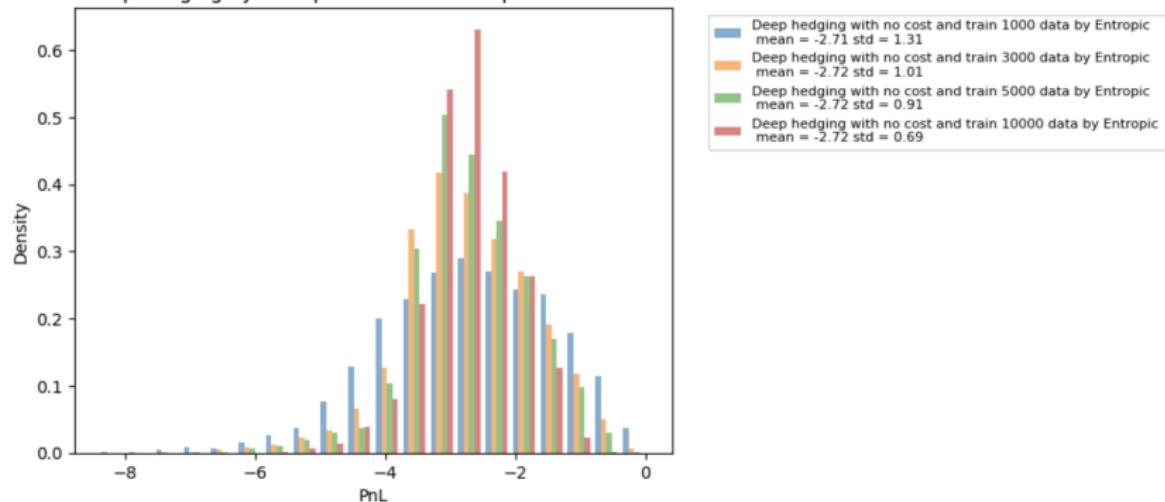
# Deep hedging(Entropic) with different epoch

Compare weight of Deep hedging by Entropic with different epoch under Black-Scholes model



# Deep hedging(Entropic) with different epoch

Compare PnL of Deep hedging by Entropic with different epoch under Black-Scholes model



## Deep hedging(Entropic) with different epoch

Loss after training

- 1000 epochs: 265.6
- 3000 epochs: 237.1
- 5000 epochs: 204.2
- 10000 epochs: 20.4

We will use training epoch 10000 on the following experiment for Entropic.

## Different transaction costs

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- Delta hedging with different cost

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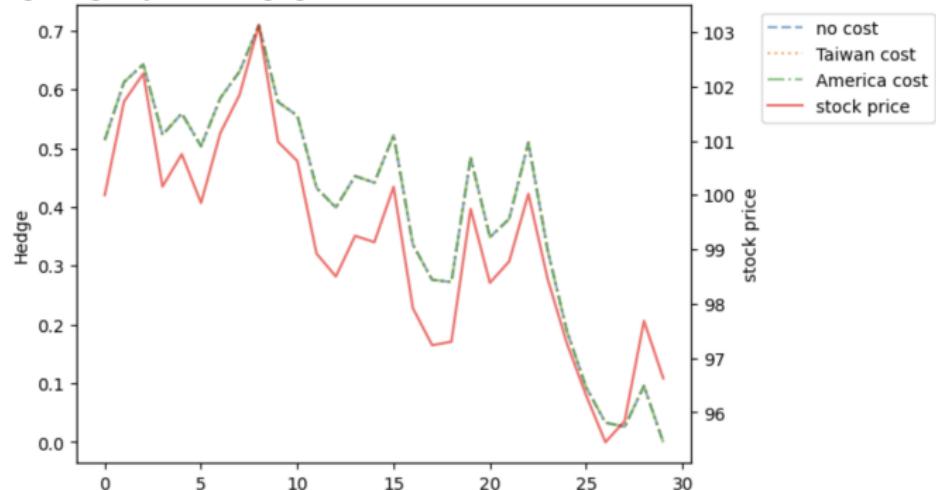
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- American Cost with Different Strategies

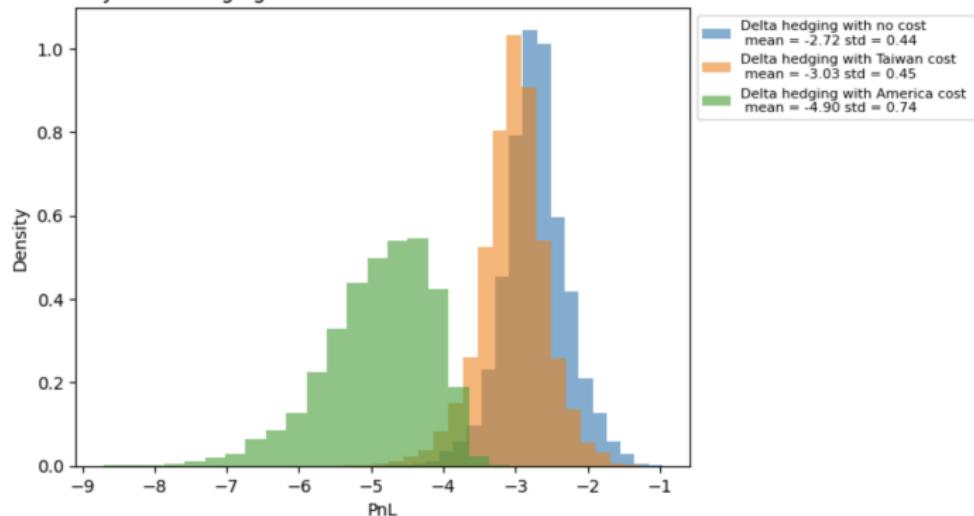
# Delta hedging with different cost

Hedge weight by Delta hedging with different cost under Black-Scholes model



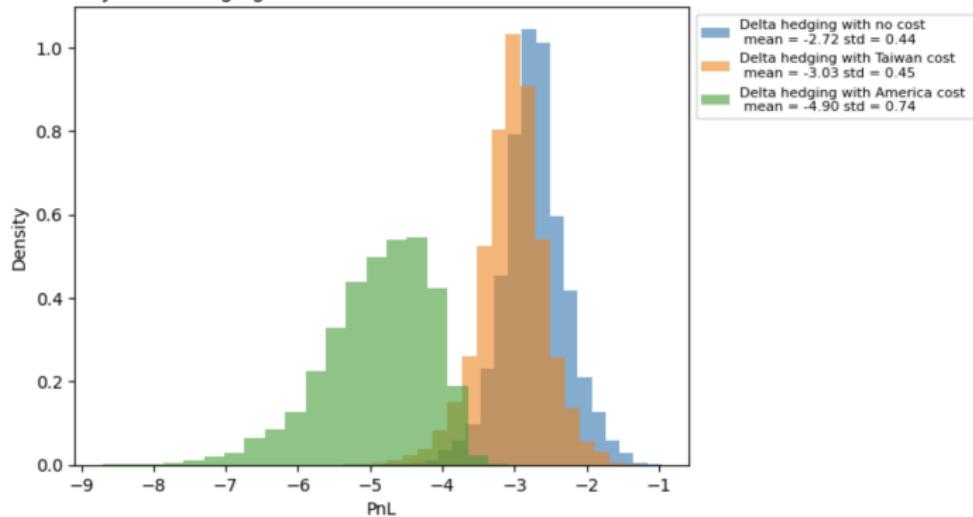
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PnL of by Delta hedging with different cost under Black-Scholes model



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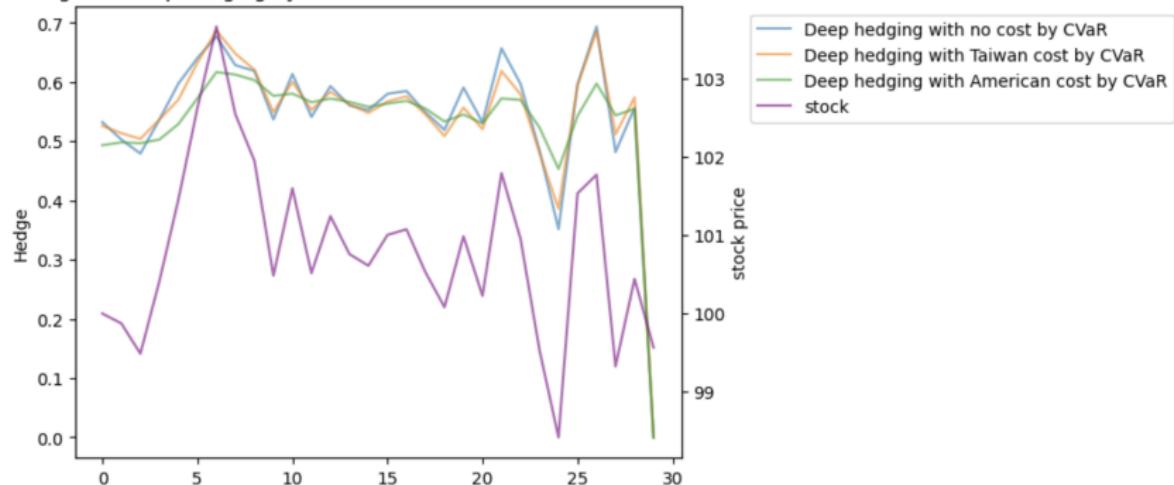
PnL of by Delta hedging with different cost under Black-Scholes model



Delta Hedging strategy shows a clear sensitivity to transaction costs.

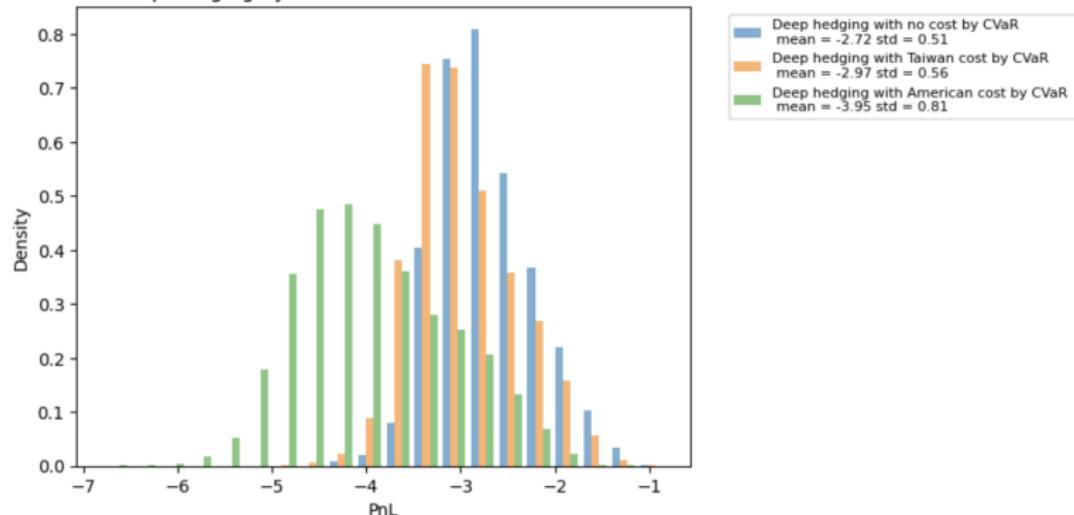
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Compare weight of Deep hedging by CVaR with different cost under Black-Scholes model



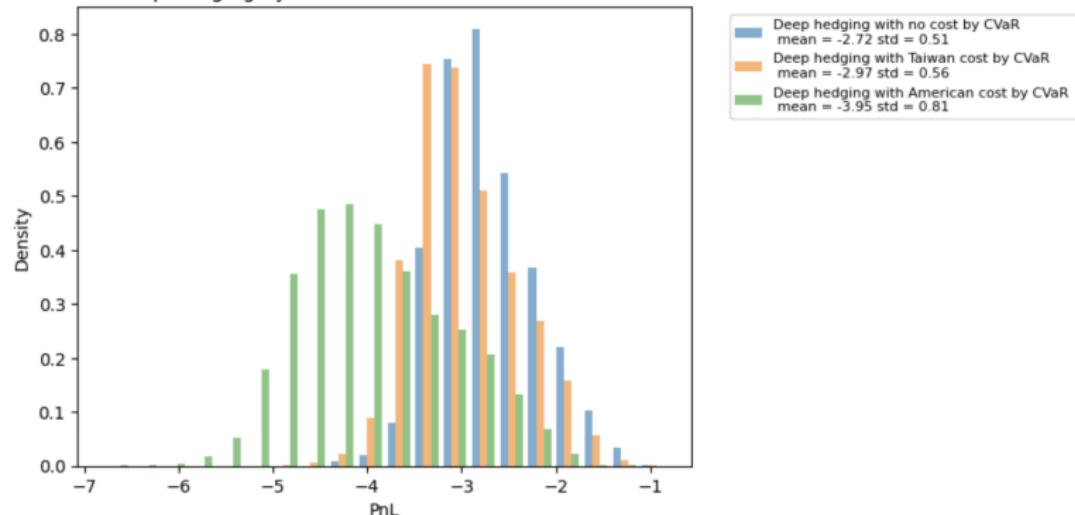
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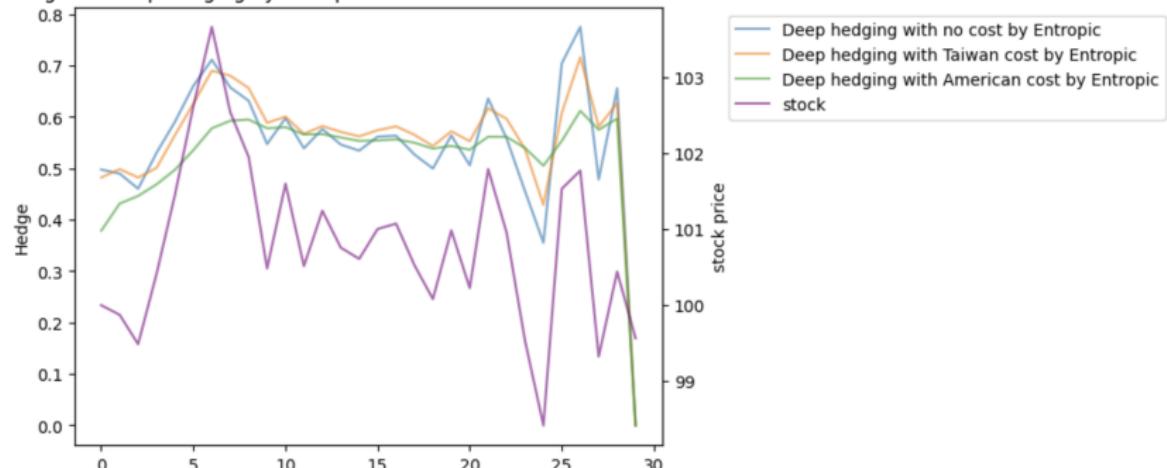
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Deep Hedging (CVaR) strategy shows the higher the fee ratio, the lower the PnL, and the fluctuation in weights also becomes smaller.

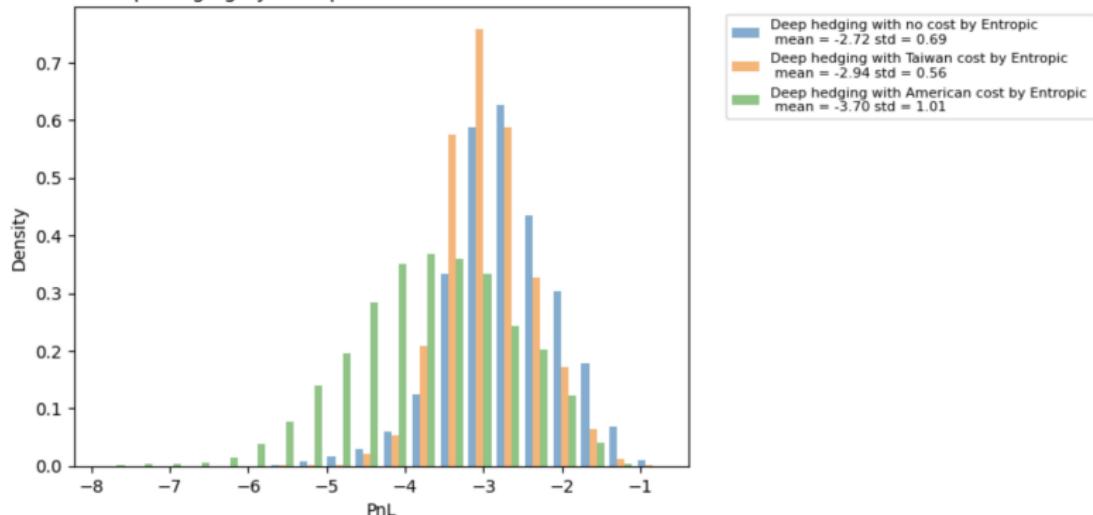
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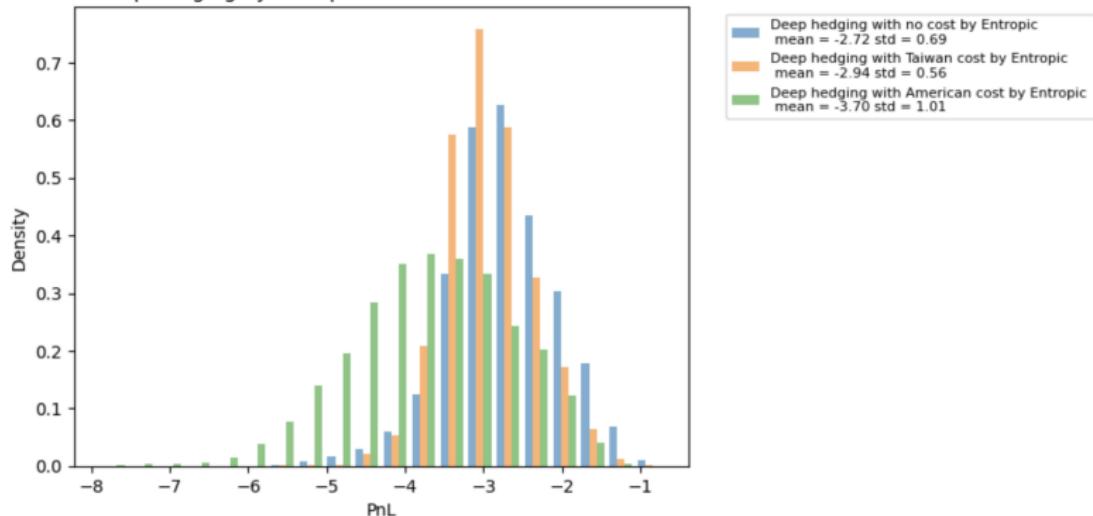
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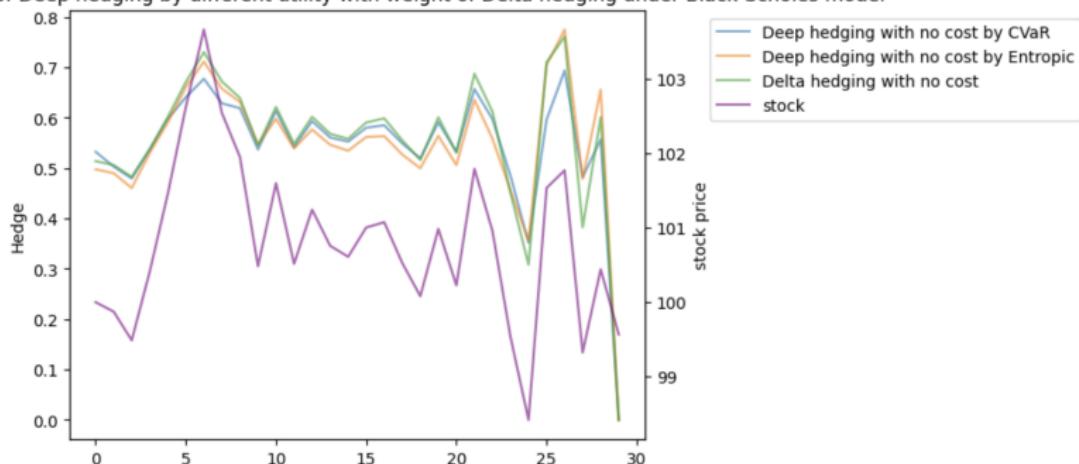
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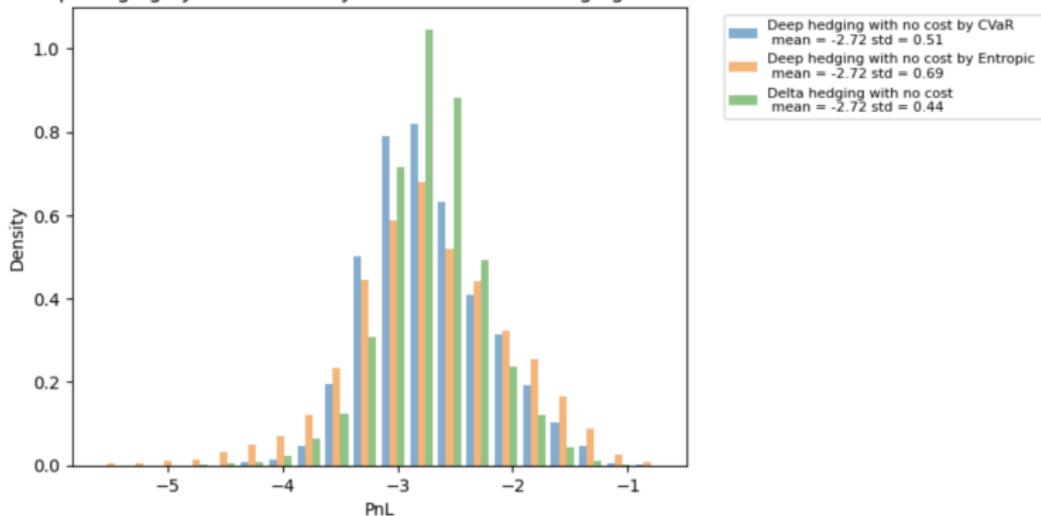
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Compare weight of Deep hedging by different utility with weight of Delta hedging under Black-Scholes model



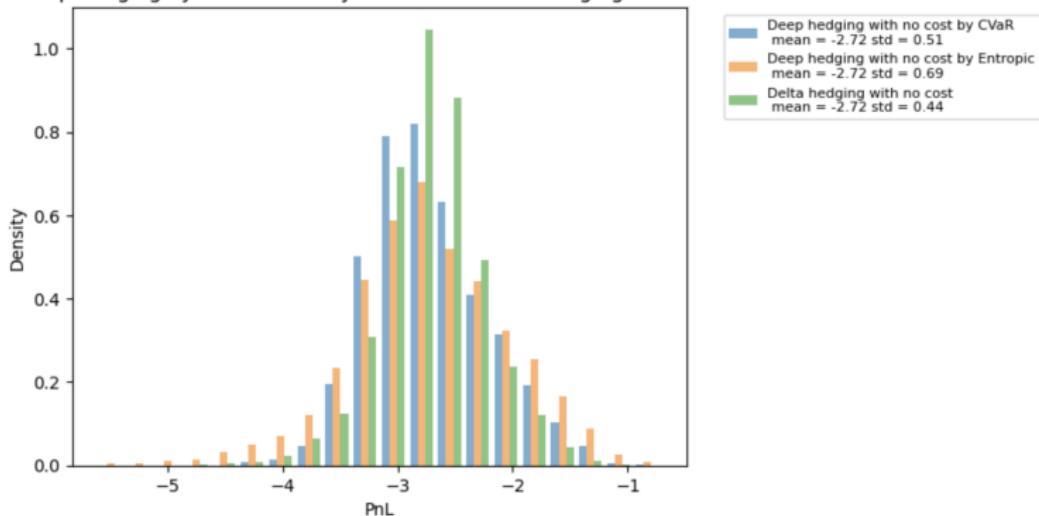
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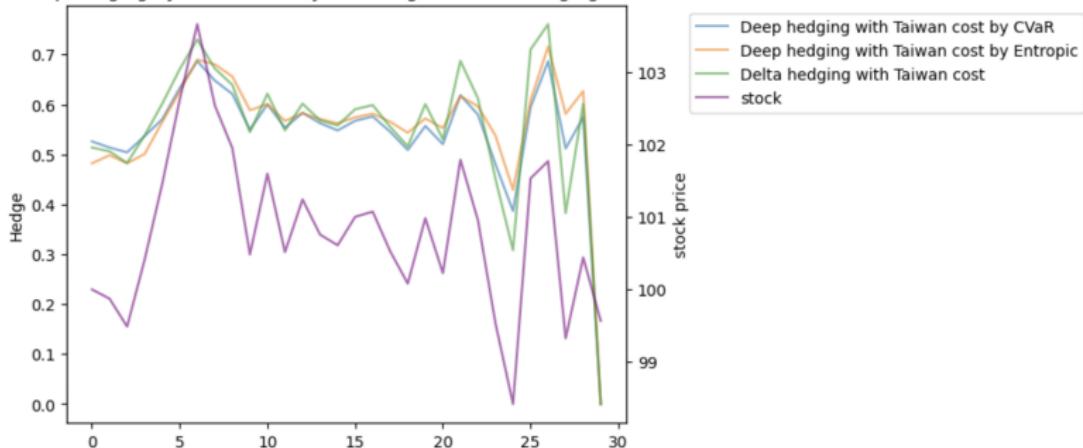
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Delta Hedging strategy shows the better outcome.

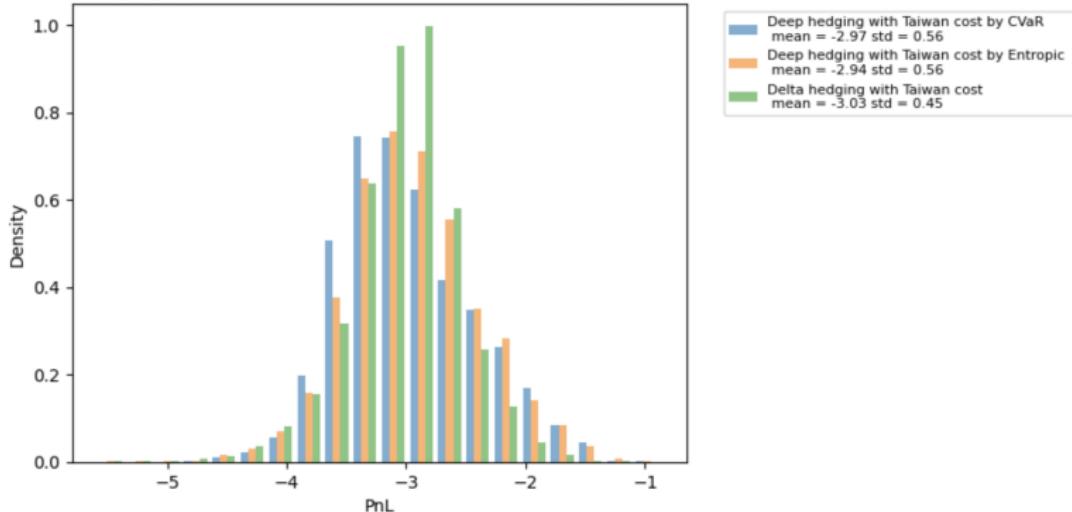
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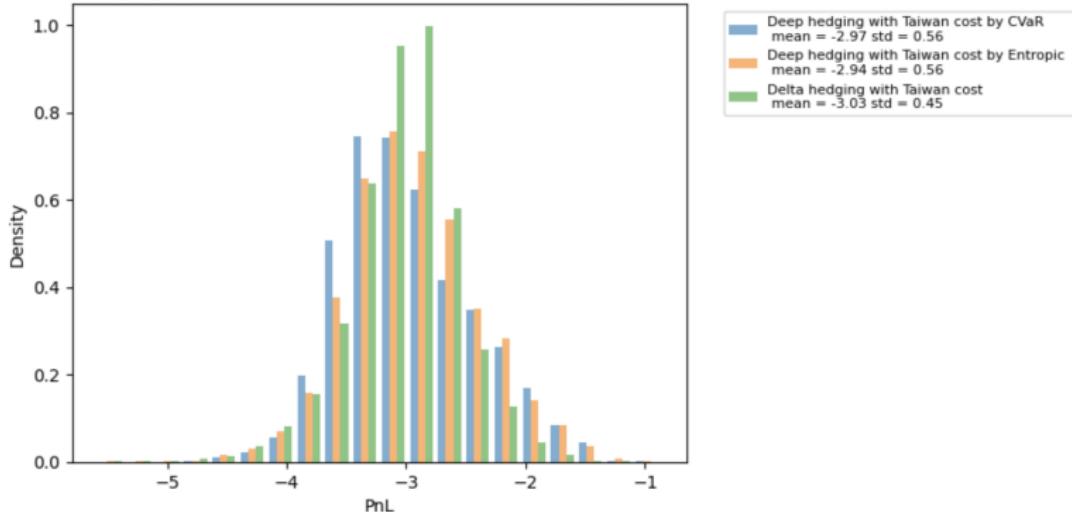
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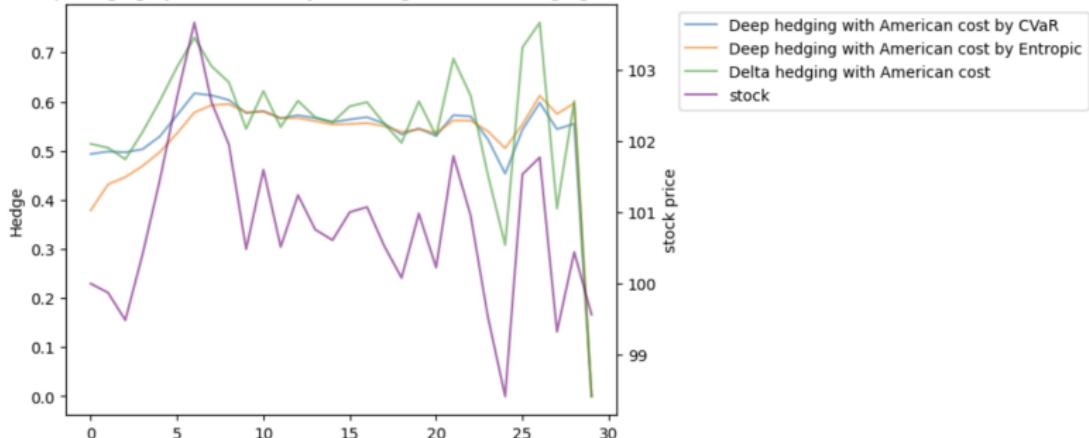
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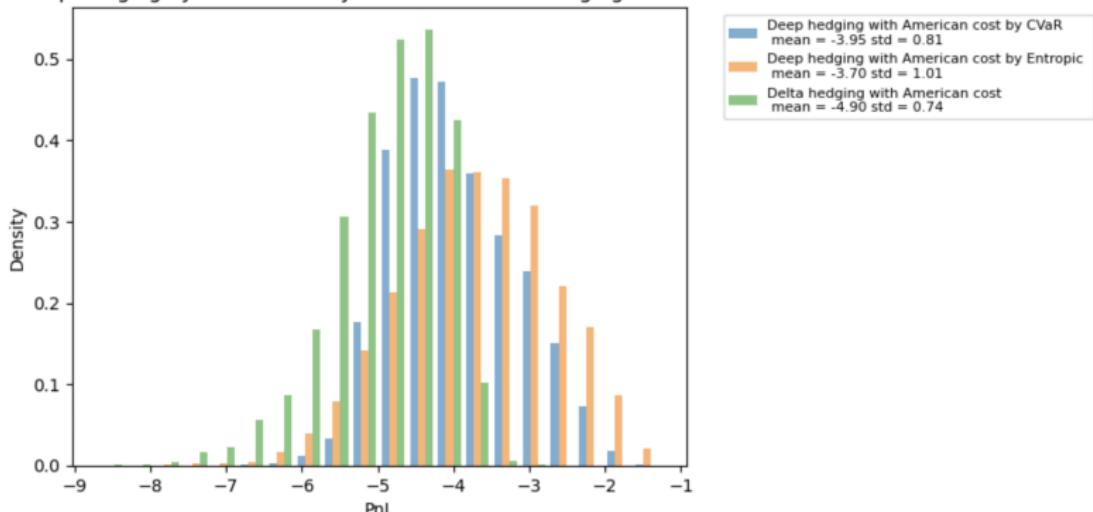
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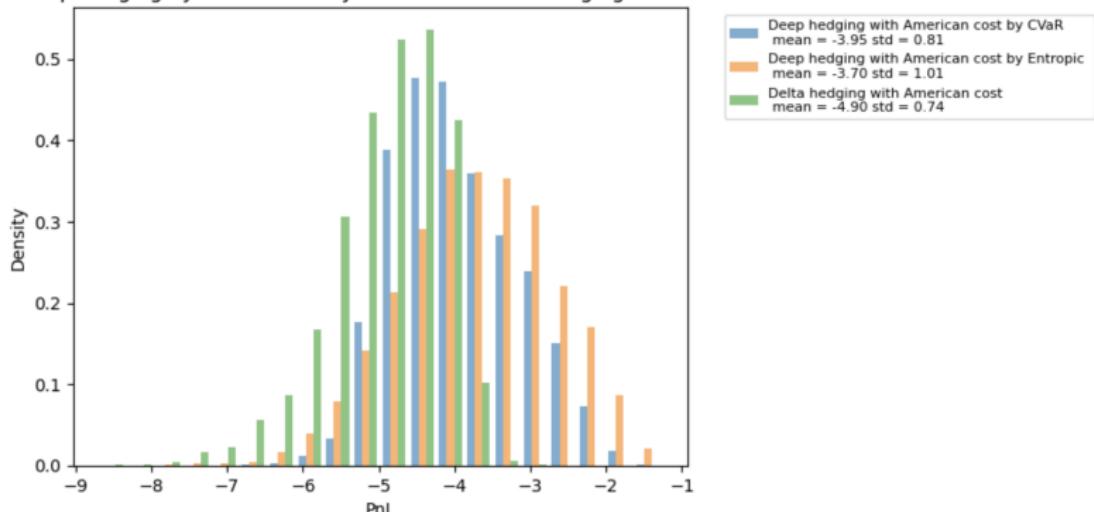
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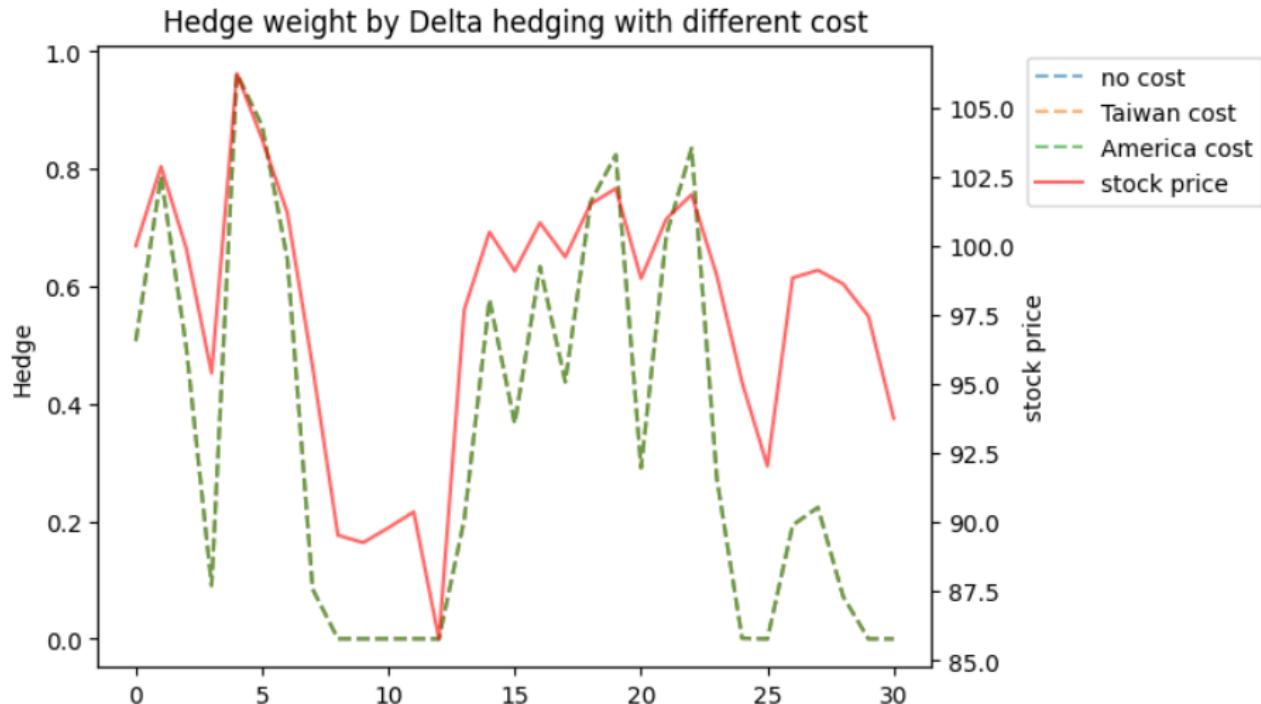
For AAPL History Data

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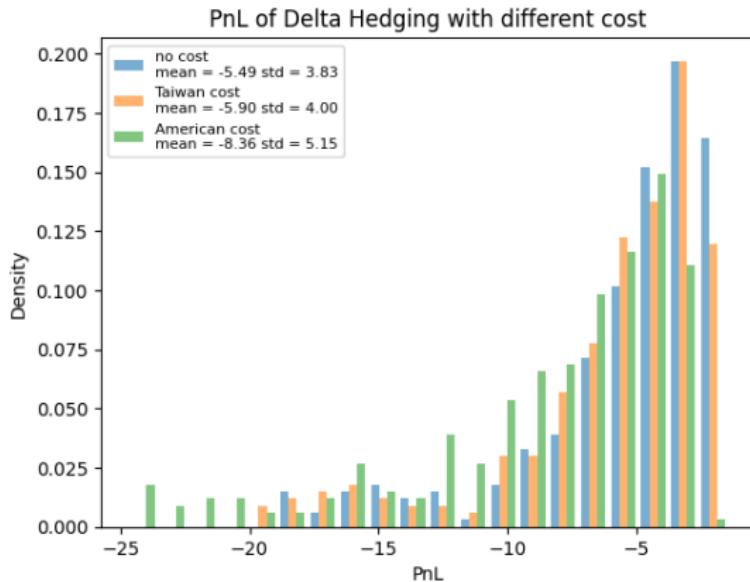
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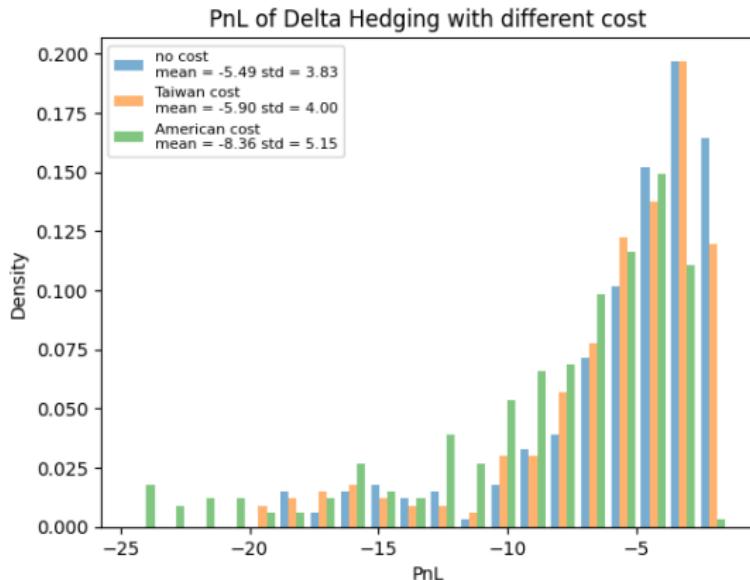
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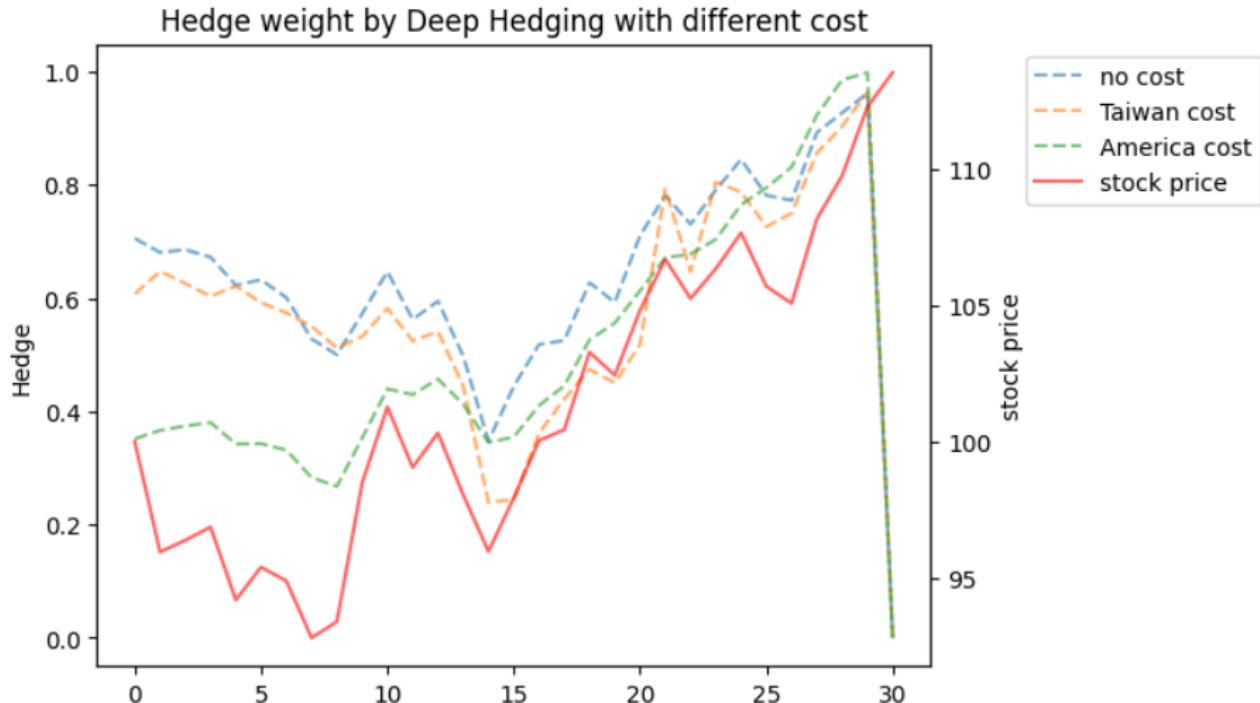


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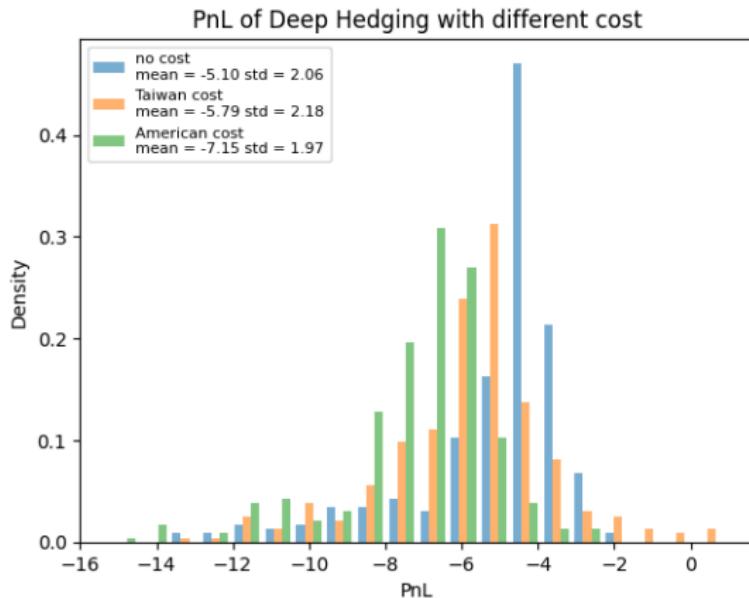


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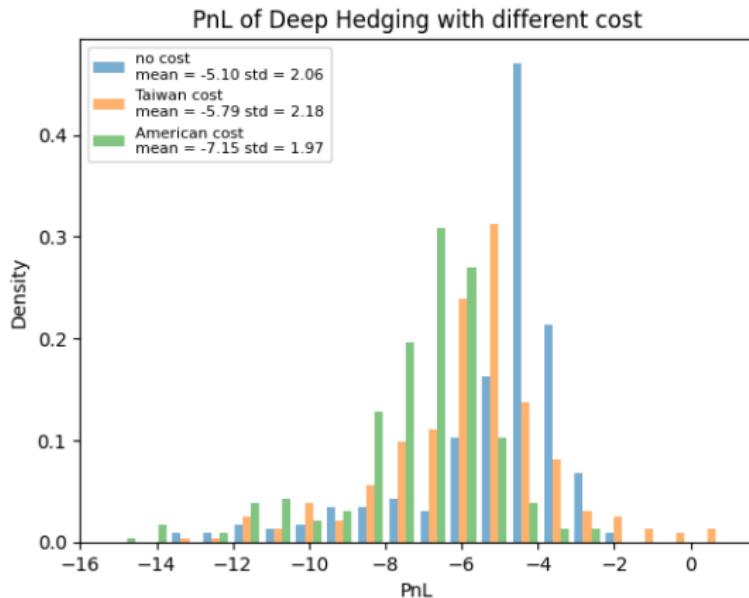
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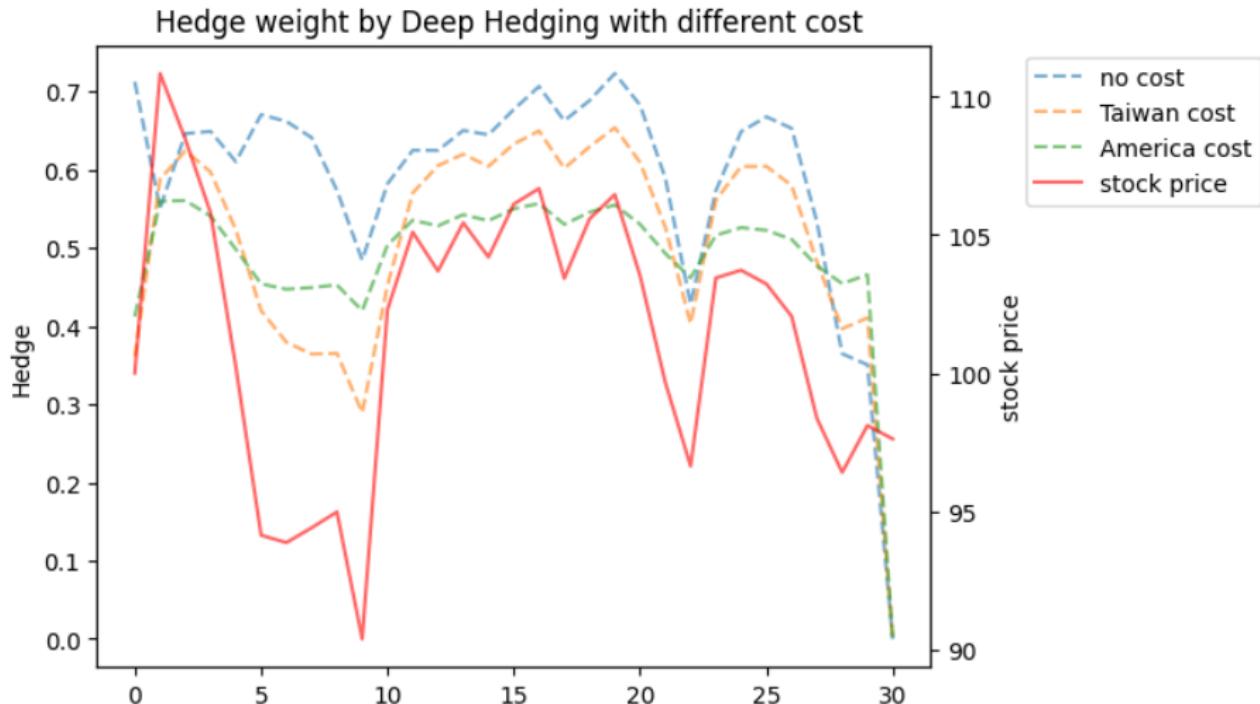


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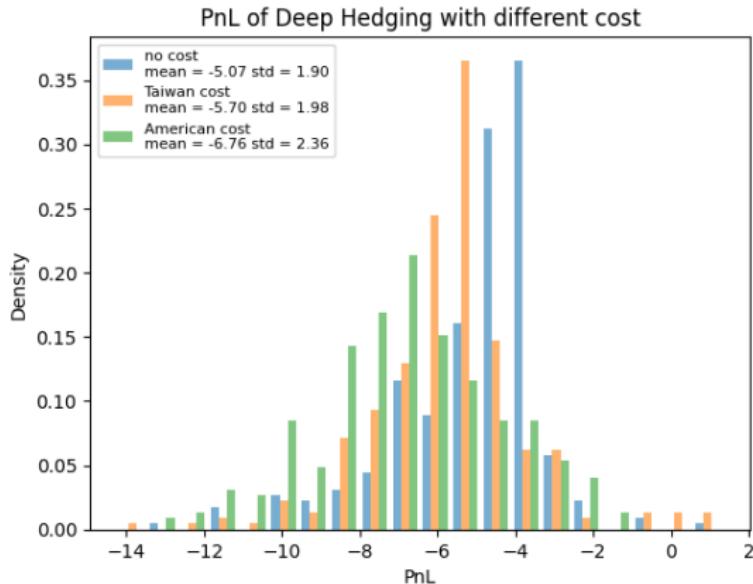


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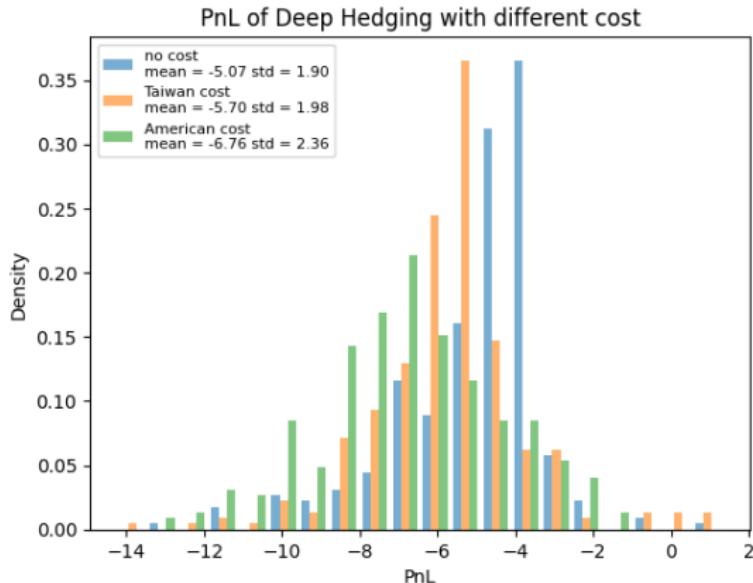
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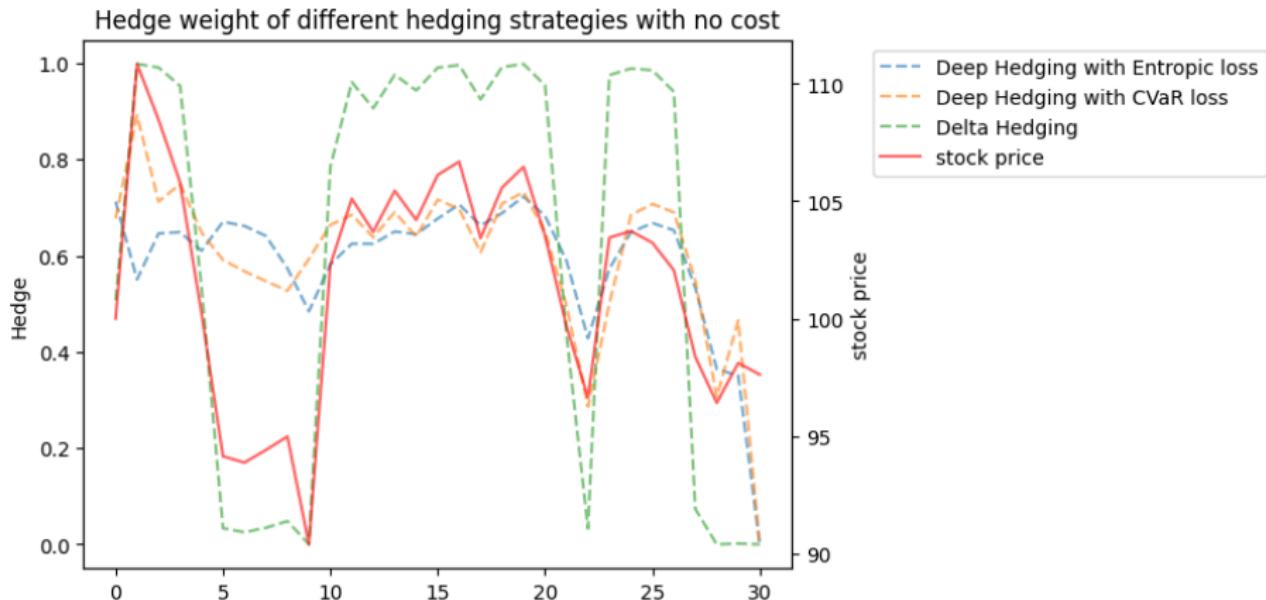


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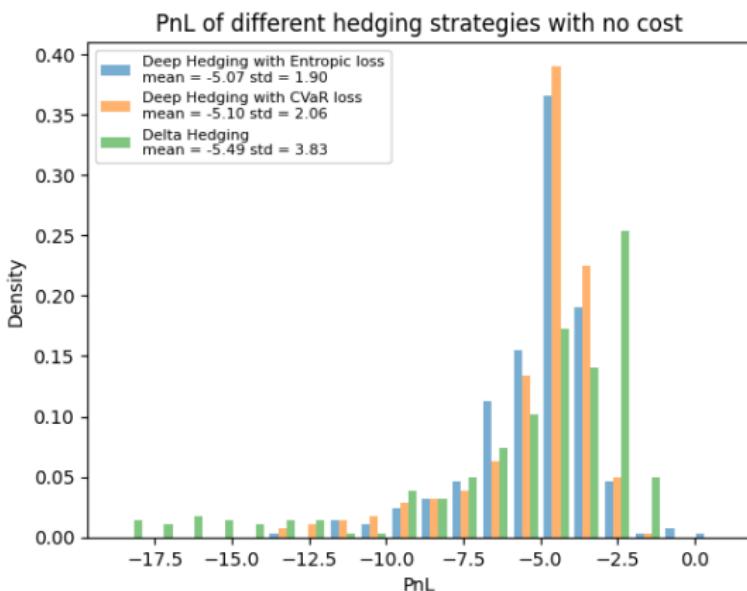


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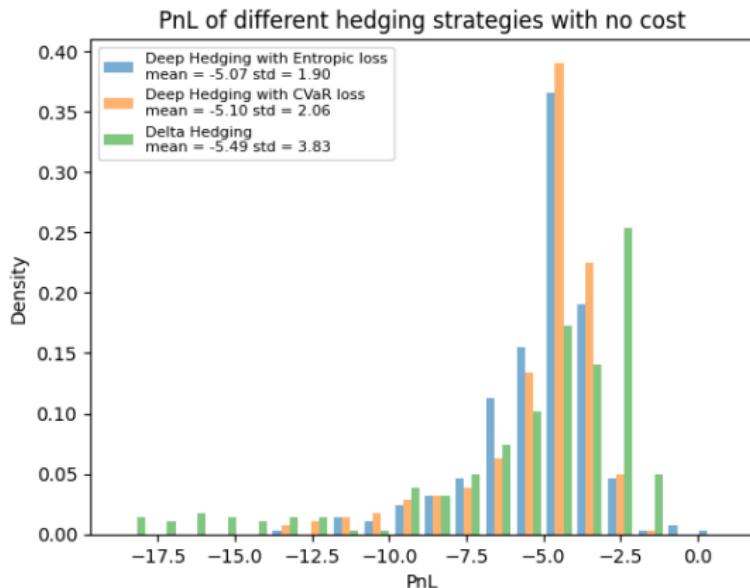
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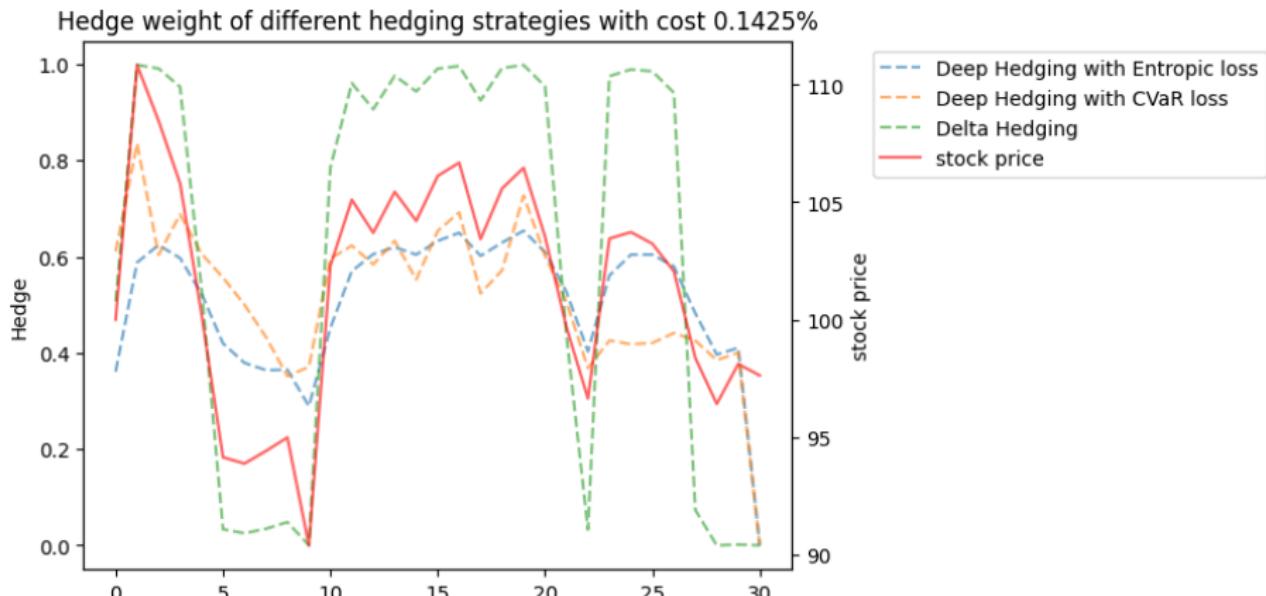


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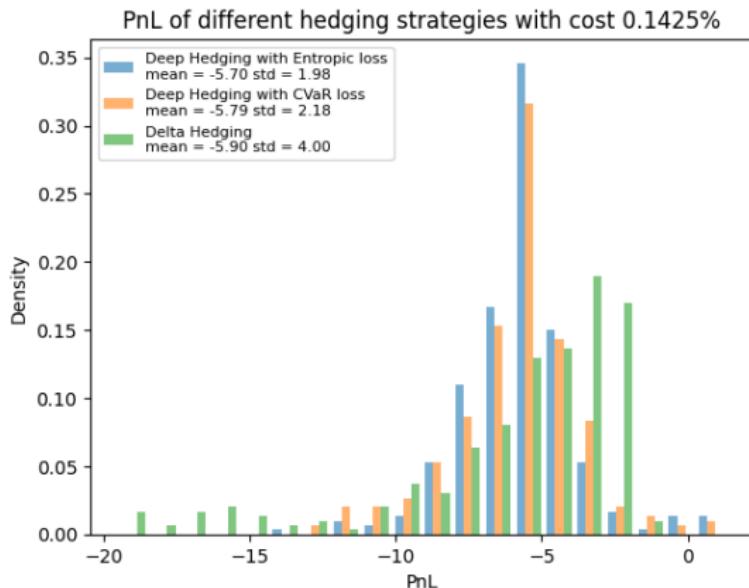


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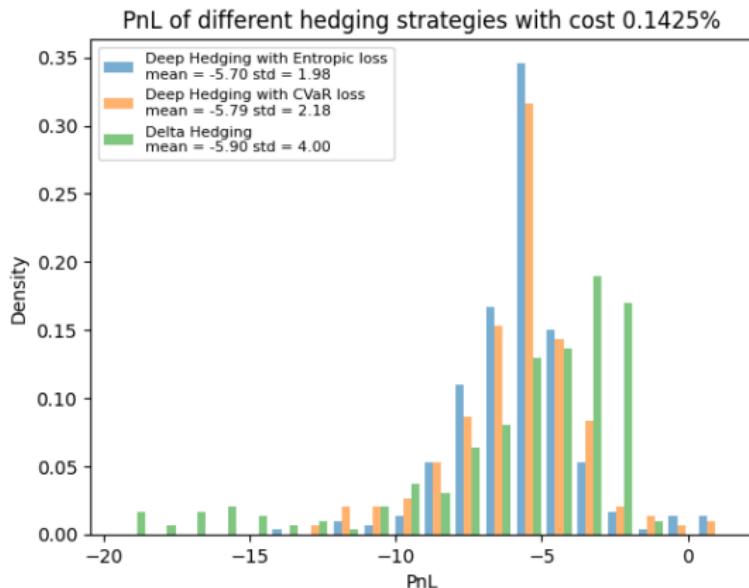
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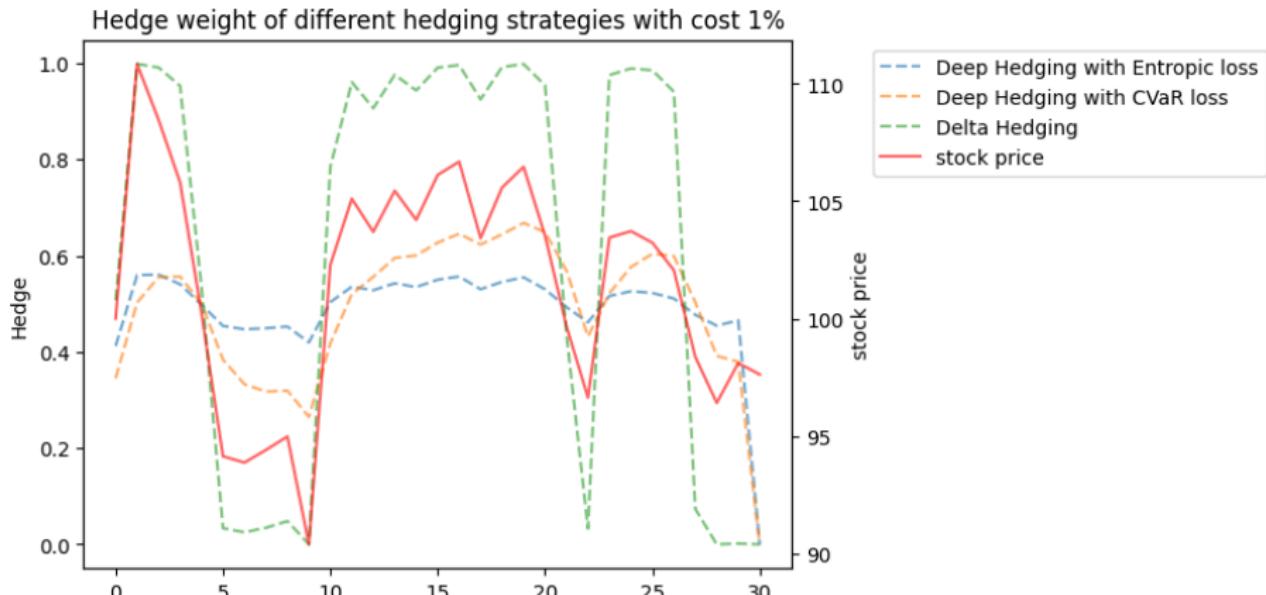


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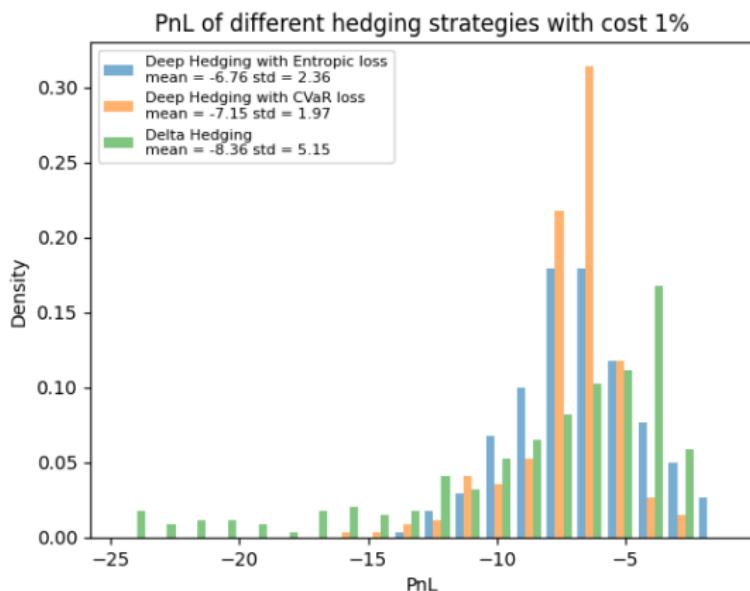


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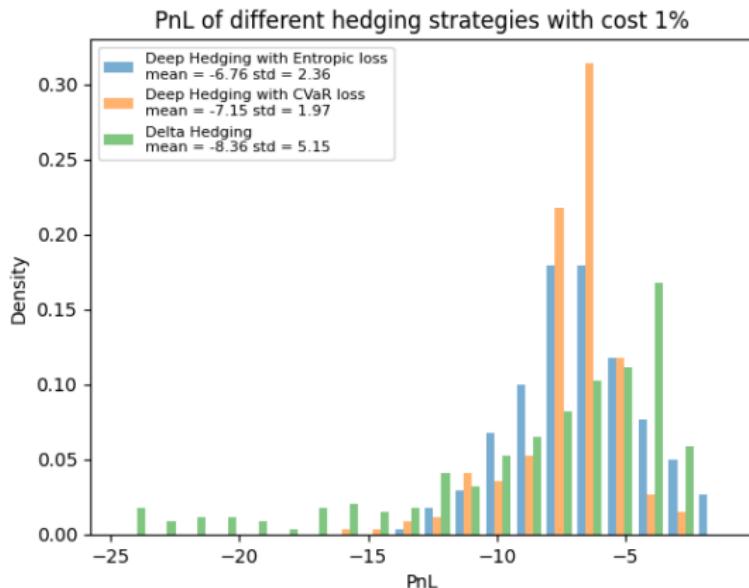
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Deep Hedging strategies offer superior performance and resilience compared to traditional Delta Hedging, particularly in the presence of transaction costs.

# Table of Contents

1 Introduction

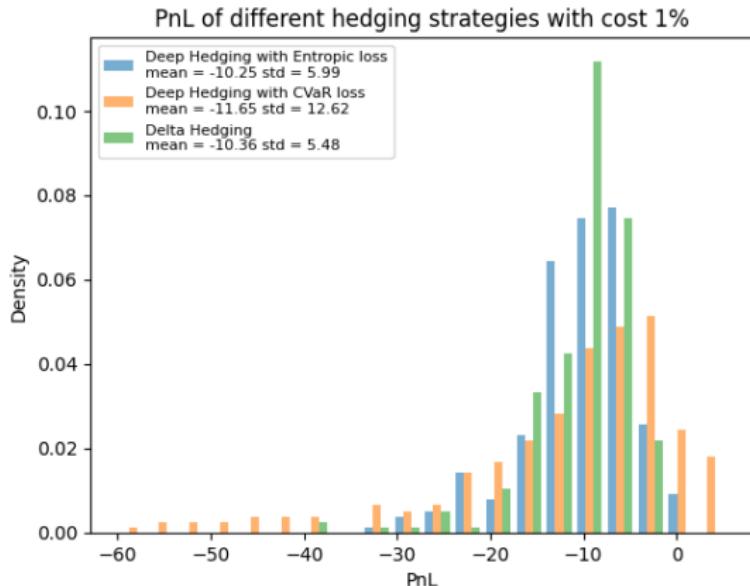
2 Research methods

3 Result

4 Limitation of Deep Hedging

# Amazon stock data

**Observation:** Deep hedging underperforms Black-Scholes delta hedging.



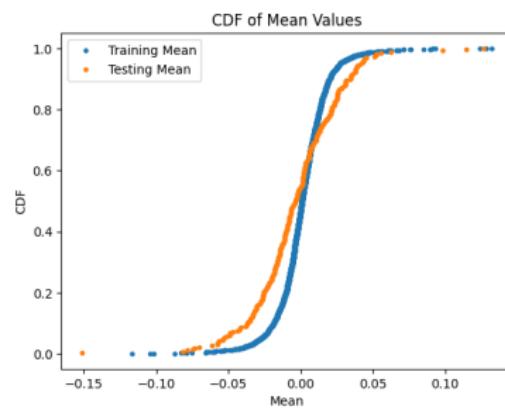
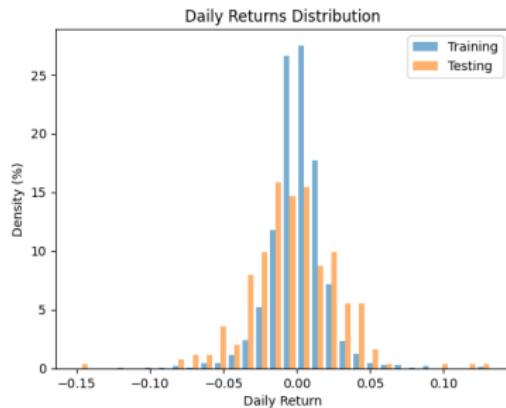
# Amazon stock data

**Action:** Changed the time period of the Amazon data.



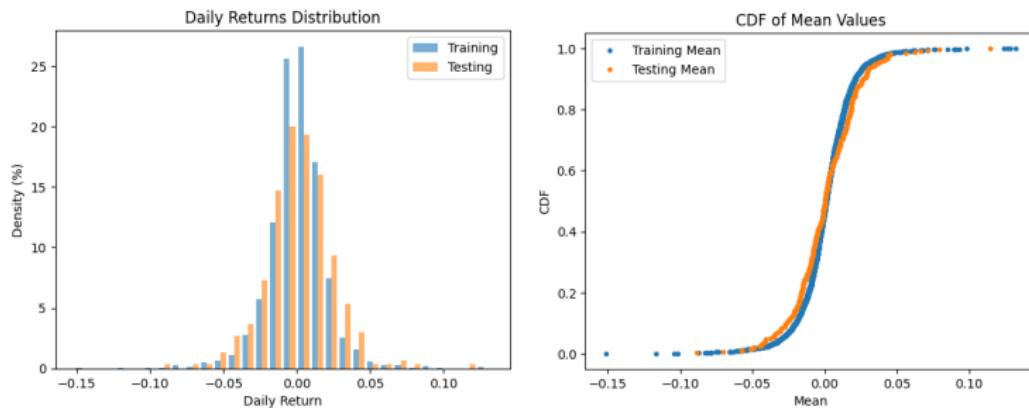
# Amazon stock data

**Observation:** The distribution of daily returns differs significantly between the training and testing datasets.



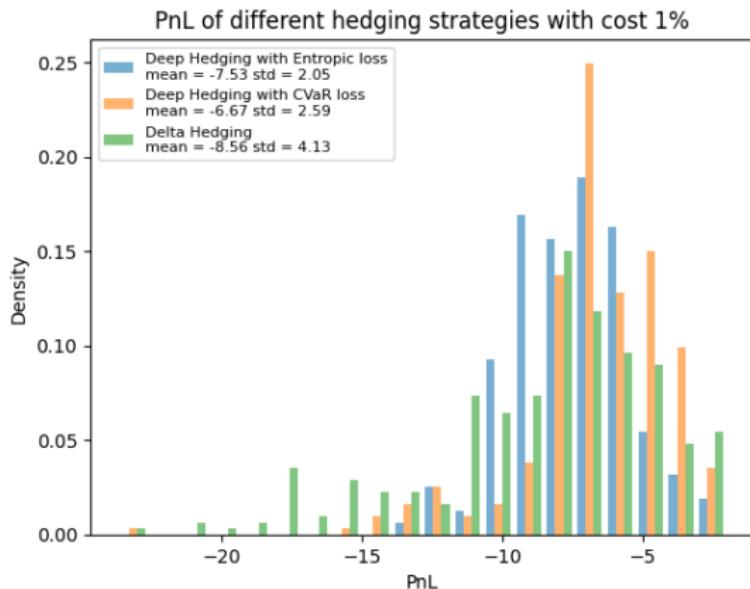
# Amazon stock data

**Action:** Reevaluated the distribution differences between the training and testing datasets. The differences are not substantial.



# Amazon stock data

**Observation:** In the revised period, deep hedging outperforms delta hedging, similar to the previous results with Apple stock data.



# Amazon stock data

## Conclusion

- Deep Hedging strategies may underperform traditional delta hedging in unforeseen market conditions.

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- Deep Hedging strategies perform optimally when the training and testing data distributions are similar.

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- Deep Hedging strategies may underperform traditional delta hedging in unforeseen market conditions.
- Deep Hedging strategies perform optimally when the training and testing data distributions are similar.
- Proper preprocessing of training data is essential, with potential use of GANs to generate synthetic data for better performance.