The Dong-Hak Ants

Namwoo Kwon, Yejin Kim, Daeun Oh, Hyeon-Wook Oh, Chan-Beom Hur

Tuesday, November.14.2023

Portfolio Strategy Development using Machine Learning for Momentum Crash Risk Management

Introduction

Momentum Effect

The Market Anomaly that creates excess returns by buying financial products with good past returns (winners) and selling financial products with poor past returns (losers). This effect has been seen consistently since the distant past, which is why many investors utilize momentum investing or momentum portfolios.

Momentum Crash

However, sometimes the opposite happens, where a financial instrument with a poor past performance outperforms a financial instrument with a good past performance. This is called a Momentum Crash, and it can cause huge losses for Momentum investors.

Dynamic Strategy

We use a Machine Learning (or Neural Network) model, inheriting from previous research on predicting momentum crashes with a statistical methodology. We perform anomaly detection by considering Momentum Effect as a normal situation and defining Momentum Crash as an anomaly. If the model predicts an anomaly, it manages the Momentum Crash Risk by assigning low leverage to the Momentum Portfolio.

Methodology

Process

- Momentum, Winner, Loser
- Anomaly Detection Model
- Anomaly Score of Validation Dataset
- Threshold & Leverage
- New Portfolio Returns
- New Sharpe Ratio

Various Leverage Function

Leverage Function 1

$$lev_t = \begin{cases} 1 & x_t < T \\ 0 & x \geq T \end{cases}$$

Leverage Function 2

$$lev_t = \begin{cases} 1 & x < T-1 \\ \frac{1}{1+(x_t - T_t + 1)^{C_t}} & T-1 \leq x < T \\ \frac{1}{1+(x_t - T_t + 1)^{F_t C_t}} & x \geq T \end{cases}$$

Leverage Function 3

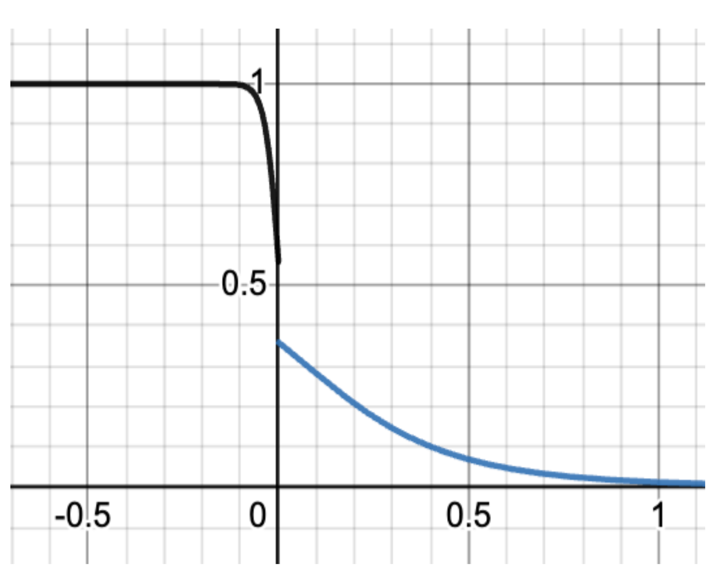
$$lev_t = \begin{cases} \frac{1}{1+(Fe^{C(x_t - t)})} & x < T \\ \frac{1}{(1+\sqrt{F})+(\sqrt{F}\,(x-t+1)^{\sqrt{F}\,\sqrt{C}})} & x \geq T \end{cases}$$

lev_t: Leverage at time t, x_t: Anomaly score at time t, T_t: Threshold at time t, F_t: F1-score at time t, C_t: Certain at time t

Define thresholds and leverage functions

The threshold is defined by the Anomaly Score and f1-score of the validation dataset. The leverage function is divided into two sections based on the threshold, and there are two different functions. The two leverage functions are defined by different equations using 'Certain' and the f1 score of the validation data set as parameters. We then multiply the portfolio returns from the test data set by the leverage to come up with a new momentum portfolio return.

High F1-Score

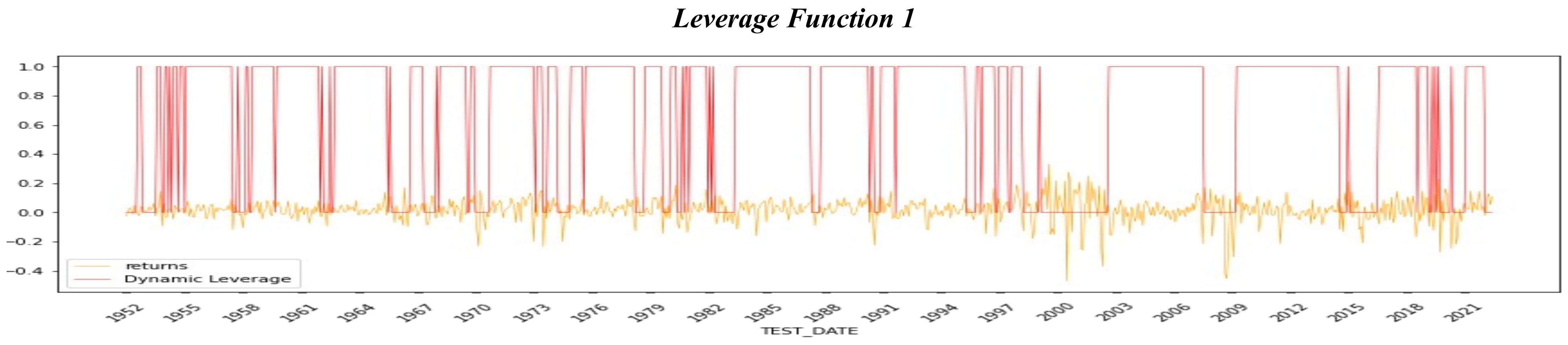


Low F1-Score

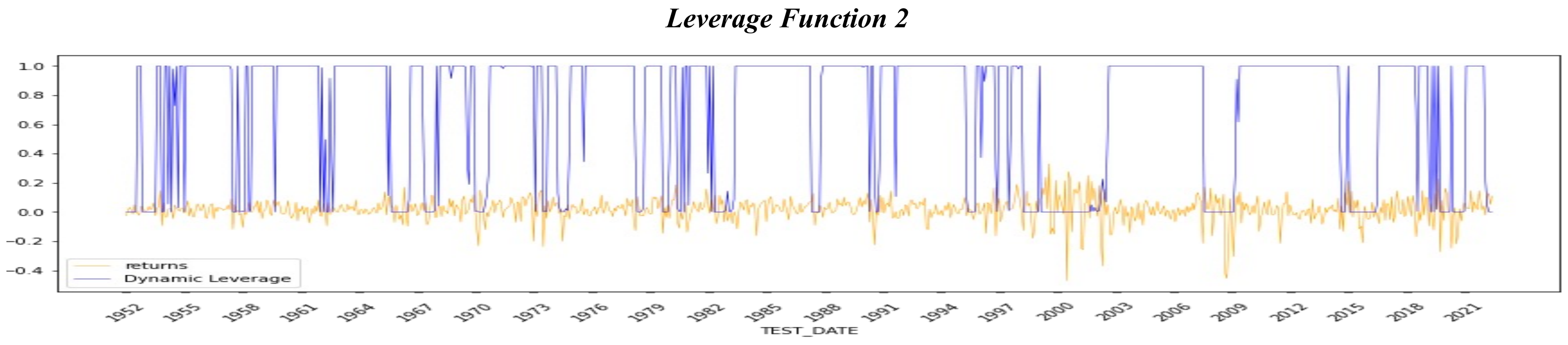
Results

Dynamic Leverage & Test Data Returns

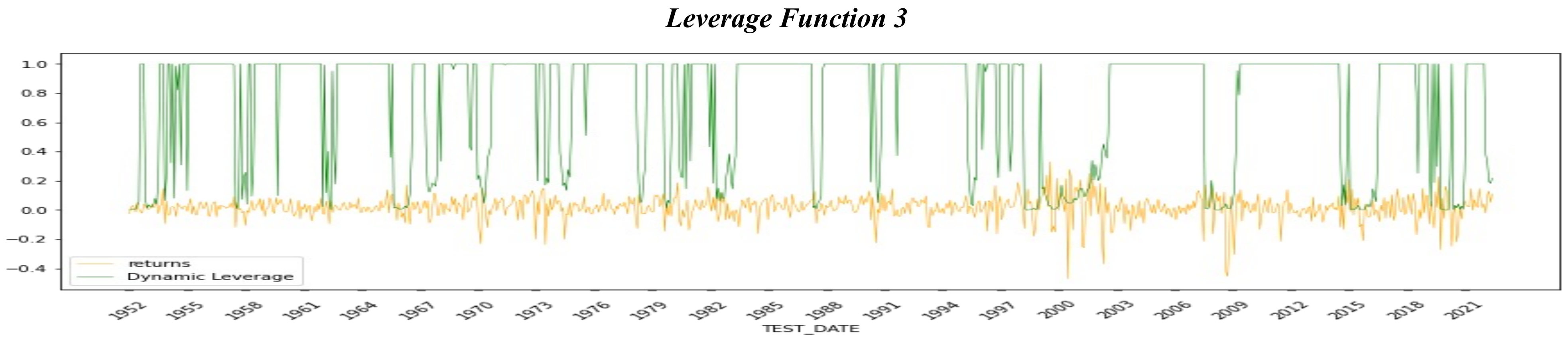
Leverage Function 1



Leverage Function 2

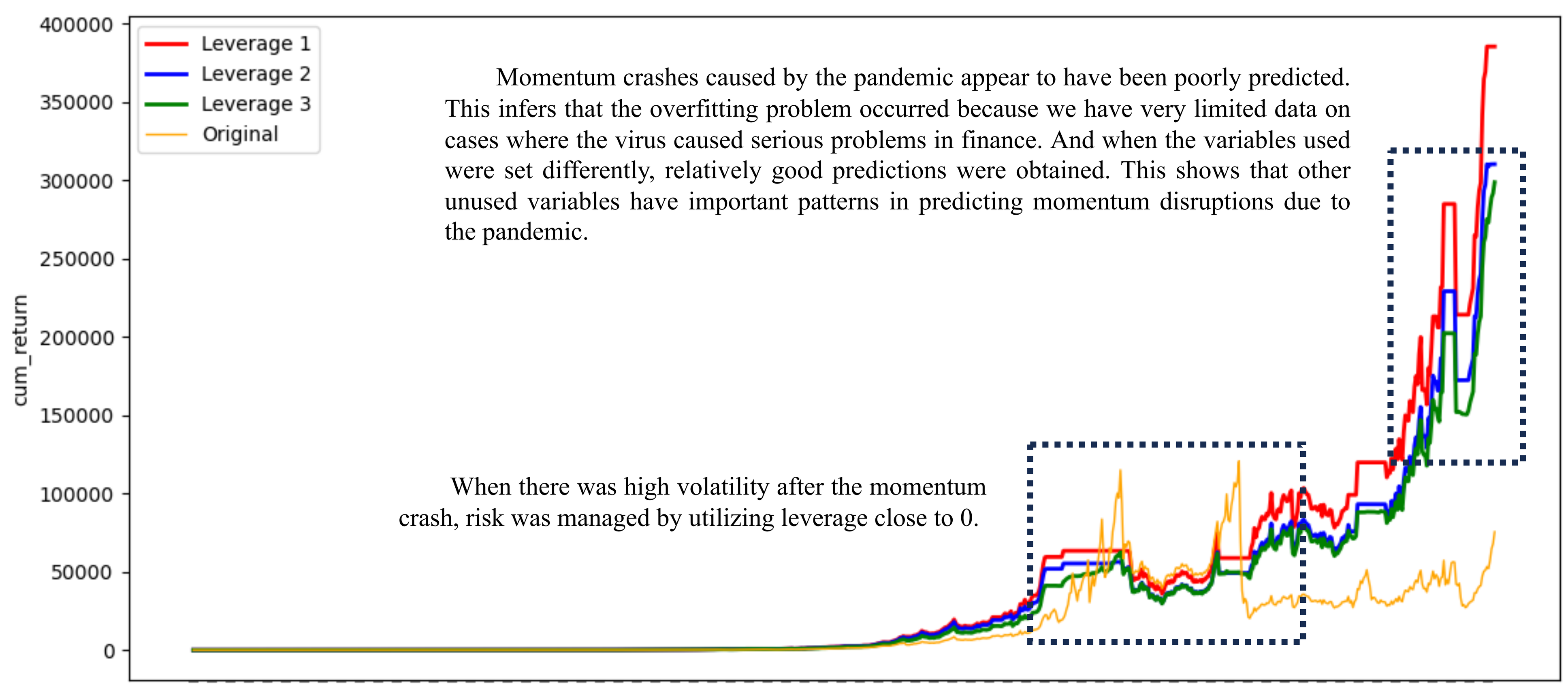


Leverage Function 3



The New Share Ratio & Cumulative Return

	Original	Leverage 1	Leverage 2	Leverage 3
Sharpe Ratio	0.730	1.165	1.146	1.121
Cumulative Return (%)	7.4 M	38.6 M	31.0 M	29.9 M



Conclusion

The content of the poster above focuses on the method that showed the highest Sharpe Ratio among the various methods studied. Among the 17 variables, 9 variables were selected and trained in the Isolation Forest model using Supervised Learning. Our proposed methodology increased the Sharpe ratio by up to approximately 59.6% compared to the existing momentum portfolio, and the most recent cumulative return increased by up to approximately 417.7%. In particular, it continued to show very low leverage, especially when volatility increased after the momentum crash. What is surprising is that when the f1-score of the validation dataset was referenced in the leverage function, leverage was output by distinguishing between momentum crash and momentum effect in the high volatility of the momentum portfolio. And through this study, we reconfirmed that momentum volatility is the most important variable in predicting momentum crashes.