2023 UCHICAGO TRADING COMPETITION

Case Packet & Information

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Career Advancement
Financial Markets

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WELCOME

On behalf of the University of Chicago and the UChicago Financial Markets Program (FM), we are pleased to welcome you to the 11th Annual UChicago Trading Competition! We are excited to have you as part of our in-person competition this year. Thank you to our FM student case writers and platform developers, and our corporate sponsors for their leadership and support.

This trading competition could not be possible without the generous support of our corporate sponsors. This year's sponsors include: DRW, Belvedere Trading, Chicago Trading Company, Citadel, Five Rings Capital, Flow Traders, Hudson River Trading, IMC, Jane Street, Optiver, Old Mission Capital, SIG, Tower Research Capital, BP and Two Sigma.

We are delighted to have DWR as a platinum sponsor this year! DWR will host our traditional poker event on Friday evening.

The trading competition will be held in-person on Saturday, April 15th at onvene Fulton Market in downtown Chicago. The focus of this event will be algorithmic trading, with three cases covering the following themes – options trading, futures & ETF trading, and portfolio optimization asset return prediction.

We are excited to have so many talented students in this year's competition, and we look forward to seeing the teams in action!

For more information about UChicago Career Advancement, visit our website.

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SCHEDULE OF EVENTS

Friday, April 14, 2023 *(all times in CST)*

Location	Time (CST)	Topic
Hyatt Centric Chicago Magnificent Mile (633 N St. Clair Street)	5:00 - 8:00 pm	Poker Tournament with Platinum Sponsor DRW

Saturday, April 15, 2023 *(all times in CST)*

Location	Time (CST)	Topic
Convene Business Center - Fulton Market (333 N Green St, Chicago, IL 60607)	8:00 – 8:45 am	Breakfast / Set up
	8:45 – 9:15 am	Welcome and Agenda Overview
	9:15 – 10:15 am	Case 1
	10:15 – 10:30 am	Intermission
	10:30 - 11:30am	Case 2
	11:30 - 12:15 pm	Case 1 & 2 Overviews (presented by Student Committee team)
	12:15 - 1:45 pm	Lunch / Career Fair
	1:45 – 2:45 pm	Case 3
	2:45 – 3:30 pm	Awards Presentation
	3:30 - 5:00 pm	Networking Reception

All sessions are required for participants to be eligible for prize money

PARTICIPANTS

We are pleased to announce that over 150 students across the United States will participate in this year's competition. The following institutions will be represented:

- Amherst College
- Boston College
- Brown University
- Carnegie Mellon University
- Columbia University
- Duke University
- Harvard University
- Harvey Mudd College
- Johns Hopkins University
- New York University
- Northwestern University
- Purdue University
- Stanford University
- University of California, Berkeley
- University of California, Los Angeles
- University of Chicago
- University of Colorado, Boulder
- University of Maryland, College Park
- University of Michigan, Ann Arbor
- University of Pennsylvania
- University of Texas at Austin
- University of Virginia
- Yale University

AWARDS

Awards will be announced during the awards ceremony. Cash prizes will be awarded to the winning team of each individual case and the top three overall winners based on aggregate scores across all cases. Participants must attend all sessions on Friday and Saturday to be eligible for prize money.

COMPETITION TECHNOLOGY

The University of Chicago Financial Markets Program (FM) is excited to show its in-house trading platform X-Change built by senior members of the FM program for the 11th Annual UChicago Trading Competition! Cases 1 and 2 for the competition will be run live utilizing this platform. Case 3 will be run before the competition and results will be played back at the event.

In the next few weeks, you will receive emails detailing instructions on accessing live virtual sessions which will be used to address competitor questions and provide important case and platform updates.

Algorithm Development

Competitors may develop their algorithms in any computing language; however, Python will be the only officially supported language. No other languages will receive explicit support from the case writing team. On the day of the competition, one user from each team will be responsible for manually starting the team's algo at the beginning of each case round.

Additional details on rules and requirements for each round can be found in the case descriptions.

Case Submission Dates

For Cases 1 and 2, all competitors must submit a draft of their code by **noon (12:00 PM CST) on Friday, April 7th.**

Competitors will run their finalized algorithms locally on the day of the competition.

For Case 3, competitors' final algorithms must be submitted by **noon (12:00 PM CST) on Friday, April 7th.**

This case will be run in advance of the competition. Teams will not run their algorithms live on the day of the competition. Final scores will be announced on the day of the competition.

CASE 1: Futures & ETF Trading

Introduction

Soybeans are one of the most commonly grown crops in the United States. However, the weather greatly impacts the ability for soybeans to be grown and harvested. For the above reasons, businesses who use soybeans as a raw input often choose to hedge their risks using futures contracts.

For this case you will be trading in the soybeans market. Along with the ability to trade soybeans, we highly recommend that you trade in the soybean futures market available to you. There will be a future expiring at the end of each month. Along with these futures, you will be trading an exchange traded fund (ETF) that is composed of a weighted combination of the next 3 futures contracts. You will be able to both redeem and create soybean futures ETFs, and we highly encourage you to do so to take advantage of inefficiencies in the market.

To ease your ability to trade these assets, your company has decided to provide you with a weather index which directly aggregates all relevant weather data to predict the price of soybeans.

Case Specifications

Each year will have a total of 252 trading days, with 21 trading days per month. Each day, you will receive the weather index from the exchange. For the purposes of this case, you may assume that the previous indices are a reliable predictor for price. At the end of each month there will be a rebalance event where the ETF will be recomposed of futures yet to expire.

For simplicity, each futures contract will be assumed to only trade 1 unit of the underlying. The contract for that month will expire on the last trading day of the month. For example, the June contract will expire on the 126th trading day of the year. Contracts at expiration will be settled into the commodity and market participants will have the ability to trade contracts up until the day of expiration. The tick size is 0.01 for all contracts.

The ETF code is LLL. The code for soybeans is SBL. The codes for the future contracts are given on the next page:

Expiration Month	Contract Code
Jan	LBSA
Feb	LBSB
March	LBSC
April	LBSD
May	LBSE
June	LBSF
July	LBSG
August	LBSH
September	LBSI
October	LBSJ
November	LBSK
December	LBSL
January Next Year	LBSM
February Next Year	LBSN

Commodity

Commodities can be bought and sold for a price on the market. Assume that all units of soybeans are interchangeable. Soybeans incur a cost to carry. For simplicity, the exchange will charge you a carrying cost of $0.20 (subject to change / finalized will be sent out with data) per unit of soybeans per day.

Futures

Futures are agreements to buy a commodity at a given time for a predetermined price. The commodity is commonly referred to as the underlying. The date for the predetermined sale is known as the expiration. The predetermined price is known as the forward price. Important: You do not pay the forward price when a contract trades. Instead, the forward price and underlying will be added/subtracted to your account at expiration.

For simplicity sake, all contracts will be for one unit of soybeans to be received at the end of the specified month.

On the next page you will find some important terms for pricing commodities futures.

- **Interest Rate**: Expected rate of return for risk-free investments. Generally is assumed to be the treasure bond yield. For this case, assume the risk-free interest rate is 2% **(subject to change)**. You will **NOT** be given access to the bond market, but assume that other market participants will be. Assume no interest rate risk (i.e. interest rate will not change during a round).
- **Carry cost**: Cost of storage of the commodity. Projected to be $0.20 per unit of soybeans per day. **Finalized carry cost will be given when exchange is sent out.**
- **Dividends**: Returns generated by the underlying between the sale of the contract and expiration. Not applicable to this case.
- **Convenience Yield**: Any costs incurred by not having possession of the underlying commodity. Assume it to be zero.

ETF

An ETF (or Exchange Traded Fund) is a basket of assets that trades like a single asset. The ETF LLL will be composed of 5 of the futures contract expiring next month, 3 of the futures contract expiring in two months, and 2 of the futures contract expiring in three months. For example, on day 28, 1 LLL is equivalent to 5 LBSB, 3 LBSC, 2 LBSD.

Here are some useful terms:

- **Creation**: A market participant can give an ETF provider the basket of assets that make up the ETF, and will be given one share of the ETF in return. You will be provided an API call to do so.
- **Redemption**: A market participant can give the ETF provider a share of the ETF and receive the basket in return. API call will be provided.
- **Rebalance Event**: At the end of every month, the basket that composes the ETF LLL will change.

Case Specifications

There will be 5 rounds corresponding to markets in the following years: 2023 (practice), 2023, 2024, 2025, 2026 (you will have data from 2017-2022. The chronology is not irrelevant to succeeding in this case).

The 2022 data will be generated independently between the first and second runs: the former will serve as practice for familiarity with the server and model parameters.

Positions and PnL are not carried over between rounds. Any positions will be cash-settled at fair value automatically at the end of the round..

Data and platform simulation will be provided so that you can train your algorithm prior to the competition.

Rules

You may take long or short positions in all futures available in a round, subject to risk limits specified below.

There is a maximum order size of 100 in this competition. Exceeding it will result in the rejection of your entire order.

Risk Limits

As a market maker, your firm stipulates that the maximum net long or short position you may hold in total for soybeans is 1000 (**subject to change**). That is, the sum of the futures contracts to buy soybeans you hold (including from holding the ETF) and units of soybeans minus the number of futures contracts to sell must be within -1000 and 1000.

If you exceed this position, all further orders for that contract that exacerbate the risk limits will be blocked by the exchange.

Scoring

At the conclusion of each round, each team will receive points corresponding to their rank.

The team with the highest Sharpe ratio will receive 1 point, the team with the second highest Sharpe ratio will receive 2 points, and so forth. Sharpe ratio will be calculated relative to the given risk-free rate.

Any team disqualified during a round will receive points calculated as (# of Teams + 1).

The lowest point total wins. Ties will be broken by final round rank.
Note that the practice round will not count towards total points.

Case Materials & Data

Python stub code and training data will be released with the case packet through the UChicago Trading Competition Ed. We will be releasing finalized coefficients with the training data.

The basic bot will outline some key functions and exchange syntax for you.

Code Submission

We are requiring a preliminary code submission by 12:00pm CT (noon) on April 7th, 2023.

Competitors will, however, run their bots from their own computers on the actual day of the competition.

Miscellaneous Tips

In order to be successful in this case (and as a market maker in general), you will need:

- A model that predicts the “fair value” of the asset you are trading
- A model that calculates risk relative to changes in the weather index for each asset
- A market making algorithm that uses the predicted “fair value” and risk to quote bids and asks while managing risk

Some possible points of consideration are:

- How to best make use of the historical data you are provided with to make predictions on unseen data?
- What modifications (if any) should you make in the way you trade if the fair price predicted by your model deviates from the mid-price of the market? What if only one side of your quotes gets filled?
- Would it make a difference for you to hold contracts till expiration, or would it make more sense to clear your positions before that?
- Is it always reasonable to quote symmetrically (in size and/or price) about your predicted fair price?
- Are there any circumstances where it would be justified to “cross the spread” as a market maker?

Note that as the exchange will fill orders on price/time priority, the speed of your market making algorithm matters. Write lines of code that submit orders more quickly and speed up the bot.

Questions

For questions regarding Case 1, please post in the UChicago [Trading Competition Ed Discussion] in the “case1” folder. We will regularly check for new messages.

CASE 2: Options Trading

Definitions

- **Option**: A financial derivative that gives the owner the right to buy or sell an asset at a pre-specified price at a pre-specified time (This case deals with European Options only. The definition of an American Option is slightly different)
- **Exercise**: Use the right granted by an option to buy or sell an asset
- **Expiration**: When the owner of an options contract must either exercise or give up. After this the contract ends.
- **Strike Price**: The pre-specified price at which the owner of an option can buy or sell the underlying asset
- **Call Option**: An option that gives the owner the right to buy
- **Put Option**: An option that gives the owner the right to sell
- **Premium**: The price of an option
- **Volatility**: The annualized standard deviations of returns of an asset. It is the only unknown input into basic option pricing formulas, so options trading is often thought of in terms of volatility.
- **Implied Volatility**: The level of volatility implied by options prices in the market
- **Realized Volatility**: The level of volatility an asset has historically experienced
- **In The Money (ITM)**: An option which could currently be exercised for a profit
- **At The Money (ATM)**: The option whose strike best matches the current price of the underlying
- **Out of The Money (OTM)**: An option which could not currently be exercised for a profit
- **Intrinsic Value**: The value of an option if it were exercised now
- **Greeks**: The risk measures typically used in options trading. Delta, Theta, Vega, and Rho measure the derivative of the price of an option with respect to the price of the underlying asset, time (measured in years), volatility, and interest rates respectively. Gamma measures the second derivative of the price of an option with respect to the price of the underlying (price of option with respect to Delta).

Use Cases for Stock Options

Options can help both hedgers and speculators take positions and are a useful tool to anybody who wants a return profile that is non-linear with respect to an underlying asset.

For example, options can help pension plans ensure that they will be able to meet their payment obligations. If a pension fund has enough money to meet its payment obligations to pensioners and has enough of a surplus to be able to survive a 10% loss, but wants to generate additional returns, the pension fund might purchase a stock and a put option with a strike price 10% down from the current price. That way, they can make money if the stock goes up but also don't become insolvent if the stock falls more than 10%.

Options can help speculators as well by allowing them to bet more heavily on a certain price move than they would otherwise be able to. For example, if a stock costs $100, the 1-month call option with a strike at $100 costs $1, and a speculator thinks the stock will go up $22 in the next month, the speculator could either buy the stock for $100 or buy two 1-month calls struck at $110 for $1 each. If the speculator is correct and they bought the stock, then they would make $22 while deploying $100 in capital. If they bought 2 options they can exercise them at expiration, buying two shares of stock for $110 each, which they can immediately sell for $122 each, netting them $22 in profit (after subtracting the option premium) with only $2 of capital deployed. With $100 of capital deployed this would net $1100.

Options Pricing Models

Options can be priced using the Black Scholes Model or using a tree model. Both models take the interest rate, the price of the underlying asset, the time to expiration, the strike price, and the implied volatility of the underlying asset as inputs. All of these are known except for the implied volatility, which can be backed out from the price of other options on the market. However, the overall level of volatility is not known, and is often a reflection of market sentiment. As a result, volatility often forms in "clusters".

Both models work by assuming risk-neutrality, constant volatility, and a lognormal distribution of underlying returns. However, these assumptions are not often true in practice, which is why different option strikes have different "implied" volatilities.

Volatility Surface

Volatility has a surface, in the strike-implied volatility-time to expiry space, which tracks the implied volatility across all strike prices and expiries. Unlike the

assumptions in Black-Scholes, the volatility surface is far from flat and often varies over time because the assumptions of the Black-Scholes model are not always true. For instance, options with lower strike prices tend to have higher implied volatilities than those with higher strike prices, since options tend to be used for hedging purposes. "Local volatility" considers the implied volatility of just a small area of the overall volatility surface. It may hone in on just a single option, either a call or a put of a specific strike price and expiration. The volatility surface may be thought of as an aggregation of all the local volatilities in an options chain.

For this case, you will only trade a single expiry, so we only care about one plane of the volatility surface - only consider volatility with respect to strike.

Case Description

For this case, you will trade options on 3 simulations of an underlying. Each "run" will have a total of 2000 underlying updates, which is partitioned into 20 mini-rounds. There will be a total of 15 option contracts, from those almost surely ITM to those almost surely OTM. The underlying will start at "100", and the options will be struck in increments of 10 from 30 to 170 (both puts and calls). You will have to create a dynamic algorithm which helps you value parameters that factor into option prices, and then quote prices based on your algorithm. The underlying represents a relatively illiquid index, which is subject to macroeconomic shocks, as well as sentiments about the index itself at a given point in time. You will not be able to change the parameters in real time during the mini-rounds/simulations, but you will be given a short period to readjust your algorithm in between mini-rounds. Options will expire beyond the time horizon, so you won't be able to "cash out" as part of your strategy.

Limit and market orders will be allowed in options, and only market orders will be allowed in equities. Teams have the choice to build their algorithms using whichever programming language that implements gRPC binding; however, Python will be the officially supported language. No other languages will receive explicit support from the case writers.

While learning how to price options is an important part of this case, you'll also have to be an efficient trader to profit from any pricing advantage that you might have. This said, an important task of yours is to synthesize market data to be able to quote orders that are both executable and offer positive expected profit.

Risk Limits

Your risk limits for each stock and associated options chain are as follows. Any relationships between stocks are not considered when assessing risk.

Delta	**2000**
Gamma	**5000**
Vega*	**1000000**
Theta	**5000**

*Volatility is typically quoted in vol points, which are hundredths of mathematical volatility (the annualized standard deviation of returns). This Vega number is with respect to mathematical volatility, not vol points. If implied volatility

increases from .22 to .23 you're permitted to gain or lose up to $10,000. If implied volatility increases from .22 to 1.22 you're permitted to gain or lose up to $1,000,000.

We do not have a risk limit for Rho because interest rates are fixed at 0 for this case. Competitors who trade through the risk limits will be auto liquidated by the exchange until they are within risk limits. No consideration will be given to the most efficient way to decrease the risk of your portfolio and forced liquidation will be triggered for all underlying assets if any of them are outside of the risk limit. This will be very costly and an inefficient way to decrease risk so try to manage your risk yourself. This will also be exploitable if you're able to trade against price insensitive competitors who are being liquidated.

Tips and Hints

- After you've built a working options pricing model, you will need a value for implied volatility to price options on an underlying asset. Perhaps start with the realized volatility for each asset to get an initial estimate of what the implied volatility level for each stock should be. What other models are used to model volatility in practice?
- Consider how each event affects the underlying price and volatility – see if you can use your deductions to build "triggers" for your option prices. What option strategies may be good to implement so your trades best reflect your hypotheses about the market? For example, how can you long volatility without betting on the price movement?
- Recall the volatility curve (a slice of the volatility curve) is typically not flat; what kind of curves are most common?
- Remember, the goal here is to profit relative to other competitors, not necessarily to be able to quote the "perfect" price. When events occur, how should you respond based on how other competitors are trading? Both profits and consistency matter, so see if there are any ways to increase your consistency, even if it means less profit on an individual time-period. Remember that you have multiple runs, each with a similar "story".

- Consider the effects of each of the Greeks on your prices. When do some Greeks play more of a part than others? Are they only dependent on what effect they are reflecting (for example, is delta only dependent on S?)?
- Be careful with risk limits. You can add the risk of all assets in your portfolio to get the risk of your entire portfolio. If you own a call option struck at 100, with .5 Delta, .03 Gamma, 10 Theta, and 90 Vega, a put option struck at 95 with -.05 Delta, .005 Gamma, 3 Theta, and 25 Vega, and a short share of stock, your portfolio's overall risk is -.55 Delta, .035 Gamma, 13 Theta, and 115 Vega. Your Delta position is -.55, not .45, because the short share of stock has a Delta of -1 (as the price of the stock goes up a dollar the short position loses a dollar). A simple way to calculate risk is by seeing how much the price moves when the risk-factor moves. For example, for some small, ε, we can compute a given option's Delta as follows:

$$\frac{\partial c}{\partial s} = \frac{1}{\varepsilon} C\left[(S+\varepsilon, \mathrm{K}, \mathrm{T}, \mathrm{r}, \sigma) - (S, \mathrm{K}, \mathrm{T}, \mathrm{r}, \sigma)\right]$$

Scoring

Competitors will be ranked based on the value of their portfolio at the end of each round. The value of their options positions will be determined based on the intrinsic value of the position at the end of the round. The value of their stock positions will be determined based on the mid-market stock price at the end of the round.

Competitors' ranks in each round will be squared and then summed to compute their final scores. The team with the lowest score wins. For scoring within the overall competition, the top placing team will receive 40 points, 2nd place will receive 39 points, etc.

Code Submission

We will require a preliminary submission by **noon (12:00 PM CST) on Friday, April 7th.** Competitors will, however, run their bots from their own computers on the actual day of the competition.

Case Materials/Data

A development toolkit, detailed documentation and training data has been released through the UChicago Trading Competition Ed Discussion Board. Training data consists solely of the price path of the underlying. We recommend checking your risk calculations against ours.

We have provided a bot that generates order flow to help you test. This is not how we will generate order flow in the competition, and we will not be providing that order-generating bot to you. You can make a couple of assumptions about the competition day bot though: more orders will be sent to options that are more tightly quoted, more orders will be sent to options closer to being at the money, and orders will be sized proportionally to your Greek limits.

Questions

For questions regarding Case 2, please post in the UChicago Trading Competition Ed Discussion Board in the “Case 2” folder. We will regularly check for new messages.

CASE 3: Portfolio Optimization Asset Return Prediction

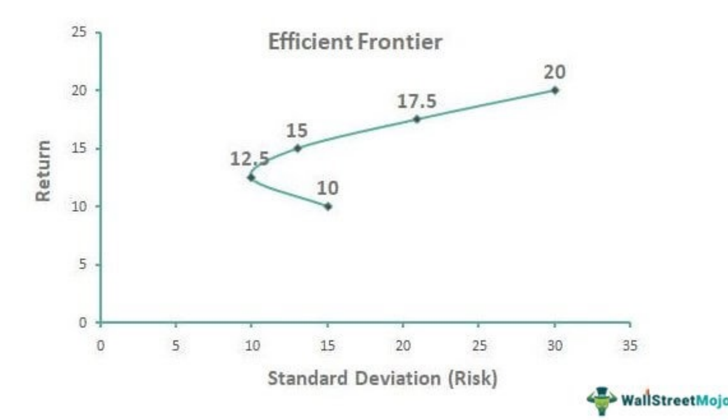
Introduction

In this case, you are a portfolio analyst tasked with allocating a fund over a ten-year time horizon across ten stocks your research team has selected. To aid you, your company has provided you with ten years of historical price data for each stock. Your goal is to develop an algorithm to construct and rebalance a portfolio aimed at maximizing returns while simultaneously minimizing returns variance. The trading begins the day after the last day of data provided.

Education

Markowitz

Obviously, a high expected return is a marker of success for any portfolio, but in addition to this, a great portfolio must also generate high returns consistently, i.e., investors must be certain their portfolio is not likely to lose money over significant periods of time. Therefore, portfolios should minimize risk while maximizing expected return. In 1952, Harry Markowitz of the University of Chicago published “Portfolio Selection,” which formalized this basic intuition and formed the basis of modern portfolio theory (MPT). Markowitz conceived of an efficient frontier of portfolios that maximize return given a certain level of risk (or alternatively minimize risk given a certain desired return). Along this efficient frontier, the actual portfolio chosen is based on the individual investor’s level of risk aversion (high risk aversion = low level of risk, and vice versa). In the absence of exact knowledge on risk aversion, portfolio managers can choose an efficient frontier portfolio based on the specific objectives given to them by their clients or firms.



Obviously, in order to implement a Markowitz portfolio, investors need some estimate of expected return and an estimate of risk. Additionally, we need some way to estimate the correlations, or covariances, between the returns of the different assets. Intuitively, a portfolio where all asset returns are highly correlated should have more risk than one with the same weights and risks for each individual asset but where all the asset returns are uncorrelated due to the fact that in the former case, one asset losing a large portion of its value means the entire portfolio likely will while this is not true in the latter case. Indeed, we see that the variance of returns in a portfolio (a measure of risk) is given by

$$
\begin{bmatrix} w_1 & \cdots & w_n \end{bmatrix}
\begin{bmatrix}
\mathrm{Var}(r_1) & \mathrm{Cov}(r_1, r_2) & \cdots & \mathrm{Cov}(r_1, r_n) \\
\mathrm{Cov}(r_2, r_1) & \mathrm{Var}(r_2) & \cdots & \mathrm{Cov}(r_2, r_n) \\
\vdots & \vdots & \ddots & \vdots \\
\mathrm{Cov}(r_n, r_1) & \mathrm{Cov}(r_n, r_2) & \cdots & \mathrm{Var}(r_n)
\end{bmatrix}
\begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix}
$$

where wi refers to the weight of the ith asset in the portfolio, ri refers to the return of that asset, and n refers to the number of assets in the portfolio. While we can reasonably estimate variances and covariances of asset returns based on historical data, empirically, historical returns have not been a strong predictor of future expected return, leading to practical difficulties in implementing a Markowitz portfolio. Since the development of MPT, investors and researchers have looked for new ways of dealing with this problem.

Risk Parity Allocation (RPA)

One approach to portfolio allocation is to simply ignore expected returns when determining how to allocate assets in a portfolio. The most naive way of doing this would be to simply find the portfolio with the lowest predicted risk, but this would simply be to invest in a risk free asset, and the return offered by such a portfolio would not entice many investors. What we want instead is a way to have a portfolio full of risky assets where more weight is given to those with lower risk. This can be done by ensuring that every asset's risk contribution to the portfolio is equal, meaning that less risky assets have more weight than riskier ones in order to equalize the risk contribution. Here, risk contribution is calculated as

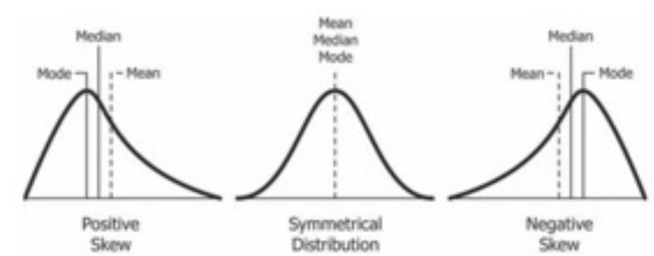
$$
\frac{w_i \left(\sum \mathbf{w}\right)_i}{\sqrt{\mathbf{w}^T \sum \mathbf{w}}}
$$

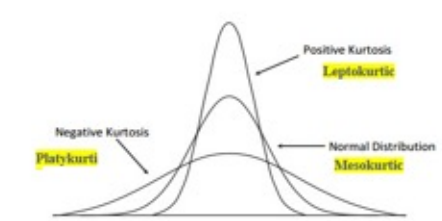
where w is the column vector of weights, and ∑ is the variance-covariance matrix from the previous equation (not a summation of w). In this calculation, assets that are uncorrelated with the rest of the portfolio contribute less to risk than correlated assets with the same risk level, which is intuitive since a drop in the value of an uncorrelated asset does not contribute as much to overall losses for the portfolio as would a correlated asset. As it has been shown that asset volatilities and correlations are relatively stable over time, historical risk contribution can be used as a reliable estimate for risk contribution.

Although the theoretical basis for RPA has its foundations in the 1960s building on the work of Markowitz, the first official RPA portfolio was implemented in 1996. RPA portfolios consistently underperform Markowitz portfolios in terms of expected return, but these portfolios became popular in the wake of the 2008 financial crisis, when their values fell far less than Markowitz and other portfolio allocation schemes.

Skew and Kurtosis

Most models assume that return distributions are log normal, however in reality, log return distributions often have some level of skew and kurtosis. Skew and Kurtosis are the third and fourth moments of distributions. Skew intuitively is a measure of how symmetric a distribution is and kurtosis is a measure of how large the tales are. In reality, the stock market is affected by shock events and may have a pattern of small gains and large losses or the converse. These patterns can increase the kurtosis of skew of return distributions. While estimations that assume normal distributions still perform well, it is possible to use other methods to account for these facts.





For instance, although risk parity and Markowitz are good under normal markets, it is possible to augment them using other metrics. One such metric is value at risk (VaR). Value at risk is a metric of the max loss ignoring a certain percentile of results. For instance, an example value at risk of a distribution could be said as the 5% VaR of the distribution is -0.5. This means that ignoring the worst 5% of cases, the max loss is -0.5. VaR circumvents some of the issues of risk parity by also taking into account the magnitude/mean of the distribution. This metric however runs into issues when the 5% of worst cases is extremely skewed. One way of dealing with that is a metric called conditional value at risk (CVaR). CVaR is the expected loss when that percentile of outcomes does happen. For instance the CVaR at 5% could be -1. This means that the max loss in the best 95% of outcomes is -0.5, however in the worst 5% of cases the expected loss is -1. This metric takes into account the magnitudes of the returns and also can be used to balance max loss. If either of these two were used to discount certain assets at certain points it might benefit Markowitz or risk parity.

With this information in mind, successful competitors will, at a high level

1. Survey literature to understand portfolio allocation schemes and asset return prediction methods.
2. Construct an investment strategy based on data provided that utilizes accurate predictions of future prices while keeping risk low.
3. Understand how non-normal distributions can affect different portfolio allocation models

Skew and Kurtosis

Most models assume that return distributions are log normal, however in reality, log return distributions often have some level of skew and kurtosis. Skew and Kurtosis are the third and fourth moments of distributions. Skew intuitively is a measure of how symmetric a distribution is and kurtosis is a measure of how large the tales are. In reality, the stock market is affected by shock events and may have a pattern of small gains and large losses or the converse. These patterns can increase the kurtosis of skew of return distributions. While estimations that assume normal distributions still perform well, it is possible to use other methods to account for these facts.

Case Specifications and Rules

The X-Change trading platform will not be used for this case. Teams are expected to develop their strategies using our Python stub code and submit their code before the competition.

We will run each competitor's portfolio allocation algorithm on a test dataset with data generated by the same process as the data you are given; this test dataset will immediately follow the period in the training dataset. There will be one round, the results of which will be computed prior to the competition and played back during the competition as if unfolding in real time. As such, you must submit your final code to the case writers beforehand.

You may use any packages (and any programming language) to study the training data we will provide, but the submitted portfolio allocation code must be in Python and will be restricted in dependencies. The environment used to run submitted competitor code will be Python 3.10 and will only have the NumPy, pandas, and SciPy packages installed (alongside base Python). Although advanced and/or complex machine learning techniques are interesting to study and are valuable to learn, they are not the focus of this case and are not required for the purposes of solving this case. We strongly advise that you test your submission using a similar environment on your local machine before submitting your final code; submitted code that does not compile or that fails to run for any timestep will be disqualified for this case and the team that submitted it will receive 0 points. Before final submission, there will be an opportunity to test if your code compiles and runs properly (note that the Sharpes yielded from this test will not be indicative of what your actual Sharpe ratio will be).

In each timestep, asset prices will be provided and teams will submit portfolio allocations among the available assets for that period. These allocations will be in the form of weights on each stock: weights can be positive, negative, or zero in each timestep, and the submitted weight vector in each timestep will be L1 normalized (this means if you put in negative weights, we will take the absolute value) before calculating portfolio returns. We assume there are no exchange fees or bid-ask spreads in the market and no liquidity concerns to deal with in allocating your portfolio.

Scoring

Teams will be ranked based on their annual daily Sharpe ratio over the 10-year test period on the daily return percent series of the portfolio. Normally, we calculate the Sharpe ratio based on the excess return series rather than just the return series, but for our purposes we will assume that the risk-free rate means relatively constant and can be ignored. The team with the highest Sharpe ratio will receive 40 points, the next highest will receive 39 points, etc.

Case Materials/Data and Code Submission

Python stub code and training data can be accessed online through this [Box file sharing link].

We are requiring the final code for this case to be submitted by noon (12:00 PM) CST on Friday, April 7th. Note that this is different from Cases 1 and 2, as we will be computing the results of this round prior to the competition. Code submitted past this deadline will not be accepted, and we reserve the right to disqualify any competitors who submit incomplete code or miss this deadline. Again, we strongly advise that you test your submission in a Python 3.10 environment with only NumPy, pandas, and SciPy installed before submitting your final code.

Miscellaneous Tips

1. Analyze returns, not prices. Prices of stocks tend to be non-stationary processes, but returns are generally stationary. Analyzing returns series will be more fruitful for your strategies than analyzing price series.
2. Don't test strategies on the same data you train them on. Strategies will likely perform well on data your model has already seen - what's relevant is how well the strategy performs on data the model has not yet seen. You should not necessarily expect that your strategy will perform as well out-of-sample as it will in-sample; holding out a portion of your training data to test on (or running any other procedure to test on new data) is strongly advisable to get a more accurate sense of how successful your strategy will be.

Questions

For questions regarding Case 3, please post in the [UChicago Trading Competition Ed Discussion Board] in the "Case 3" folder. We will regularly check for new messages.

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