UCHICAGO TRADING COMPETITION

2021

Participant Case Packet

THE UNIVERSITY OF CHICAGO | Career Advancement Financial Markets

The University of Chicago Financial Markets Program (FM) is excited to show its in-house trading platform χ-Change built by senior members of the FM program for the 9th 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 the trading platform and practice data and on accessing Piazza, 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 9th**.

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 10th**.

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: Foreign Exchange Dynamics and Monetary Policy

Introduction

You have recently been assigned to the foreign exchange futures desk at your firm, whose strategy revolves around predicting announcements of the Federal Open Market Committee and the Federal Funds Rate. Fortunately, you receive a dataset containing information about their announcements and historical daily interest rates to help you out. Now, your objective is to join the foreign exchange market and use your knowledge to execute your trading strategies.

This case centers around three currencies (from three countries, two of which are fictitious), and consequently three currency pairs. The currencies of interest are the United States Dollar (USD/$), Rockefeller Rock (ROR/₭), and the Harper Penny (HAP/₱). Similar to the Federal Reserve of the United States, which meets 8 times per-year to announce interest rate changes, Rockefeller's central bank meets 5 times a year and Harper's meets 6 times a year to announce their potential interest rate changes. Meeting dates are evenly distributed throughout the year.

In this case, participants will act as designated market-makers for these currency pair futures. In addition to other competitors, the market will be populated by other participants against which you must trade.

Case Specifications

Settlement

In this case we opt to cash-settle the foreign exchange futures. Suppose the ROR/USD March contract is trading at $3.50 and the contract size is $100,000 USD. If you long 1 contract and the exchange rate rises to $3.52, you will receive a cash settlement of

$$100{,}000 \times (3.52 - 3.50) = \$2{,}000$$

upon expiry of the contract on March 31st. Here we assume that there is same-day settlement, and competitors retain the ability to trade until the day of expiry. Due to the risk-limitations imposed on you, 95% of your HAP/ROR contracts will be liquidated to USD at the spot rate and the remaining 5% will be held as ROR/USD contracts that cannot be traded.

Trade-able Assets

Another important caveat is trading on spot markets versus futures markets. In this case, one futures contract (corresponding to HAP/ROR) will be settled in ROR, which means you will have access to the ROR/USD spot market. In this example, ROR is the Base Currency and USD is the Quote Currency. The price will always be listed in terms of the quote currency, indicating the number of USD required to purchase 1 ROR. During the competition, you will have access to both the spot and futures markets, as well as a running feed of all trades, prices, and orders on the book. The contract specification to trade spot foreign exchange pairs is ROR/USD.

The following tables will assist you in placing orders in the futures markets:

Code	Month	Expiration
H	March	Day 63
M	June	Day 126
U	September	Day 189
Z	December	Day 252

Figure 1. Month Codes.

Code	Pair	Contract Unit	Minimum Tick Size (per Base increment)
6R	ROR/USD	$100,000	0.00001
6H	HAP/USD	$100,000	0.00002
RH	HAP/ROR	₭500,000	0.0001

Figure 2. Pair Code

The asset codes and contract specifications for each future are listed in Figure 2, with the expiry month codes displayed in Figure 1. The proper identifier for each specific contract is, without brackets, [Currency Pair Code][Month of Expiry]. For example, when trading the ROR/USD contract that expires in December we input orders using 6RZ.

Your trades will be executed on the χ-Change platform. Orders from each team will be placed in a common pool subject to priority constraints and could interact with one another. The market Microstructure, along with more information about market-making, will be laid out with detailed documentation during our subsequent platform and devkit release.

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. Manual trading is not permitted and not supported.

Order Fill Allocation and Price Limits

An important part of an electronic trading platform is the matching algorithm. Previously, pit trading allowed for the broker to choose which client would have their open order matched. The FIFO

(First-In-First-Out) algorithm solely uses price and time to determine order matching. Orders are then filled on a price priority followed by time priority. Orders at the closest price level that have been in the order book the longest will have matching priority. Real world examples include the NASDAQ and many CME futures.

In terms of market limits, exchange rates must be strictly positive and are contained in (0,∞). This applies to all orders submitted for any of the futures contracts as well as spot market orders.

Market Dynamics

Interest Rate Parity

This concept, and the derivation below, relies upon two idealized assumptions: perfect capital mobility between nations as well as the perfect substitutability of domestic and foreign assets. In other words, you and other investors are theoretically indifferent to holding bonds with equal risk/reward profiles in USD or in Rocks. From this we can conclude that expected return on domestic assets will equal the exchange rate adjusted expected return on foreign assets. In formulaic representation:

$$(1 + i_{\$}) = \frac{E_t(ROR/USD_{t+k})}{ROR/USD_t}(1 + i_{\text{₭}})$$

$$= \frac{(6R_{t+k})}{ROR/USD_t}(1 + i_{\text{₭}})$$

At any time t, the expected spot exchange rate over k additional periods is exactly determined by the relative interest rates (Uncovered Interest Rate Parity).

In the above example, $i_{\$}$ and $i_{\text{₭}}$ are the weighted-average interest rates of the dollar and of the rock respectively. The last equality represents covered interest rate parity, where the price of the forward exchange rate at time t+k is just the expected spot interest rate at time t+k. Empirically, the alternative Covered Interest Rate Parity is strongly suggested to hold, while UIRP typically does not. In this case, however, we assume that the only assets in all three nations are risk free fixed income products at the federal funds rate, such that both CIRP and UIRP hold.

Triangular Arbitrage
Also known as cross currency arbitrage or three-point arbitrage, this involves three separate currency pairs, which increases the chance for market inefficiencies to present arbitrage opportunities. In essence, whenever

$$\frac{ROR}{USD} \times \frac{HAP}{ROR} \times \frac{USD}{HAP} = 1$$

does not hold, there is an opportunity to profit by consecutively trading the currency pairs to lock in profit. Keep in mind there are many ways to implement these two arbitrage strategies in different markets and across contracts. Although these opportunities may not always appear, they can be profitable if executed correctly.

Additional Information
There are many interesting things going on in the FOREX currency markets. For example, Bid/Ask spreads fluctuate throughout the day, narrowing early in the day and widening out towards the evening as demand for liquidity wanes. Leverage ratios can get very large as the initial margin permits you to buy contracts many times that figure. Feel free to research more of these quirks and see if they are observable in the markets.

Market Players

The market will be populated by other entities alongside you and other competitors:

A bulk of these participants are (1) **businesses and banks** seeking to hedge currency risk or speculate on positions. These players are price-insensitive and place market orders at their own discretion to attain some position. Due to volume of trade, these players are more active in some markets than others.

A small minority of the participants are (2) **hedge funds.** The hedge funds also exclusively use market orders, but they only take positions when their fundamental research tells them that one currency pair will move in a direction not currently priced into the market.

The last market participants are (3) **major financial institutions and central banks/treasuries**. They use limit orders on the spot market to prevent their own currency from devaluing relative to their peers.

Round Specifications

There will be five 6-minute rounds corresponding to markets in the following years: 2021 (practice), 2021, 2022, 2023, and 2024. (You will have data from 2011-2020. The chronology is not irrelevant to succeeding in this case). The 2021 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, PnL, and Risk Limit timeouts/violations are not carried over between rounds.
To help train your algorithm, you will have access to the announcement and interest rate data as well as an AWS server continuously running a randomly selected dataset from a sample of 2021 data.

The number of trading days in each year will be fixed to 252. FOMC rate change meetings will occur based on the following formula:

$$\left\{ \left\lfloor \frac{252}{m} \cdot k \right\rfloor \text{ for } k \in \{0, 1, \cdots, m\} \right\}$$

where m indicates the number of meetings for the corresponding central monetary authority. Here the inner brackets denote the floor ("greatest integer") function, rounding this result to the nearest integer (whole trading day). FOMC notes are actually not announced until the next day, so interest rate changes will occur before all information is publicly exposed. Note that the expiration of the contracts automatically assumes 21 days per month.

Rules

a. You may take long or short positions in all futures available in a round.

b. Your position in the spot market will be held on a ROR/USD currency contract. Your position in absolute value cannot exceed 100 contracts. Note: Holding KOR currency will not accrue interest, and may be treated identically as holding currency.

c. You will be permitted to trade expired contracts up until the conclusion of the year when all contracts are settled. There are many practical examples of this.

d. There is a risk limit on the absolute number of contracts you can hold in any one contract, which will be specified on Piazza at a later date.

e. If you exceed the maximum outright exposure or maximum contract exposure at any time during the round, you will initially be timed out from placing orders that will push you further over risk limit violations. After continuous risk limit violations, you will be steadily penalized at a fixed rate, also to be specified with the subsequent Piazza release. Please keep a lookout for these exchange updates, as penalties will leave you at a significant disadvantage!

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

Scoring

At the conclusion of each round (with the omission of the practice run), each team will receive points corresponding to their rank. The team with the highest PnL will receive 1 point, the team with the second-highest PnL will receive 2 points, and so forth. 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.

Case Materials/Data and Code Submission

Python stub code and training data will be released with the case packet through the UChicago Trading Competition Piazza. The basic bot will outline some key functions and exchange syntax for you.

We are requiring a preliminary code submission by **noon (12:00 PM) CST on Friday, April 9th, 2020**. Critical feedback will be reported with respect to risk limit violations, as algorithms in continuous violation of our risk limits will be disqualified from the round.

Miscellaneous Tips

1. **Interest rate announcements:** Make sure to model the structure of these announcements from the central banks for each country. Additionally, take note of the range of possible values here as you progress to calculate daily interest rates.
2. **Real-time adjustments:** You will be getting updates from the exchange regarding announcements and interest rate information. Pay attention to this market news as well as any updates about the orders and trades on the exchange.
3. **Day count conventions.** Note that interest is only calculated for trading days, excluding weekends and holidays. We simplified the dating system, so make sure you understand how this may interact with the market.
4. **Speed of orders**: Arbitrage opportunities as mentioned above heavily depend on latency of your orders. The aim is to place orders quickly, particularly on days or periods of high volatility to prevent bad fills. FIFO fills prioritize orders that were submitted chronologically earlier. Write lines of code that submit orders more quickly and speed up the bot.
5. **Risk limit management:** Make sure that you manage risk across all your assets. Penalties are severe for a reason, as is often the case when you are ignoring risk in the markets. In particular, keep track of the flow into and out of your account in ROR to avoid freezes or fees here.

Questions

For questions regarding Case 1, please post in the UChicago Trading Competition Piazza in the "case1" folder. We will regularly check for new messages.

CASE 2: Options Market-Making Crash-Course

Introduction

In this case, you play the role of a Market-Maker on [European](#) equity options corresponding to the same underlying, and you must compete against rival market-makers while adhering to strict risk limits. The goal is to develop an algorithm which can competitively price and trade options, taking advantage of any and all profitable opportunities you might come across in the market.

Options trading is a gateway to many advanced topics in quantitative finance, situated at the intersection of statistically-complex modeling techniques and high-frequency market-making techniques. This case provides an introduction to hands-on options pricing, along with an opportunity to decipher market behavior in real-time to execute profitable trades. In doing so, you'll perhaps uncover some insight into the use-cases and popularity of equity options.

All trade-able options will correspond to the UC Equity (ticker: UC) underlying, denominated in $USD. The UC equity is relatively volatile compared to its peers (liquid, American, publicly-traded stocks), and you're given no fundamental information about the price of the stock in future periods. For this reason, along with some further coercion from our risk limits, you're incentivized to market-make options rather than bet directionally on the UC Equity itself.

Before diving into case specifications, please see below for some important definitions concerning options, along with more options trading theory thereafter.

Term	**Definition**
Option	A contract which gives you the right to buy/sell* a certain quantity of the **underlying** at a specified price at a specified time in the future * *Call options* give the right to buy. *Put options* give the right to sell.
Underlying	The actual instrument based upon which the contract is created - in our case, this is plain equity (shares)
Expiration/ Expiry	The time at/by* which a decision must be made regarding the option - i.e. whether you want to **exercise** the option, sell it, or do nothing) * This case involves European options, which can only be exercised AT expiry.
Strike (Price)	The price specified in the option contract (i.e. the price at which the holder of the option is allowed to buy/sell the underlying asset)
Spot (Price)	The current trading price of the underlying asset

Volatility - **Realized** - **Implied**	Annualized standard deviation of returns in the underlying, based on… - … the underlying's historical underlying trading data - … the actual prices of options on the underlying being traded
Optionality	The idea that between now and expiry, the price of the option might change, and therefore there is a non-zero probability of its value increasing.
Time Value vs. Intrinsic Value	The **time value** value of an option is the value stemming from its optionality. The **intrinsic value** of an option is its profit if it were exercised immediately, or the positive difference between strike and current underlying price. The price at which the option actually trades on the market is the sum of these two quantities.

Pricing European Options

Common Formulations

First developed by Fischer Black, Robert C. Merton, and Myron Scholes in 1968, the Black-Scholes Model presented a method to price options given a series of five intuitive inputs:

1. Strike Price
2. Underlying Price
3. Time to Expiration
4. Market Volatility
5. Applicable Interest Rate*

(*In this case, we won't worry about the interest rate, which we assume to be 0. Furthermore, you can assume that the underlying equity asset will NOT be affected by dividends, stock splits, or the like.)

As you'll note, volatility is something we initially think of as a historical measure over some previous period. In Black-Scholes, the volatility that we seek is the instantaneous volatility of the underlying asset. In practice, this is unknown, leaving it up to traders to estimate market volatility through a combination of historical data and current market conditions, as will be addressed in the following subsection. The reliance on this unknown parameter, along with the underlying assumption that underlying prices follow a lognormal distribution, are notable drawbacks of the model.

An alternative model with powerful implications is the Binomial Options Pricing Model (Sharpe, 1979). This model essentially views time as a series of discrete steps, calculating the price of the underlying asset at each step via function of its price at the previous step. Specifically, the simplest model assigns a static probability to the event that the price will increase/decrease by a static factor in the next time step. Based on this, a binary tree can be generated, and a distribution of the possible prices of the option at a specific time in the future can be determined. Of course, these transition probabilities are intrinsically tied to market volatility, and thus much of the core estimation problem of Black-Scholes still remains.

A recommended reference for understanding Options Pricing is *Option Volatility & Pricing* by Sheldon Natenberg.

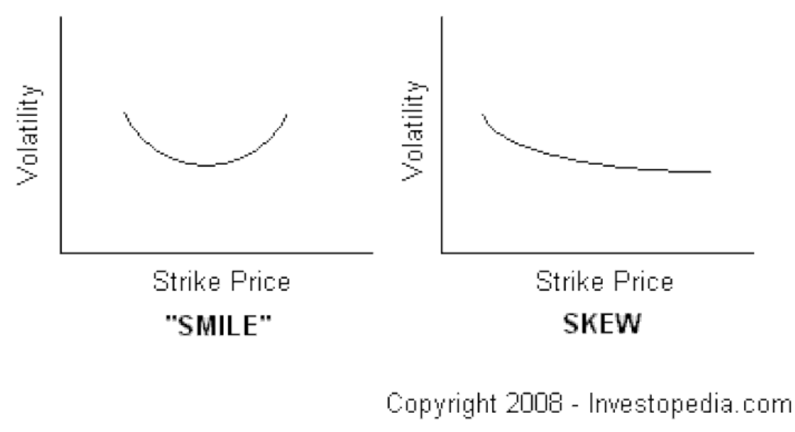
Modelling Market Volatility

Your guess for the current level of market volatility may be informed by the market's consensus at the time. If you are using a volatility-parameterized options-pricing framework, you should be able to numerically calculate the level of market volatility by taking the "inverse" of the market price under your formula with the other known inputs held constant; the resulting value is called the implied volatility. This practice assumes that everyone in the market is using your exact pricing framework, but is nonetheless a common way of interpreting market sentiment. In fact, traders often quote options prices not in dollar/nominal amounts, but rather by the implied volatility level which they calculate from said nominal prices.

Estimates of volatility can also be improved by considering historical volatility. This primarily refers to historical realized volatility, or the volatility that actually manifested in the market in some previous period, but we might also be interested in comparing these values to the implied volatilities at previous times as well. There are many methods by which we can predict volatility given historical data--we'll enumerate some examples of these models in the supplementary materials released on Piazza.

Retooling Assumptions

One assumption of the Black-Scholes model, which is empirically untrue in the equities markets we're concerned with, is that options with the same underlying and time to expiry all share the same implied volatility, regardless of strike price (note: this does not mean that all of the options have the same market price!). The falsity of this assumption owes itself to the way in which options are used, and traders might assign more or less relative value to an option based on its distance and direction from the strike price. Historically, the actual relationship between implied volatility and strike price for the S&P 500 has deviated from the theoretical expectation in the following shapes:



Under Black-Scholes, we would expect both plots to be horizontal lines, reflecting constant implied volatility against strike. In the "smile" example, the market highly values both far-in-the-money and far-out-of-the-money call and put options. In the "skew" example, the market highly values far-in-the-money call options and far-out-of-the-money put options, but relatively undervalues the opposite case. By reconstructing the volatility curve using market data--potentially uncovering consistent directional mispricings for certain strikes--you may be able to further inform your trades and volatility predictions. That said, whether or not the volatility curve is a presence in this case will have to be uncovered by competitors through analyzing underlying and trading data.

Trading Considerations

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.

Reliability of Market Information

The market is a good source of information: the absolute volume of orders put out by other competitors is usually much larger than what any individual market maker is able to produce. However, if the market always knew everything, there would be no opportunity for consistent profit or arbitrage, and a lot of hedge funds and proprietary trading firms would lose a lot of money!

Traders grapple with the question of whether or not information from the markets should be incorporated into their models every day, and that is something you will face when your algorithm is competing against others' algorithms. Try to understand how the market's movements should (or should not) affect your model if confronted with an order book that disagrees with your calculations for an option's value.

As in Case 1, the market will be populated by different (non-student) entities that may deploy different trading strategies at different times, whether or not those strategies could be deemed informed and/or effective. Additional information may be provided via Piazza on some of the tactics that they (and you) may deploy as you place orders in the market.

Trading Ideas

Because of the case's relatively strict delta risk-limit, it is in your best interest to devote most of your time to market-making rather than pursuing directional strategies. That said, you might want to also consider analyzing the market microstructure in order to profit off of short-term arbitrage or profit opportunities which might deviate from your broader, systematic market-making strategy. Note that these might be subtle - you might, for instance, need to be looking across multiple strikes in order to find an arbitrage opportunity based upon some mispriced assets.

Market Players
To simulate real-world trading, there will be different players in the market which you are making. Be aware of how different investors price assets and place orders - this is something which you can, if you are careful, exploit to your advantage.

Case Specifications

Round Breakdown
There will be 4 rounds in this case, each 7 minutes long and consisting of 200 price updates per day across one week of trading days. This corresponds to 1000 = 200 * 5 underlying price updates during each round's trading period.

While these day conventions will assist you in your volatility modeling, please note that the underlying price updates in the trading period occur at constant time intervals rather than under some predefined day structure. Specifically, there will be a constant 2.38 = 1000 updates/(7 minutes×60 seconds) price updates per second.

The first round is designed to give all competitors a taste of what the exchange will look like when there are other competitors in the market. For this round only, we will provide competitors with their Greek positions at the end of the 2nd and 4th day of price updates, corresponding to price updates 400 and 800. All positions and scores will, however, be nullified before the commencement of the 3 actual rounds. During the second, third, and fourth rounds, competitors' risk limits and PnLs will be recorded and used for scoring purposes. Note that liquidity may be provided or taken by the trading bots; you as competitors are expected to be able to handle, and profit off of, all such behaviors. Only market orders will be allowed in the underlying (equities) market, whereas both market and limit orders will be allowed in the Options market.

Options Chain
The options chain for this case will consist of 5 strikes and one expiry date for contracts with the UC Equity as the underlying. The strike prices will be the same for each round regardless of the underlying price path, and will consist of the set {96, 98, 100, 102, 104}. All options will expire one month (21 trading days) after the end of each round, consistent with a time to expiry of (21+5)/252 years at the beginning of each round's trading period.

At the end of each round, competitors' outstanding positions will be valued according to our calculation for the true fair prices of each available option, which is based on the probability distribution for each option's intrinsic value a month into the future. You need not worry about the method we use in calculating this, but please note that this adds a level of complexity to the end of each round.

Placing Trades
When placing trades, you will need to specify the code corresponding to the asset which you want to trade. The code for the underlying is "UC". The code for a Call (Put) at strike S is simply "UC{S}C" ("UC{S}P"). For example, "UC96P" represents the 96 Put and "UC102C" represents the 102 Call.

Risk Limits & Penalties

The risk limits in this case pertain to each team's entire position across the options chain and underlying, rather than in any contract individually. The risk limits themselves will consist of constraints to your position's Greeks, or measurements of the sensitivity of your position's value with respect to different market variables. Specifically, we'll be placing numerical limits (to be specified on Piazza at a later date) on the following Greek measures:

Delta	Change in price for a $1 change in the underlying price
Gamma	Change in Delta for a $1 change in the underlying price
Vega	Change in price for a 1% change in implied volatility, where implied volatility is measured as the annualized standard deviation of underlying returns.
Theta	Change in price for the passage of a single day of time

(Traders are often also interested in Rho, their position's sensitivity to interest rate changes, but we disregard this metric with a constant zero interest rate.)

Accordingly, penalties will be imposed upon competitors whose total risk measures (which can be expressed as a sum of risk measures across individual holdings) exceed those specified by the risk limits. Like the risk limits themselves, the precise penalties will be specified on Piazza. This said, you should know that penalties will consist of fees to your team's running PnL, and may result in disqualification if your risk limits are exceeded by excessive amounts or for long periods of time.

Scoring

At the conclusion of each round (with the omission of the practice run), each team will receive points corresponding to their rank. The team with the highest PnL will receive 1 point, the team with the second-highest PnL will receive 2 points, and so forth. 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.

Code Submission

We will require a preliminary submission by **noon (12:00 PM) CST on Friday, April 9th, 2021**. 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 3.8 environment with only NumPy, pandas, and SciPy installed before submitting your final code.**

Case Materials/Data

Python stub code and training data will be released with the case packet through the UChicago Trading Competition Piazza. Training data will take the form of rudimentary sample bots, along with sample underlying price data. Each price path will be generated independently, and will follow the history/trading split that occurs 3 months into each round.

Miscellaneous Tips

1. **Focus on volatility modeling.** After you've built a working options pricing model, you will need a value for implied volatility in order to price options on an underlying asset. We recommend looking at the realized volatility for each asset to get an initial estimate of what the implied volatility level for each stock should be.
2. **Scale volatility calculations with time.** As mentioned below the risk limits table, volatility is generally quoted in hundredths of mathematical volatility, or the annualized standard deviation of returns. Given the daily standard deviation of returns, you can annualize this by multiplying it by sqrt(252), or the root of the number of trading days in a year. For this case specifically, annualizing volatility estimates involves dealing with both the number of trading days and the number of updates per day. That said, if we have some value for annualized volatility in mind, we expect the volatility corresponding to each price update to be Annualized Volatility/(sqrt(252)×sqrt(200)).
3. **Use the underlying to hedge your position.** As conveyed by the risk limits, market-makers are not free from directional risk exposure to the underlying. In practice, traders attempt to limit this by Delta-Hedging, or continuously attempting to ensure that your position's value doesn't change with respect to small changes in the underlying. The UC Equity has the potential to be particularly unforgiving to those who don't insulate themselves from swings and shocks.
4. **Balance profitability and consistency**. Consider the way the case is scored when trying to optimize your performance across rounds. Both profits and consistency matter. See if there are any ways to increase your consistency.
5. **Consider market information.** Make your guess at a fair implied volatility level at least partially-dependent on the level other competitors are pricing. Even if you're right, making a bet that volatility will rise or fall will use up your risk limit and constrain your ability to market-make. This might make sense if you have reason to believe the mispricing will resolve quickly, but the longer the position must be held, the greater the market-making opportunity cost. You can be more aggressive trading against mispricings that require less risk.
6. **Be mindful about positions near round-end.** Since competitors are not able to observe in-advance the theoretical values to which we will mark their outstanding options positions when

trading ceases, it is wise to meticulously monitor your position as we approach round-end. Even if a contract is relatively in-the-money at round-end, it might find itself far out-of-the-money after another 21 days of underlying price updates. Since we compute theoretical options prices at round-end probabilistically, you shouldn't worry too much about being marked to a value that differs extremely from your current calculations. However, the effect of this adjustment on your PnL can quickly grow with added size and uncertainty, so you should be mindful about how large of a position you will allow to be subjected to this adjustment (i.e. how much you'll hold).

7. **Keep risk calculation simple.** You can add the risk of all individual holdings in your portfolio to get the risk of your entire position, which will consist of both equity options and the UC Equity underlying. A simple way to calculate the risk for an option is by seeing how much the price moves when the risk-factor moves a small amount. An example is included below:

$$\text{delta} = \frac{\text{OptionPrice}\left(S+\varepsilon, K, T-t, \sigma, r\right) - \text{OptionPrice}\left(S, K, T-t, \sigma, r\right)}{\varepsilon}$$

Questions

For questions regarding Case 2, please post in the UChicago Trading Competition Piazza in the "case2" folder.

CASE 3: Multi-Class Portfolio Allocation & Risk Diversification

Introduction

You have been given the responsibility of managing one of your hedge fund's portfolios for the next 10 years, with securities across the **stock market, bond market, and commodities market**. There are several restrictions placed on the portfolio, however. You must always invest 100% of your capital, you can only take long positions, and your portfolio allocation decisions must be entirely systematic. Your focus is to dynamically diversify your portfolio in order to maximize returns and minimize risk, so before the portfolio launches, you obtain 10 years of historical price data that you can use to test out various models and trading strategies.

As you'll need to consider not only the behavior of assets themselves, but also their relationships with other assets and combinations thereof, there are many potential strategies (and pitfalls) at your disposal. The following sections provide an introduction to how this problem has been tackled both academically and in practice.

Modern Portfolio Theory (MPT)

In Theory

In 1952, Harry Markowitz of the University of Chicago introduced Modern Portfolio Theory, which took a quantitative approach to designing portfolios that balanced the goals of maximizing returns and minimizing risk. This proposed framework formalized the merits of diversification and, through mean-variance analysis, it lays out a method to theoretically maximize portfolio return for a given level of risk, or to minimize portfolio risk for a given level of return. All that is required is historical data, from which one can compute the assets' expected returns and the covariance matrix for input into the optimization problem.

In Practice

There are many criticisms of some key attributes of the MPT framework, and caution must be exercised in its implementation. To begin, MPT assumes that an asset's returns follow a normal distribution, which is not empirically true. It's also heavily reliant on assumptions that historical data provide adequate estimates of future asset behavior, when in reality, asset price behavior is quite dynamic and price shocks cannot be anticipated.

When naively put into practice, mean-variance analysis can often lead to portfolios that are extremely sensitive to recent data, causing portfolio allocations to change dramatically over time or to be heavily concentrated in a few historically-well-performing assets. This can be detrimental in the presence of transaction costs and/or downturns in the heavily-concentrated areas of your portfolio.

Moving Forward
Evidently, optimally allocating a portfolio is a non-trivial task – there is no single correct answer. However, we know that there are tremendous benefits to diversification in the long run, and that analyzing the historical expected returns, covariances, and variances of assets are the main tools to make systematic portfolio allocation schemes. There are many directions to go from here.

Research has often shown that expected returns are relatively unreliable to predict based on historical price data, whereas covariances are more predictable, and individual variances even more so. This has led many to avoid reliance on some of these estimates, to develop more in-depth models to create estimates, or focus on different forms of diversification.

Alternative Methods

Some ideas to get you started are given below. We encourage you to research your chosen methodology in further detail.

Risk Diversification
A naive approach to diversification might simply place 1/N of a portfolio's capital into each of the N assets it considers. This would be a simple form of "capital diversification," which focuses foremost on the amount of capital allocated to each asset. Another common strategy is "risk diversification," which places more emphasis on the amount of risk each asset contributes to the overall portfolio risk, which is usually not evenly distributed in the equally-weighted case. Many risk diversification strategies fall under the name of Risk Parity, which has gained popularity over the past couple of decades.

This is particularly common when we are able to group assets together based on common characteristics, such as industry or asset class – risk is then diversified across the groups, and then various methods can be used to allocate capital or risk within each group. Some risk diversification strategies even ignore covariances as well, relying only on variance estimates of each asset. For example, from variance estimates alone we can choose weights such that we have an equal amount of variance from each asset. If two assets are perfectly correlated though, then a portfolio would have twice as much exposure to their risk than to other assets' risk. As more estimates such as covariances are included in the strategy, the exact computations needed to balance risk become more complex. Evidently, there are many routes to go down in terms of the exact goals and methods of allocating risk to each group or asset class.

Modified Modern Portfolio Theory
Mean-variance analysis remains a strong tool for choosing portfolio weights, and there are many ways to optimize or extend the strategy to obtain desired results. For example, one could place additional constraints on the overall framework, or optimize parameters such as lookback windows for using historical data. Many have also adapted modern portfolio theory to use more empirically-based models for asset prices, or to avoid having to rely on historical data entirely to compute expected returns estimates, as displayed in the Black-Litterman Model.

Financial Time Series Modelling and Analysis

In general, more in-depth financial time-series analysis is often used to improve existing allocation strategies, or even to devise new ones. With a reliable and more sophisticated model for returns, covariance, or variance, one can use historical estimates as a stepping stone to compute smarter estimates of future behavior. A recommended reference for additional reading on financial time series analysis and models is *Analysis of Financial Time Series* by University of Chicago's professor Ruey S. Tsay.

One common method that professionals and researchers have used to model asset prices is Factor Modeling, whereby an asset's returns are assumed to be driven by underlying factors, such as the type of industry or asset class that it is a part of, it's dependence on macroeconomic trends, or even it's dependence on underlying statistical relationships.

Case Specifications and Rules

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

We will run each competitor's portfolio allocation algorithm on a test dataset with data generated using the same set of fundamentals 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 3.8** 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.**

In each timestep, the current asset prices (which are not influenced by competitors!) 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 only be positive, and the submitted weight vector in each timestep will be L1 normalized before calculating portfolio returns.

Scoring

Teams will be ranked based on their annualized daily Sharpe ratio realized over the ten-year test period. The annualized daily Sharpe ratio S_p is given by

$$S_p = \frac{E[R_p - R_f]}{\sigma_p} * \sqrt{252}$$

where $E[R_p - R_f]$ denotes the mean of the daily excess return (daily portfolio return minus the daily risk-free rate) time series and σ_p denotes the standard deviation of the daily excess return time series. However, you may assume a **zero risk free rate** for the purpose of this competition. **Transaction costs of 30 basis points (bps) will be factored into your performance and may affect what strategy you choose.** The team with the highest annualized daily Sharpe ratio over the test period will receive [# of Teams] points, the team with the second-highest annualized daily Sharpe ratio will receive [# of Teams - 1] points, etc.

Since this case is scored on Sharpe ratio, teams can improve their standings by either improving their mean daily returns or by reducing the variance of their daily returns. Both factors should be taken into account when developing a successful strategy.

Case Materials/Data and Code Submission

Python skeleton code and training data will be released with the case packet through the UChicago Trading Competition Piazza.

We are requiring the **final code** for this case to be submitted by **noon (12:00 PM) CST on Saturday, April 10th, 2021**. 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. Please ensure that your code compiles correctly before you submit. Again, **we strongly advise that you test your submission in a Python 3.8 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 focus entirely on individual securities.** There may be relationships between different securities that can be used to tweak and optimize your allocation strategy! Be careful about the assumptions you make and their implications.
3. **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.
4. **Pay attention to day count conventions.** Note that the Sharpe scoring formula implies that each year consists of 252 trading days, and thus each month consists of 21 trading days.

Questions

For questions regarding Case 3, please post in the UChicago Trading Competition Piazza in the "case3" folder.