THE UNIVERSITY OF CHICAGO

Financial Markets Program

UCHICAGO MIDWEST TRADING COMPETITION

2020

WELCOME

On behalf of the University of Chicago and the UChicago Financial Markets program (FM), we are pleased to welcome you to the 8th Annual UChicago Midwest Trading Competition!

The trading competition will be held virtually on Saturday, April 18th. The focus of this event will be algorithmic trading, with three cases covering the following themes – market making, options trading, and time series analysis. Please read through the remainder of this packet to find the three trading cases and respective logistics for completing the cases.

Each case requires preparation before competition day, and we recommend you prepare your algorithms well in advance. Cases 1 and 2 will require draft code submission due on April 10th, with the final code being run live on the day of the competition. Case 3 will be run in advance of the competition and will require final code submission due on April 10th. See case descriptions for further detail.

On the day of the competition, you will have the opportunity to test your strategies against students from around the country and compete for valuable prize money! Details for how to participate on the day of the competition will be shared in e-mail communications.

We are excited to have so many talented students in this year's competition, and we look forward to seeing your strategies play out on April 18th!

Good Luck!

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PARTICIPANTS

We are pleased to announce that over 150 students across the United States will participate in this year's competition. The following 33 institutions will be represented:

- Amherst College
- Baruch College
- Carnegie Mellon University
- Cornell University
- Duke University
- Georgia Institute of Technology
- Harvard University
- Indiana University Bloomington
- Johns Hopkins University
- Lake Forest College
- Massachusetts Institute of Technology
- New York University
- Northwestern University
- Rice University
- Rutgers University
- Smith College
- The University of Chicago
- University of California Berkeley
- University of California Irvine
- University of California Los Angeles
- University of California San Diego
- University of Colorado Boulder
- University of Michigan
- University of Minnesota Twin Cities
- University of Nebraska
- University of Notre Dame
- University of Pennsylvania
- University of Rochester
- University of Texas at Austin
- University of Washington
- University of Wisconsin - Madison
- Washington University in St. Louis
- Yale University

AWARDS

Cash prizes will be awarded to the winning teams of each individual case and the top three overall winners based on aggregate scores across all cases. Participants must virtually attend all scheduled sessions to be eligible for prize money. Further details about receiving prize money will be shared in e-mail communication.

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Competition Technology

The University of Chicago Financial Markets Program (FM) is excited to utilize its in-house trading platform χ-Change built by student members of the FM program for the 8th Annual UChicago Midwest Trading Competition! Cases 1 and 2 for the competition will be run live utilizing this platform. Case 3 will not utilize the platform, it will be run before the competition and results will be played back during the event.

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. The FM case writing team will respond to questions within 24 hours of posting on Piazza.

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.

Competition Preparation & Training Sessions

Training sessions and live webinars/Q&A sessions will be held before the competition by our FM platform development team. Details on dates and times will be communicated via Piazza.

Case Submission Dates

For Cases 1 and 2, all competitors must submit a draft of their code by Friday, April 10th. Competitors will run their finalized algorithms locally on the day of the competition.

For Case 3, competitors' final algorithms must be submitted by 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.

If you have not received the email invitation to join the Piazza channel by Tuesday, March 17th, please contact vishaljain@uchicago.edu.

CASE 1: ELECTRICITY FUTURES MARKET MAKING

Introduction

Fundamental to nearly all trading activities is the concept of market making. Market makers trade with producers and consumers who need financial products for their businesses as well as speculators, none of whom arrive at the marketplace at the same time or with the same size. These liquidity providers hold positional risk for short periods of time, allowing other market participants to get into positions faster, cheaper, and for bigger size than they would otherwise. In return, the market makers collect the bid-ask spread.

In the real world, and in this case, the underlying value of a financial instrument is not known to the trader. They must therefore adjust to market news as well as the activities of informed players in order to correctly price contracts as well as to avoid unnecessary risk.

This case is designed around a fictional Chicago electricity market. The city of Chicago produces electricity in 3 ways: from Natural Gas generators, at a cost of $2/MWh, and from coal generators, at a cost of $3/MWh, and "peaker" plants. The city of Chicago starts with a stockpile of natural gas and coal every year and, if it runs out of either, it cannot use that method of production until the start of the next year. Note that the city doesn't necessarily start with the same amount of natural gas and coal every year, and the city cannot carry stock from one year to the next.

If the city runs out of both natural gas and coal, it will rely on a third method of production: a network of private "peaker" power plants. These plants have different levels of efficiency but are generally less efficient than the city's plants. Because these plants sell their cheapest to produce units of electricity first, the marginal cost of buying electricity from these units increases with the total number of units purchased from them. Specifically, the initial cost is $3.01/MWh, but the cost increases by $0.01/MWh for every MWh produced. For example, if the peaker plants have already produced 99 MWh, then the price of the next MWh of electricity will be $2.01 + 99 * $0.01 = $3/MWh. As you'll see, peaker plants are rarely used in January, giving power plant producers time to reset the plant, so the prices start at $2.01/MWh every year.

There is no limit to the amount of peaker electricity used. The city will totally exhaust its natural gas before switching to coal and totally exhaust its coal before switching to the peaker plants. By its own regulations, the city sells its electricity on the Chicago Electricity Spot Market at the cost the city obtained it at.

Chicago businesses buy electricity directly from the city on the Chicago Electricity Spot Market, where the city is the only seller. In addition, because electricity prices tend to fluctuate, businesses hedge their exposure in the Chicago Electricity Futures Market.

In this case, participants will act as designated market makers for the Chicago Electricity Futures. Other than the competitors, there are two types of participants in this market. Most of the participants are businesses that are trying to hedge risk. These businesses are price insensitive, and place market orders in order to achieve whatever position they want to have. A minority of the participants are hedge funds. The hedge funds also exclusively use market orders, but they only take positions when their fundamental research tells them the current electricity future price is incorrectly valued.

Case Specifications

Upon expiration, Chicago Electricity Futures convert into cash, specifically the amount of money (rounded to the nearest cent) used to purchase the last MWh of electricity on the spot exchange prior to the expiration. You will have access to the June, August, October, and December contracts designated with the following symbols:

Code	Month	Expiration
M	June	6/30
Q	August	8/31
V	October	10/30
Z	December	12/31

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 will be laid out with detailed documentation during our subsequent platform and devkit release. Specifically, this market will follow a Pro-Rata allocation scheme; please see the case materials for the specific details.

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 possible.

The asset code for each future is EF[month of expiry]. For example, the future expiring at the end of June would be EFM.

In addition to being able to access the futures market, you will get access to a running feed of trades and prices of trades being executed on the spot market.

Round Specifications

There will be four 6-minute rounds corresponding to markets in the following years: 2020, 2021, 2022, and 2023 (you will have data from 2010-2019. The chronology is not irrelevant to succeeding in this case).

Positions and PnL are not carried over between rounds.

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

Rules

1. You may take long or short positions in all futures available in a round.
    a. There is a risk limit on the absolute number of contracts you can hold in any one contract of 1000 lots.
    b. If you exceed the maximum outright exposure or maximum contract exposure at any time during the round, while you are over the risk limit an automatic market order will be placed on your behalf until you are under the risk limit.
2. There is a maximum order size of 100 lots in this competition. Exceeding it will result in the rejection of your entire order.

Penalties

We reserve the right to disqualify teams if we think that they are making uninformed directional bets. The discretion will be exercised sparingly. Disqualification usually results from outright exposure significantly outside the limits set in the previous section or by teams aggressively attempting to influence the order book with orders they do not intend to see filled (i.e. spoofing).

Scoring

At the conclusion of each round, each team will receive points corresponding to their PnL. The team with the highest PnL in each round will receive 40 points, the team with the second-highest PnL will receive 39 points, and so forth. Any team disqualified during a round will receive 0 points for that round.

Code Submission

We will require a preliminary submission by April 10th at 12pm CST.

Tips for Success

As part of the case materials, we will provide a simple market making bot, which will help illuminate how to use χ-Change. In addition, we hope that this bot will serve as a starting place for your bot in this case. We have thought of some potential improvements you can implement to help the performance of this bot.

1. **Initial Estimates and Parameters**: It is important to model initial natural gas and coal stockpiles, as well as how they change over time to get the best possible estimates for the future's price. This will provide a good fair price for you to trade around, as well as increase your confidence and allow you to trade tighter.
2. **Speed**: In trading, being the first one to react is always an advantage, especially when avoiding bad fills. In addition, the first person on each price level will get priority in our pro-rata fill allocation scheme. See if you can improve the speed of the bot and implement methods for using this.

3. **Real time Adjustments**: You should take advantage of information you receive through the spot markets.
4. **Timing**: Competitors should market make most of the time. Is it ever advantageous to not participate? Can you use the historical data to figure out when these times might be?
5. **Pro-Rata Fills**: Quoting bigger size might help you get more and better fills than your competitors because of the pro-rata allocation scheme. When can you quote for size?

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.

The following is taken from *Trading and Exchanges: Market Microstructure for Practitioners* by Larry Harris, pages 398 and 399:

LIQUIDITY DIMENSIONS

Searches are productive processes in which searchers use inputs to produce outputs. In the search for liquidity, the primary input is the time spent searching. The main outputs are good prices and adequate sizes.

We can characterize the expected outcome of a search problem as a production function that explains how the inputs to the search are related to the expected products of the search. This characterization of the search problem allows us to easily recognize trade-offs among various dimensions of liquidity. In particular, when traders are willing to search longer, they can generally expect to find more size at a given price, or a better price for a given size. Likewise, when traders want to trade more size, they can expect to obtain a worse price or spend more time searching. Finally, when traders offer better prices to other traders, they can expect to find greater size or spend less time searching. Table 19-2 summarizes these trade-offs.

These inputs and outputs of the bilateral search process correspond to the following three dimensions of liquidity to which traders commonly refer:

• *Immediacy* refers to how quickly trades of a given size can be arranged at a given cost. Traders generally use market orders to demand immediate trades.

• *Width* refers to the cost of doing a trade of a given size. For small trades, traders usually identify width with the bid/ask spread. It also includes brokerage commissions. Width is the cost per unit of liquidity. Traders often refer to market width by the term *market breadth*.

• *Depth* refers to the size of a trade that can be arranged at a given cost. Depth is measured in units available at a given price of liquidity.

Breadth and depth are closely related. Mathematicians say that they are *duals* to each other. Traders who want to minimize the cost of trading a given size solve a problem that is essentially identical to that of traders who want to maximize the size they trade at a given cost. The strategies that best solve both problems are the same. In both cases, traders must search for efficiency. Depth - the size you can trade at a given price - and breadth - the price at which you can trade for a given size - therefore summarize essentially the same information about liquidity conditions.

These three dimensions of liquidity help us understand why traders are often confused about the nature of liquidity. Impatient traders focus primarily on immediacy and its cost, which for small trades is represented by width. Large traders focus on depth. Different traders focus on different aspects of the search problem.

To summarize, liquidity is the ability to quickly trade large size at low cost. “Quickly” refers to immediacy, "size," to depth; and "cost," to width

Since liquidity is the ability to trade, we can characterize liquidity as a function that tells us the probability of trading a given size at a given price, given the time we are willing to put into your scratch. This characterization allows us to consider many other factors besides size, price, and time that affect the probability of trading. Some of the more important factors involve the following issues:

• Why do you want to trade? Traders are far more willing to trade with uninformed traders than with well-informed traders. Liquidity thus is different for traders who are known to be uninformed than for those who are known as informed traders. Markets may be liquid for the former but not for the latter. In practice, traders often do not know who is well informed. Traders who can convince others that they are not well informed generally obtain better prices or more size.

• What is being traded? Instruments that interest large numbers of traders trade in much more liquid markets than do instruments that interest only a few traders.

• How well do traders know fundamental values? Instruments for which fundamental values are not well known tend to trade in illiquid markets because liquidity suppliers are afraid that they might trade with better-informed traders.

• When is the trade to be arranged? Trades are harder to arrange when markets are closed this when they are open. Markets are also less liquid when traders suspect that some traders have information that is not yet in the prices.

• What are other traders doing? It is easier to buy while prices are falling then when prices are rising.

• Is there an imbalance between displayed buying and selling orders? Imbalances often indicate that liquidity will be cheap for one side and expensive for the other side.

• Who is trading? All other things held constant, a good trader is more likely to complete a trade than is a poor trader. Good traders know to display their interest, who wants to trade and how to approach traders.

Citation:

Harris, Larry. “LIQUIDITY DIMENSIONS.” In Trading and Exchanges: Market Microstructure for Practitioners, 398–99. New York: Oxford University Press, 2003.

χ-CHANGE PRO-RATA ALLOCATION

Traders use their expertise and their ability to take on short term risk to provide "better fills" to participants coming to the market for their business. When you provide a "better fill" to a counterparty, it means that you have improved the "liquidity" of the market. This can be achieved in a few ways, such as improving the price or offering more size. The attached reading (Harris 398-399) provides a coherent definition of liquidity and the dimensions along which it can be improved. It should be noted that the precise definition of liquidity and its dimensions is still a subject of academic debate. If you are interested, check out Díaz & Escribano (2020) for a recent literature review of the subject.

However, Harris's classical definition is sufficient to determine the rationale behind Pro-Rata allocation. When hedging or performing other financial activities, market participants want to execute their trades cheaply, quickly, and for the right size. However, the order in which they prefer those characteristics is not always known. FIFO allocation, which is used by the NYSE and NASDAQ, as well as most of the derivatives traded in the US, assumes price first, speed second. Thus, when a market order arrives to the exchange, the person who offers the best price (highest bid or lowest ask) gets the fill, with ties being broken by the time at which that order was placed on the book. Hence, in environments where pricing is relatively well understood, traders are incentivized to be fast, but not necessarily quote large size. This works well, but for some products, hedgers and institutions may want to do much larger size than is reasonably available on the books. If they trade it to traders directly, they might see a lot of price slippage before they get their full size off. In the real world, these institutions operate through brokers, who split up the position and try to trade the parts to traders. The insertion of the brokers, who charge much higher bid ask spreads than screen traders, drastically decreases market efficiency.

An alternative to a secondary broker market is a Pro-Rata allocation scheme. Pro-Rata allocation or Pro-Rata allocation combined with FIFO is used in a variety of important markets, including US Treasuries, US Treasury futures, rate futures (including Eurodollar and SOFR), as well as agricultural and livestock futures and options. All these markets are characterized by participants who need to do large sizes at one time. Pro-Rata is similar to FIFO in that a market participant who quotes the best price receives fills before anyone else. The difference is that in Pro-Rata markets, when market participants are quoting the same prices, the number of lots in an incoming order is distributed to the market participants based on how many lots they are quoting. Before any other orders are filled, the "top order" (oldest order at that price level) has priority; i.e. it is matched with the incoming order until it is filled completely. After the top order is exhausted, the remaining size is distributed among the rest of the level. Specifically, if a market participant i is quoting one order of size L_i lots at a price where a total of L lots are being quoted, and a market order of size S comes in, participant i will receive $floor\left(\frac{L_i}{L} * S\right)$ number of lots (where the floor function removes any decimal part). You may notice that due to the truncation, some lots of the initial order are left unfilled. These fills are distributed via FIFO among the remaining orders.

Let's consider an example:

Four bidders place bids at the same price level in the following configuration:

Bidder	Time	Size
1	1:00	5
2	1:30	50
3	2:00	55
4	2:30	95

At 2:31, this price level becomes the best bid, and a market order of 105 lots is placed in the market. Because Bidder 1's order is currently the oldest, it is the top order. Thus, it receives 5 lots. There are 100 lots remaining. Of this size, Bidder 2 gets $floor\left(\frac{50}{200} * 100\right) = floor\,(25) = 25$ lots, Bidder 3 gets $floor\,\left(\frac{55}{200} * 100\right) = floor\,(27.5) = 27$ lots, and Bidder 4 gets $floor\,\left(\frac{95}{200} * 100\right) = floor\,(47.5) = 47$ lots. Notice we have only filled 104 lots. The last lot goes by FIFO order; because Bidder 1 is completely filled, Bidder 2 gets the last lot. A summary of the trade and the remaining level structure is:

Bidder	Traded Size	Size Remaining
1	5	0
2	26	24
3	27	28
4	47	48

Notice that Bidder 2 is now the top order, and will have priority when the next order hits this price level.

CASE 2: OPTIONS TRADING AND VOLATILITY MODELING

Definitions

- Option: A financial derivative that gives the owner the right to buy or sell an asset at a prespecified price at a prespecified 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. After this the contract ends.
- Strike Price: The prespecified 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 deviation of returns of an asset. It is the only unknown input into basic options pricing formulas, so options trading is often thought of in terms of volatility
- Implied Volatility: The level of volatility implied by options prices
- Realized Volatility: The level of volatility an asset has historically experienced
- Options Chain: All calls and puts with the same expiration on a given security
- In The Money: An option which could be exercised for a profit
- At The Money: The option whose strike best matches the price of the underlying
- 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 relative 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 price of the underlying.

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.

Both models work by assuming a lognormal distribution of underlying returns, a condition not actually found in the market. To adjust for this, options are typically priced using different implied volatilities at different strike prices to replicate a different distribution of underlying returns and to adjust for different levels of supply and demand for different risk exposures (there are more people who need to hedge a long stock position than a short one, meaning that all else equal, the implied volatility of options with lower strikes will be higher). For stock options this is usually a curve, but we encourage you to form your own hypothesis about what the shape of the vol curve should be for these particular stocks.

Case Description

For this case, you will write a bot to trade options on simulated stock data for 10 non-dividend paying stocks. For each round, you will be given 1 year's worth of historical stock price data before the start of each round, called the historical data. This will be spread out over 1800 stock price updates. During the round you will trade options on the next 3 months of data, called the trading data. This will be spread out over 450 stock price updates. 25 stock price updates before the end of the round trading will cease and risk limits will stop being enforced. All options will expire at the end of each round. There will be 3 12-minute rounds.

While we have provided you with a rudimentary liquidity providing bot written by the case writers to ensure your bot can properly interact with an order book, on competition day this bot will not be in the market. All liquidity will be provided by you and the other competitors. We expect teams to make money by filling orders sent by bots we have written to take liquidity. The challenge of this case is pricing options competitively enough to trade against the liquidity-taking bots while both pricing options accurately enough to not get picked off by other competitors and managing risk.

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.

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 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.
- 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.
- 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.

- 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. An example is included below.
    - Delta = (OptionPrice(stock_price + small_number, strike, time, volatility, rate) - OptionPrice(stock_price, strike, time, volatility, rate)) / small_number

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 off of the intrinsic value of the position at the end of the round. The value of their stock positions will be determined based off of 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 April 10th at 12pm CST.

Case Materials/Data

A development toolkit, detailed documentation and training data has been released through the UChicago Trading Competition Piazza. 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 Piazza in the "case2" folder.

CASE 3: TIME SERIES ANALYSIS & EQUITY MODELING

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 ten years of price data for each stock alongside market returns and monthly risk-free rate measurements from the same time period. Your goal is to develop an algorithm that will construct and rebalance a portfolio to maximize returns while simultaneously minimizing returns variance.

Education

Can you beat the market? If your personal portfolio of equities is more involved than a few index fund holdings, you're probably concerned with how your performance fares against the market at-large. To quantify both relative performance and market exposure, a number of models — the Capital Asset Pricing Model and Fama-French Factor Models, to name a few — have been devised to parse out this information (that is, the slope (beta) and intercept (alpha) gleaned by regressing the returns of a given security against those of the market.)

Describing Relative Performance

The economic interpretation of alpha and beta is relatively simple, but exercising control over these parameters in your portfolio means the world in terms of your relative performance. **Beta** is the measure of an equity's volatility in relation to the overall market. As historical stock betas are generally obtained via a regression of some stock's returns against that of the market (expressed via an index or other basket of stocks), they can be calculated via the form for a simple linear regression coefficient:

$$\beta = \frac{Cov(R_m, R_e)}{Var(R_m)} = Corr(R_m, R_e) * \frac{Std(R_e)}{Std(R_m)}$$

where R_m and R_e are variables representing the returns of the market and of the equity of interest, respectively.

Beta is the preferred metric used to represent your position's systematic risk, or dependence on broader market movements, over a given time period. Those wishing to diversify away market risk in their equity investments use historical beta to measure their dependence on market movements. It is possible to construct a portfolio about a target beta, which can vary depending on your expectations about the near-term performance of the broader market. Whether expectations of this type are justified in the context of this case will be a question for you to decide using the training data. Regardless of your findings, blindly taking positions in equities that depend on the market (without first understanding this dependence!) is a naive way to approach this case.

Alternatively, **alpha** is described as the "excess return" on the equity investment, or the return that is not a result of general movement in the greater market. Active investors try to seek out positive-alpha investments; in particular, portfolios with low absolute-value beta and high alpha represent low-market-risk, high-relative-reward opportunities for active equity investors. These are tough to come by, however, and often do not stand the test of time. Furthermore, single equities and industries exhibit idiosyncratic risk in their own right, and this cannot be quantified by Beta alone. As UChicago students, we tend to give the Efficient Market Hypothesis credit where it is due, and don't believe too strongly in single-stock investments that consistently beat the market. That said, estimates of this type can still be informative in the near-term, less the presence of shocks.

Predictive Modeling

In practice, the aforementioned metrics are primarily performance metrics that summarize your portfolio or stock's performance relative to the market over some given time horizon. With no certainty can you make the assumption that your calculated parameters (i.e. the result of your linear approximation to the security's returns) will remain true going forward, though they can be informative about your investment's characteristics in the near-term. Furthermore, predicting the market return can be a task in itself - specifying an economically sound model explaining why the premium on U.S. equities is so high relative to other assets is an open problem! (See the Wikipedia article on the equity premium puzzle for more details.) As a result, this class of equity return models are generally not used for predictions outside of corporate finance.

For this case, however, you may operate under the assumption that, by utilizing the proper model form for the given equities and through diligently re-calibrating said model, you are able to make sound predictions about a security's performance in the future. That is, the basket of equities you will be supplied with are at least partially determined by the path of the market. Specifically, if you can predict the relative nature of a security's return in some future state, then you can construct a strategy to trade upon the outcome. In doing so, you'll first need to devise a feasible model form that, given the right parameters, fits closely to the data that you are given. These parameters will be time-varying, so you'll need to find a way to dynamically re-tune your model to accurately predict a security's next-period return, and to quantify your error in doing so. You also may want to think about feasible models for how any unobservable parameters might evolve over time — two common examples are a mean-reverting process or a random walk. You'll want to exercise careful intuition about your strategy here — after all, the absolute performance of any security in this case will be dependent on future, unrealized market premia (excess return).

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

1. Survey literature to understand fundamental models and principles of asset pricing
2. Apply model(s) of asset pricing in a time-varying framework to forecast relative asset returns
3. Construct an intuitively sound investing strategy that maximizes risk-adjusted return by reducing uncertainty where possible.

A recommended reference for additional reading on financial time series analysis is *Analysis of Financial Time Series* by UChicago professor Ruey S. Tsay.

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 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 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, asset prices, the market price, and the prevailing risk-free rate for that timestep will be provided, and teams will submit portfolio allocations among the available assets for that period (the market price and risk-free rate provided are not tradeable). 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 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 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. The team with the highest annualized daily Sharpe ratio over the test period will receive 40 points, the team with the second-highest annualized daily Sharpe ratio will receive 39 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 stub 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 Friday, April 10th, 2020**. 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 3.8 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 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.
3. **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. In addition, the risk-free rate is reported in an annualized form; you will have to convert it to a daily rate using the day-count convention.

Questions

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