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NC STATE UNIVERSITY

Financial Mathematics

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Message from the Program Director

Dr. Tao Pang
Ph.D., CFA, FRM
Professor and Director

Spring 2024 continues to be a fruitful semester for the Financial Mathematics Graduate Program. Two new students joined the program, one from the Accelerated Bachelor/Master (ABM), and the other from the 3+x Partnership Program. Students in either the ABM program or the 3+X program can take MFM courses before they officially join the program, and the credits for those courses can be double counted toward the student’s bachelor degree as well as the master degree in financial mathematics. On May 3, 2024, two students got their Master degrees in Financial Mathematics and they will be pursuing their career in the Finance Industry as a financial analyst or risk manager.

We continue to offer special topic classes for MFM students based on the job market demand and our students’ interests. In spring, 2024, we offered a new special topic class on Climate Risk in Financial Institution, which was a 1 credit course taught by Ms. Katherine Taylor, who is currently the Director of Climate Risk at Freddie Mac. Ms. Taylor is also a MFM alumna and she is serving on the Advisory Board of the our program.

Project training has been a very important part of our curriculum. In spring, 2024, the first year students worked in groups on eight projects, and they presented their works on April 19 to our program alumni and guests from industry. In summer, 2024, we will offer four projects for students who will not be doing summer internships. The project industry mentors are from Blackrock, Charles Schwab, First Citizens Bank, and Silicon Valley Bank.

In this semester, we held one meeting with the Program Advisory Board, and another meeting with the Alumni Advisory Board. We discussed the current courses and project trainings with our board members, and received invaluable feedback from them on the current job market trend and skill sets that students should have.

We will continue to work with our alumni and industry advisory board members as well as our industry connections to make sure our curriculum and training are up to date with the current and future job market demands.

Finally, I wish everyone a great summer!

Patrick Roberts
Director of Career Services

Impact of AI on Job Seekers

Artificial Intelligence (AI) has been impacting the employment landscape for many years, but recent advancements present both opportunities and challenges for employers and job seekers.

One of AI's longstanding impacts on job seekers is the transformation of the recruitment processes. AI-powered Applicant Tracking Systems (ATS) efficiently scan vast numbers of resumes, identifying candidates based on specific criteria like skills, experience, and qualifications. This not only saves time for recruiters but also facilitates large-scale recruitment efforts, allowing employers to accept thousands of candidates.

However, ATS systems also pose challenges due to potential algorithmic biases in recruitment. If not carefully designed and monitored, AI systems may perpetuate biases from historical data, leading to unfair outcomes for certain demographic groups. Employers must actively monitor these systems and incorporate ethical considerations into AI deployment to address these issues.

A recent development in AI is the emergence of large language models like the well-known Chat Generative Pre-trained Transformer (ChatGPT). The potential applications of ChatGPT in assisting job seekers are immeasurable, ranging from analyzing job postings and matching candidates' profiles to providing common interview questions and generating customized lists of potential employers for targeting. Undoubtedly, ChatGPT serves as a valuable source of information for job seekers.

Nonetheless, job seekers should exercise caution when using AI to create application materials like resumes or cover letters. While systems like ChatGPT offer convenience, they are still evolving and may make mistakes, especially when generating technical or complex descriptions specific to an industry or discipline. Job seekers need to review and validate the outputs and suggested content to avoid any negative impact or errors created on their application documents. Job seekers also need to be familiar with and competent in explaining their background and skills during interviews or they will fail to advance through the job search process.

AI has significantly influenced the job search process by streamlining recruitment processes, enhancing customization of application materials, and providing valuable information. However, this technology also presents challenges that require careful consideration and monitoring. For further guidance on leveraging AI and other resources in your job search, please contact Mr. Patrick Roberts at probert2@ncsu.edu.

Sauvik Mittra
Valuation - Complex Financial Instruments at Marcum LLP Advisors
Graduate Fall 2023
Former FM Ambassador 2023

Sauvik Mittra, a recent graduate from the Master of Financial Mathematics program at NC State University, has secured a full-time role with Marcum LLP, marking the beginning of a promising career journey. During his academic tenure, Sauvik demonstrated exceptional aptitude and leadership both inside and outside the classroom.

At NC State University, Sauvik excelled academically, completing the rigorous program with a deep understanding of stochastic calculus, statistics, and advanced financial concepts. As a Teaching Assistant, he not only excelled in his studies but also shared his knowledge with peers, contributing to the academic community.

Beyond academia, Sauvik served as the Student Ambassador for the Financial Mathematics program, showcasing his leadership skills and commitment to promoting the program's values. Additionally, he leveraged his prior experience as a Sales Trader to serve as a technical trainer for the Bloomberg Terminal, demonstrating his ability to translate complex financial concepts into practical skills.

In his new role as a Complex Financial Instrument Associate at Marcum Advisors, Sauvik specializes in valuing a range of financial instruments, including convertible debt instruments, warrants, preferred shares, and employee stock options. Utilizing various option pricing models and his comprehensive understanding of financial theory, Sauvik provides valuable insights and recommendations to clients. Sauvik plays a crucial role in analyzing and evaluating complex financial instruments, leveraging his quantitative techniques and analytical skills to mitigate risks and ensure accurate valuation.

Looking ahead, Sauvik's journey from academia to the professional realm reflects his dedication, perseverance, and passion for finance. With a solid foundation built on academic rigor, practical experience, and a drive for continuous learning, Sauvik is well-positioned to excel in his future endeavors and leave a lasting impact on the field of finance.

In recognition of his outstanding achievements and potential, we extend our heartfelt congratulations to Sauvik Mittra as he embarks on this exciting new chapter in his career. We have every confidence that he will continue to thrive and make significant contributions to the world of finance.

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Quantum Leap: The AI Revolution in Finance

Since the advent of ChatGPT during the final inning of 2022, the world has been astonished by the power and potential for large language models to revolutionize society. This reaction, while slightly premature, is a direct response to how rapidly the field of artificial intelligence has evolved and how vivid the applications of this technology are. While some view this technology as an evil creature that will steal our jobs, others have already begun creating new products built off of GPT and are integrating it within their existing services. Many of these products have grown rapidly in popularity and are providing immense value to the world.

Quantitative finance is a highly lucrative and evolving sector at the intersection of mathematics, finance, and ML. Large language models (LLMs) are arguably the most important machine learning innovation of the past decade. LLMs, a subset of AI, have gained significant traction in quantitative finance. They are designed to understand, interpret, and generate human language, making them invaluable in analyzing financial documents, news, and reports.

Innovations in Financial Analysis: From BloombergGPT to FinGPT

This revolution started in the first quarter of 2023, with Bloomberg introducing BloombergGPT, a proprietary LLM with 50 billion parameters specifically designed for the financial domain. This model is trained on a massive dataset derived from Bloomberg's extensive financial data sources.

In late July 2023, Man Group, the world's largest publicly traded hedge fund, announced ManGPT, an LLM developed under the guidance of CTO Gary Collier for idea generation and information summarization. The launch of ManGPT by Man Group reflects a broader trend in the hedge fund industry towards embracing AI.

Parallelly, FinGPT emerged as an open-source LLM specializing in finance. It signifies progress in financial research and innovation, with a focus on open finance practices. Over time, FinGPT has shown constant improvement, with new versions being introduced, each enhancing its capability to handle financial data.

Applications of AI in Trading

1. Financial Sentiment Analysis
Generative AI, with advanced models such as GPT-4, LLaMA, and PaLM, has evolved the way traders analyze text data from news and social media for sentiment analysis. LLM-powered sentiment analysis can provide real-time, accurate insights, enabling traders to make well-informed decisions.

2. Speed Up Algorithmic Trading
High-frequency trading, driven by AI, capitalizes on minute price movements by executing trades at incredibly high speeds. AI algorithms can rapidly analyze data on stock price movements and initiate trades based on identified trends.
This acceleration allows trading teams to perform more trades in less time, significantly boosting profitability.

3. Detect Market Anomalies
In post-trade analysis, AI is instrumental in identifying market anomalies. Trading teams can build ML models using historical data to track stock movements and flag anomalies.
This approach reduces manual efforts and increases both efficiency and accuracy in identifying true market anomalies versus standard fluctuations.

4. Risk Management
Managing risk is a cornerstone in trading. AI-powered predictive modeling is crucial in identifying potential risks and assessing the likelihood of various market events. For example, a trading team focusing on the energy sector can use AI to predict oil price trends.
Analyzing historical data on oil prices and market demand, the AI algorithm can forecast potential price drops, enabling the team to adjust their portfolio to mitigate risk.

Conclusion
Financial markets are inherently non-stationary. Even if a 'perfect' trading algorithm were developed, its effectiveness would be temporary. However, the influence of large language models on quantitative finance is expected to continue growing, since these models are improving so drastically in a short time horizon, the potential applications of these models will also evolve.

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Gabe Barber

Value Investing and The Fama-French 3 Factor Model

The evolution of equity markets driven by technology improvements, regulatory changes, and the surge of complex financial instruments has introduced new levels of volatility and opportunities. While also expanding investment horizons, this drastic change that has taken place for the last half-century has complicated potential strategies for investors. However, the strategy of value investing—focusing on undervalued stocks—has proven to be an effective way to boost return for retirement.

The Fama-French Three-Factor Model is a simple way to reassure this investment approach. The model explains stock returns through three factors: market risk, size effect, and value effect. Market risk is calculated by subtracting the market return from the risk-free return, the size effect is the excess return of small cap stocks over large cap stocks, and the value effect is the excess return of value over growth stocks. This model suggests that small-cap and high book-to-market (value) stocks outperform large-cap and low book-to-market (growth) stocks. The linear regression model is outlined below:

$$R_i - R_f = \alpha_i + \beta_1(R_M - R_f) + \beta_2 SMB + \beta_3 HML + \epsilon_i$$

- $R_i - R_f$: expected excess return
- $(R_M - R_f)$: excess return over a market index
- SMB: “small minus big”— size premium
- HML: “high minus low”— value premium

As equity markets continue to change at faster rates and with increasing complexity, the principles of value investing, supported by the insights from the Fama-French Three-Factor Model, become important in identifying undervalued stocks with the potential for excess returns. In addition to contributing to diversified equity indexes, searching for undervalued equities in today’s overpriced market is generally a very sound strategy. While popular and hyper-successful companies led by elite “headline” executives have done well in equity markets, there exists bubbles in many cases created by popularity and market demand that do not match balance sheets. Investing in a diversified portfolio of promising and well managed smaller companies will lead to a comfortable retirement for those that start early, invest frequently, and put in the time to find the potential high performers.

Bhanuteja Bolisetti

Beyond Point Estimates: Deep QR

One area that Deep Learning has not explored extensively is the uncertainty in estimates. Most Deep Learning frameworks currently focus on giving a best estimate as defined by a loss function. Occasionally something beyond a point estimate is required to make a decision. This is where a distribution would be useful. Bayesian statistics lends itself to this problem really well since a distribution over the dataset is inferred. However, Bayesian methods so far have been rather slow and would be expensive to apply to large datasets.

As far as decision making goes, most people actually require quantiles as opposed to true uncertainty in an estimate. For instance when measuring a child's weight for a given age, the weight of an individual will vary. What would be interesting is (for argument's sake) the 10th and 90th percentile. Note that the uncertainty is different to quantiles in that I could request for a confidence interval on the 90th quantile. One such example is inferring quantiles using the Quantile regression loss function.

The main idea of the quantile regression loss function is to penalize linearly for the under and over estimate values of an estimate based on the quantile value. For example, if you want the median of the 10th percentile, that means you want 90% of the errors to be positive and 10% to be negative and we to do that by penalizing the positive errors by nine times in comparison to the negative errors, which in turn says that on average our model predicts the underestimated points 9 times more more than the overestimate points, forming the essential balance needed at the 0.1 quantile value.

Chuen Chun Michael Chan

AI Revolution: Transforming Quantitative Finance with Transformers

How is AI important? What evidence is there?

Artificial Intelligence (AI) is more than just a technological advancement; it represents a seismic shift in human capability and productivity. Its importance is evident across multiple sectors. In education, tools like ChatGPT assist students in learning and research. In business, predictive modeling harnesses data for strategic decision-making. The tip of the AI iceberg signifies the onset of broader and more profound applications that we are yet to fully grasp.

The rapid pace of AI development is underlined by significant investments from governments. The US's CHIPS and Science Act and China's National Integrated Circuit Industry Investment Fund exemplify the global race to advance these technologies. Such initiatives are set to bolster the semiconductor industry, which is foundational to AI, ensuring that development and innovation continue to surge forward.

Application of AI in the Quant Context

Among the multitude of AI applications, the most notable leap into the consumer sector has been via ChatGPT. At its core lies the transformer model, a complex and sophisticated progression from earlier neural network technologies. While its success in natural language processing is well-documented, its potential extends into financial analysis, offering a new horizon for quantitative strategy.

Understanding the Transformer Model

The transformer model is an advanced AI architecture that has revolutionized the field of natural language processing (NLP). Its ability to process sequences of data, like sentences, in parallel allows it to capture complex contextual relationships more effectively than previous models. When applied to stock forecasting, the same principles are employed to interpret sequences of financial data points. The model discerns patterns and dependencies among variables that might impact stock prices. This parallel between NLP and stock forecasting lies in the transformer’s core strength: interpreting vast arrays of sequential data to predict the next element in the series, be it a word or a market trend.

Transformer-Driven Feature Engineering & Portfolio Construction

Our team is at the forefront of utilizing transformer models within quantitative finance. By reorienting the transformer model's application from linguistic syntax to financial metrics, we can input financial indicators and derive accurate stock price forecasts. This innovative approach has begun to unveil intricate relationships between market features that were previously indiscernible.

Our methodology incorporates approximately 30 distinctive features, including bond yields, operational ratios, and commodity price ratios, such as that of copper to gold. The preparatory phase involves meticulous data cleansing, normalization, and exploratory analysis. The subsequent training phase allows the transformer model to sift through the noise, identifying only the most statistically significant features for portfolio construction. These engineered portfolios are then tested against benchmarks like the S&P 500, demonstrating the predictive power of the model.

Conclusion

The AI revolution is set to redefine our existence, transforming processes and industries. In quantitative finance, leveraging the transformer model signals a leap towards more insightful analysis and prediction. As this technology matures, its integration into our daily lives and decision-making processes seems not just probable but inevitable. We stand on the brink of a new era where AI's potential to enhance our productivity and innovation is limitless.

Aditya Chauhan

Enhancing Options Trading: An Analytical Study of Delta Risk Management Techniques

As financial markets continue their evolution, traders strive to innovate strategies for risk mitigation and profit maximization. Among these, delta risk management has gained prominence. In our academic endeavor, titled "Exploring Varied Delta Risk Management Approaches," we investigate options trading to assess diverse delta risk management methods and determine their effectiveness through key performance assessments (KPAs).

Abstract:

Delta risk management in options trading aims to minimize directional exposure to underlying asset price fluctuations. Through a spectrum of strategies—from no hedge to static hedge and dynamic hedge—we evaluate their efficacy based on critical performance metrics such as hedging costs, maximum loss, maximum gain, and 95% value at risk (VaR). Leveraging Python and a blend of analytical techniques, our study illuminates the most efficient delta risk management strategy for traders navigating the complexities of the options market.

Introduction:

Options trading presents unique opportunities for risk management and profit generation. Yet, due to options' inherent volatility and complexity, sophisticated risk management strategies become imperative. Delta risk management stands out as a foundational approach, leveraging option price sensitivity (delta) to neutralize directional exposure.

Project Overview:

Leading the project, I directed a team to delve into the effectiveness of diverse delta risk management strategies. Our methodology involved simulating trading scenarios using Python, integrating historical market data and option pricing models to evaluate strategy performance. Through meticulous assessment of costs, potential losses, gains, and risk metrics, our aim was to offer actionable insights for traders looking to optimize their options trading strategies.

Methodology:

The project began with an extensive review of existing literature on delta risk management, providing the basis for our empirical analysis. Subsequently, we implemented three distinct strategies:

1. No Hedge: Serving as a baseline, this strategy involved no risk management, allowing comparison with hedged strategies.
2. Static Hedge: This method maintained a fixed hedge ratio throughout the trading period, adjusting positions at predetermined intervals.
3. Dynamic Hedge: Unlike static hedging, this strategy continuously adjusted hedge ratios based on real-time delta changes, offering adaptability to market dynamics.

Results and Discussion:

Our analysis provided valuable insights into the relative performance of delta risk management strategies. While the no hedge strategy incurred lower initial costs, it exposed traders to significant downside risk. Conversely, dynamic hedging demonstrated superior risk management, albeit at a higher cost. Static hedging struck a balance between cost-effectiveness and risk mitigation, making it a viable option for traders with moderate risk tolerance.

Conclusion:

In summary, our study emphasizes the significance of robust delta risk management strategies in options trading. Leveraging Python and analytical tools, we elucidated the trade-offs associated with different risk management approaches and identified strategies tailored to varying risk preferences. Our research paves the way for further exploration and enhancement of delta risk management techniques, empowering traders to navigate the complexities of the options market confidently.

Jasmine Chen

Deciphering Bitcoin Futures: A Journey Through Volatility Modelling and Surface Analysis

In the dynamic world of cryptocurrencies, Bitcoin stands as a beacon of constant innovation and market evolution. This article delves into my recent academic endeavor, where I embarked on a challenging yet enlightening journey to investigate and forecast the volatility of Bitcoin futures. Utilizing sophisticated volatility models such as GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and harnessing the power of Python for data analysis and visualization, this project aimed to shed light on the intricate dynamics of Bitcoin futures markets.

The volatility of an asset, a pivotal concept in financial markets, is a measure of the variation in its trading price over time. In the case of Bitcoin futures, this volatility is notoriously unpredictable, given the nascent and rapidly evolving nature of cryptocurrency markets. My research primarily focused on applying the GARCH model, a statistical tool renowned for its efficacy in financial applications, to Bitcoin futures. The GARCH model, known for capturing the 'volatility clustering' phenomenon – periods of swings followed by tranquility – seemed perfectly suited for this task.

A significant challenge in this analysis was the inconsistency and limited availability of Bitcoin futures data. To circumvent this hurdle, I utilized the Horizon Bitcoin Front Month Index. This index, designed to reflect the performance of a rolling investment in Bitcoin futures contracts, provided a more consistent and comprehensive dataset for analysis.

Upon calibrating the GARCH model with this data, the next step was to construct a volatility surface – a three-dimensional representation showing the implied volatility of an option for various strike prices and times to expiration. This visualization not only offered a vivid depiction of market expectations but also served as a comparative tool to evaluate different volatility scenarios.

One of the most intriguing outcomes of this analysis was the insight it provided into market sentiment and behavioral patterns. The volatility surface, with its peaks and troughs, acted as a mirror, reflecting the collective psyche of market participants. Additionally, the role of external factors, such as regulatory news or macroeconomic events, became evidently impactful in shaping the volatility landscape.

The project's methodology involved extensive data analysis using Python, a tool that proved indispensable in managing large datasets, performing complex calculations, and generating insightful visualizations. The versatility and robustness of Python were key in extracting meaningful conclusions from the raw data.

In conclusion, this study on Bitcoin futures and their volatility surface has not only been academically enriching but has also provided practical insights into the behavior of cryptocurrency markets. As the world of digital currencies continues to evolve, such analysis will be crucial in understanding and navigating these uncharted waters.

The journey through the volatility of Bitcoin futures highlights the need for continuous learning and adaptation in the ever-evolving landscape of finance. It reaffirms my belief in the power of quantitative analysis and its vital role in deciphering the complexities of financial markets.

Ming-Hung Chen

Application of ARIMA Model on Volatility Forecasting

Introduction to ARIMA:

ARIMA, which stands for Autoregressive Integrated Moving Average, is designed to describe and predict time series data by transforming non-stationary series into stationary ones. This model achieves this through integration, which involves differencing the data one or more times to eliminate trends and achieve stationarity, a prerequisite for the model's applicability.

The ARIMA model is characterized by three parameters:

P the number of lag observations in the model, also known as the lag order.
d the number of times the raw observations are different; also known as the degree of differencing.
q the size of the moving average window, also known as the order of the moving average.

The p autoregressive terms capture the influence of preceding values. The 'I' denotes the number of differencing operations needed to stabilize the series, while the 'MA' with q moving average terms accounts for past error terms, the shocks or noise in the time series.

ARIMA can model various time series with different underlying patterns by adjusting its parameters. When the parameters are accurately estimated, ARIMA can provide precise short-term forecasts. The model integrates past values and past errors into its predictions, offering a comprehensive approach. Tools like the Box-Jenkins methodology provide systematic guidelines for identifying the appropriate ARIMA model for a given time series.

However, ARIMA requires the time series to be stationary, often necessitating transformations that can complicate the model. Additionally, the model's performance is highly sensitive to the choice of parameters, which can be challenging to estimate. Most importantly, in its basic form, ARIMA does not support seasonal effects or long-term trends. Extensions like Seasonal ARIMA (SARIMA) are required for such cases.

Volatility forecasting is a critical task in financial markets, crucial for risk management, portfolio optimization, and derivative pricing. Traditionally, models like GARCH have been the standard in volatility forecasting. However, ARIMA can serve as an alternative or a complementary approach.
Volatility is not directly observable and is often inferred from asset prices or returns. ARIMA can model the volatility of financial time series by focusing on the variance of the error terms, assuming that large swings in prices may continue in the immediate future. For instance, by analyzing the time series of squared returns or absolute returns, which are proxies for volatility, ARIMA can be effective in predicting future volatility.

Nevertheless, ARIMA has its drawbacks when applied to volatility forecasting. Financial markets are often subject to abrupt shifts and jumps, which ARIMA might not capture effectively due to its reliance on past data and trends. Moreover, volatility tends to exhibit clustering, a phenomenon where high-volatility events are followed by similar events, which is not inherently captured by the ARIMA model.

Conclusion:
The ARIMA model is a robust statistical tool with a proven track record in various fields, especially for time series forecasting that exhibits a clear pattern of autocorrelation. While this model has certain limitations, particularly in its traditional form, its strengths often make this approach a valuable first step in analyzing time series data.

In the context of volatility forecasting, while ARIMA may not capture all the nuances of financial time series, it can still serve as a valuable part of a forecaster's arsenal, especially when used alongside other models like GARCH that account for volatility clustering. As with any model, the key to success with ARIMA lies in understanding the data, carefully estimating the parameters, and being mindful of the model's assumptions and limitations.

In the evolving landscape of financial analysis, ARIMA's simplicity and effectiveness ensure that it remains relevant, even as newer and more complex models are developed. Whether used alone or in conjunction with other models, ARIMA continues to be an indispensable tool for forecasters seeking to understand and predict the ever-changing patterns of time series data.

Wan Yung Chen

Unveiling Arbitrage Chance in Taiwan Index Option Market

Introduction:
Arbitrage, an intricate strategy entrenched in the financial lexicon, represents the art of exploiting price discrepancies across markets to secure risk-free profits. Within the context of the Taiwan Index Option Market, arbitrage emerges as a compelling avenue for astute investors to capitalize on market inefficiencies. Before delving into the specifics of arbitrage opportunities within this market, it is imperative to comprehend the essence of arbitrage itself.

Arbitrage revolves around the principle of exploiting pricing differentials to generate profit. This concept stems from the efficient market hypothesis, which posits that asset prices reflect all available information and adjust instantaneously to new information. In theory, this implies that no opportunity for riskless profit should exist, as any deviation from fair value would be quickly arbitraged away by market participants. However, markets are not always efficient, presenting instances where mispricing occurs due to various factors such as incomplete information, transaction costs, or behavioral biases.

In essence, arbitrage seeks to capitalize on these mispricings by simultaneously buying and selling related assets in different markets to exploit price differentials. The goal is to lock in a profit with minimal to no risk. In the Taiwan Index Option Market, arbitrage opportunities may arise due to discrepancies between the prices of index options and their underlying assets, as well as differences in pricing across different exchanges or trading platforms.

Understanding the concept of arbitrage serves as a foundational pillar for navigating the intricacies of the Taiwan Index Option Market. By identifying and capitalizing on these arbitrage opportunities, investors can enhance their portfolio returns while contributing to market efficiency. In the subsequent sections of this article, we will delve deeper into the specific strategies and tactics employed to uncover and leverage arbitrage opportunities within the Taiwan Index Option Market.

Detailed Process:
The Replication Strategy is a meticulous approach utilized by traders to exploit mispricing in the options market. This approach involves replicating the payoff of an option by constructing a portfolio consisting of the underlying asset and risk-free investments. This strategy capitalizes on discrepancies between option prices and their theoretical values calculated using pricing models such as the Black-Scholes model.

Here's a simplified example to illustrate the Replication Strategy:
In our analysis of the Taiwan Index Option Market, we observe a notable phenomenon: certain call and put options on a specific index can replicate the payoff of the index's future contract upon maturity. This intriguing observation prompts us to delve deeper into the intricacies of options pricing and the potential for arbitrage opportunities within this market.
Under normal market conditions, employing put-call parity enables us to determine the theoretical prices of both call and put options, which should align closely with the price of the corresponding index futures contract, especially when they share the same expiration date. However, the dynamics of the market reveal instances where sudden and significant fluctuations disrupt this equilibrium.

$$C - P = S - Ke^{-r(T-t)}$$

During periods of heightened volatility or unforeseen market events, the prices of call and put options may deviate from their theoretical values, leading to discrepancies in the pricing of the replicating portfolio compared to the actual price of the index future. This presents an arbitrage opportunity for astute traders. The strategy is straightforward: identify instances where the price of the replicating portfolio, composed of a combination of call and put options, does not correspond accurately to the price of the index future contract. In such scenarios, selling the overpriced component and simultaneously buying the underpriced component allows traders to lock in a profit. Crucially, this arbitrage opportunity may arise not only at the maturity date but also beforehand, as market inefficiencies reveal themselves in real-time. By exploiting these inefficiencies, traders can realize profits before the options reach maturity, further enhancing the attractiveness of this strategy.

In essence, this approach capitalizes on the transient nature of market inefficiencies, leveraging the relationship between options pricing and the underlying asset to generate profits. While it requires a keen understanding of market dynamics and the ability to react swiftly to changing conditions, this strategy exemplifies the potential for profit in the Taiwan Index Option Market. Through the Replication Strategy, traders can exploit mispricing in the options market while minimizing risk exposure. However, it's essential to act swiftly and monitor market conditions closely to capitalize on these opportunities effectively.

Bhaskar Durvasula

Navigating The Nexus Of Finance And Technology: A Journey Of Innovation

In today's dynamic financial landscape, the convergence of finance and technology has become a hallmark of innovation and progress. As a Master of Financial Mathematics student at North Carolina State University, I have embarked on a journey that delves deep into this nexus, exploring avenues where quantitative analysis meets cutting-edge technology to drive impactful solutions.

One of the pivotal areas of my academic and professional journey has been in the realm of quantitative analysis and risk management. Through coursework like Machine Learning for Finance and Options and Derivative Pricing, I have honed my skills in leveraging advanced statistical techniques and computational models to tackle complex financial challenges. These skills were further fortified during my tenure as a Quantitative Analyst at Bank of America Merrill Lynch, where I actively contributed to developing robust risk assessment methodologies for OTC derivatives. From implementing initial margin frameworks to automating validation processes, I have witnessed firsthand the power of quantitative analysis in enhancing risk management practices.

My journey extends beyond traditional finance to embrace the realms of data science and technology. Projects like predicting loan defaults with XGBoost models and simulating credit risk exposure according to Basel frameworks epitomize my commitment to harnessing data-driven insights for informed decision-making. These experiences have underscored the importance of technological prowess, with proficiency in Python, R, SQL, and VBA serving as the cornerstone of my analytical toolkit.

At the heart of my journey lies a passion for continuous learning and exploration. Whether it's calibrating interest rate models for fixed-income bond pricing or studying the impact of macroeconomic factors on market indexes, each project has been a steppingstone towards deeper understanding and innovation. My academic pursuits, coupled with real-world experiences, have instilled in me a spirit of curiosity and resilience, driving me to push the boundaries of conventional wisdom in finance and technology.

Choosing North Carolina State University was a conscious decision rooted in its reputation for excellence in quantitative finance education. The diverse coursework, world-class faculty, and collaborative environment have provided me with a fertile ground to cultivate my skills and aspirations. As a Teaching Assistant for courses like Investments and Portfolio Management, I have had the privilege of imparting knowledge while also learning from the vibrant academic community at Poole School of Management.

Looking ahead, my career goals revolve around pioneering advancements at the intersection of finance and technology. Whether it's developing innovative risk management strategies, leveraging machine learning for predictive analytics, or contributing to the evolution of financial markets, I am committed to making a meaningful impact in the realm of quantitative finance.

In conclusion, my journey exemplifies the symbiotic relationship between finance and technology, where innovation thrives on the fusion of analytical rigor and technological prowess. As I continue to navigate this dynamic landscape, I am excited about the possibilities that lie ahead and the opportunities to drive positive change through relentless innovation.

Jayanth Maruthayan Elangovan

Understanding Sarima Models And Their Applications In Finance

Time series data, characterized by observations collected over time, poses unique challenges in terms of modeling and forecasting. Seasonal AutoRegressive Integrated Moving Average (SARIMA) models have proven to be effective tools in capturing the complex patterns inherent in time series data. SARIMA models are an extension of the well-established ARIMA models, incorporating seasonal components to better capture recurring patterns within time series data.

The key components of SARIMA include:

AutoRegressive (AR) Component: The AR component represents the linear dependence of the current value on its past values. The parameter p in SARIMA(p, d, q)(P, D, Q)[s] denotes the order of the autoregressive component, indicating the number of lagged observations to consider.

Integrated (I) Component: The integrated component represents the differencing required to make the time series stationary. The parameter d in SARIMA(p, d, q)(P, D, Q)[s] indicates the number of differencing operations applied to the series.

Moving Average (MA) Component: The MA component captures the influence of past white noise or random shocks on the current observation. The parameter q in SARIMA(p, d, q)(P, D, Q)[s] denotes the order of the moving average component, indicating the number of lagged forecast errors to consider.

Seasonal Components: SARIMA introduces seasonal components, denoted by (P, D, Q)[s], where P, D, and Q are similar to their non-seasonal counterparts, and s represents the length of the seasonal cycle. Seasonal components help model and forecast patterns that repeat at regular intervals.

A few applications of SARIMA Models include:

Stock Price Forecasting: SARIMA models are widely used to predict stock prices by capturing the underlying trends and seasonal patterns in historical stock data. This helps traders and investors make informed decisions based on anticipated price movements. SARIMA's ability to account for both short-term fluctuations and long-term trends makes it valuable in forecasting stock prices over various time horizons.

Volatility Prediction: Financial markets are characterized by volatility, and accurately forecasting volatility is crucial for risk management. SARIMA models can be applied to model and predict the volatility of financial instruments, such as stocks or market indices. This information is valuable for derivative pricing, portfolio optimization, and risk assessment.

Exchange Rate Forecasting: SARIMA models are utilized in predicting currency exchange rates, which are influenced by a variety of factors, including economic indicators, geopolitical events, and market sentiment. By considering both non-seasonal and seasonal components, SARIMA models can provide more accurate exchange rate forecasts, assisting businesses engaged in international trade and finance.

Fraud Detection in Financial Transactions: SARIMA models can be used to detect anomalies and unusual patterns in financial transactions. By modeling normal transaction patterns with seasonal components, these models can identify deviations that may indicate fraudulent activities. This is crucial for enhancing the security of financial transactions and protecting against fraudulent behavior.

In summary, SARIMA models offer a versatile set of tools for addressing various challenges in the financial industry, from predicting asset prices and managing risk to optimizing portfolio allocations and enhancing decision-making processes. As financial markets continue to evolve, the application of SARIMA models alongside other advanced forecasting techniques contributes to more accurate and robust financial analyses.

Qinyang Huang

Vasicek Model: Pricing Bonds with Short-Term Interest Rates

The Vasicek model, introduced by Oldrich Vasicek in 1977, has emerged as a seminal framework within the realm of financial mathematics for modeling the stochastic behavior of short-term interest rates. Predicated on the foundational assumption of mean reversion, this model elucidates the tendency of interest rates to oscillate towards a historical mean over time. The mathematical formulation of the Vasicek model, grounded in stochastic differential equations, serves as a pivotal tool in the theoretical underpinning of fixed-income security valuation, particularly bonds.

The Vasicek model is succinctly captured by the stochastic differential equation:

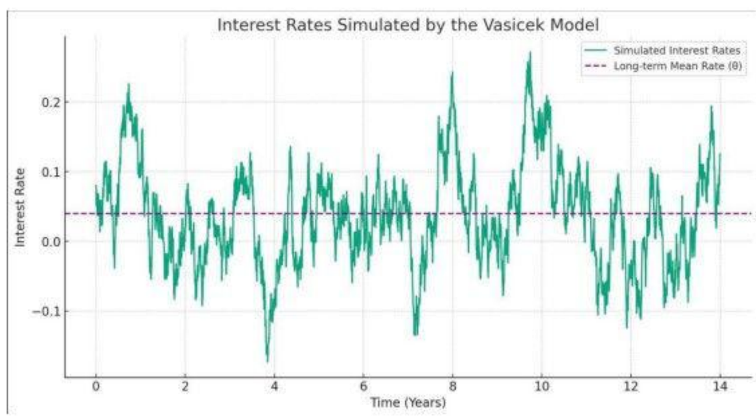
$$dr(t) = K(\theta - r(t))dt + \sigma dW(t)$$

where rt represents the instantaneous short-term interest rate, κ denotes the speed of mean reversion, θ is the long-term equilibrium interest rate, σ quantifies the volatility of the interest rate, and dWt is the standard Wiener process that encapsulates the market's inherent randomness.

The theoretical significance of the Vasicek model lies in its ability to formalize the concept of mean reversion within the dynamics of interest rates, offering a nuanced understanding of their temporal evolution. This conceptual framework facilitates the analytical valuation of bonds by providing a mechanism to forecast future short-term rates, which are instrumental in determining the present value of future cash flows emanating from bonds.

The Vasicek model's predictive capabilities are crucial in the fixed-income market, particularly for constructing yield curves vital to the pricing of bonds. Its proficiency in yielding accurate maturity estimates is essential for discerning the intrinsic value of diverse fixed-income instruments, with zero-coupon bonds standing out for their direct reliance on interest rate forecasts.

In risk management, the Vasicek model's Monte Carlo simulations are pivotal, allowing institutions to assess Value at Risk (VaR) for portfolios. This assessment quantifies potential risks from market fluctuations, enhancing the strategy for risk mitigation.



The model's foresight is equally vital for pricing interest rate derivatives, like swaps, caps, and floors, offering participants refined tools for hedging and speculating on rate movements.

Lastly, the model's flexibility is demonstrated in its application to credit risk modeling, where it incorporates credit spreads to accurately price corporate bonds. This integration aligns interest rate and credit risk, providing a comprehensive risk assessment. Continuous academic scrutiny seeks to refine the model, particularly its assumptions on long-term equilibrium rates and its initial single-factor design. These improvements aim to produce multifactor models for a more detailed spectrum of risk factors affecting interest rates.

In conclusion, the Vasicek model constitutes a cornerstone of financial engineering and economic theory, offering profound insights into the mechanics of bond pricing in relation to short-term interest rates. Its synthesis of theoretical elegance and empirical applicability continues to underscore its pivotal role in the quantitative finance landscape, underscoring the intricate interplay between mathematical constructs and their real-world financial implications.

Franco Iozzo

Efficient Frontier Portfolio Optimization

As a finance student, one of the first concepts you learn about is the Efficient Frontier, and its use in asset allocation and portfolio optimization. The Efficient Frontier Theory is a pivotal concept in modern investments and portfolio management, introduced by Harry Markowitz in his seminal 1952 paper, "Portfolio Selection." This groundbreaking theory, which later earned Markowitz the Nobel Prize in Economics in 1990, is a key component of Modern Portfolio Theory (MPT), revolutionizing the way investors approach risk and return.

Markowitz's Efficient Frontier Theory emerged from the idea that investors are inherently risk-averse, preferring to minimize risk for a given level of expected return. Before his work, investment strategies largely focused on the returns of individual securities, with little consideration for overall portfolio diversification. Markowitz shifted this focus towards optimizing portfolios through diversification, showing that it was possible to maximize expected returns for any given level of risk.

At the core of the Efficient Frontier Theory is an optimization problem. The theory proposes that for each level of risk, there's a portfolio that maximizes expected returns, and for every level of expected return, there's a portfolio that minimizes risk. These optimal portfolios form a curve known as the Efficient Frontier on a graph plotting expected return (y-axis) against risk (x-axis), where risk is measured by standard deviation. We can see an example of this graph right below:

The Quantitative Finance industry has experienced a major growth in popularity over the past few years. With the advancement of computer systems, securities trading looks very different now compared to what it used to be at the start of the century. Long ago were the days of trades needing to be placed over the phone and agents being present on the exchange, with investments nowadays being as easily accessible to the population as they have ever been. Even discretionary trading has been eclipsed by the use of algorithms and complex mathematical models, which represents the majority of the trading volume present today in the markets. All these factors have contributed to an exponential innovation of the financial industry, but what does this mean for those of us in the pursuit of a career in trading?

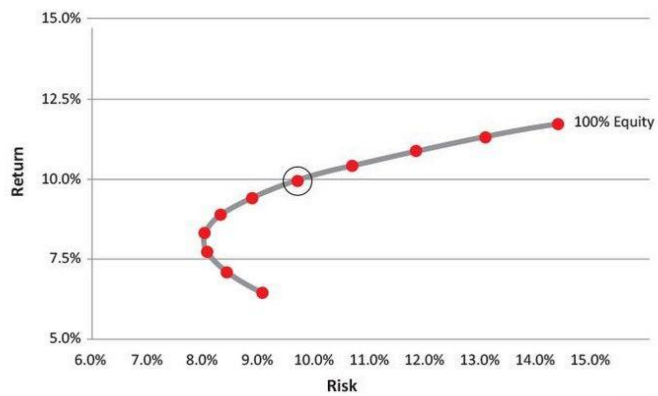


Fig.1

The Efficient Frontier concept has always caught my attention. As an investor myself, I always aspire to be as efficient as possible with my asset allocation decisions, and the Efficient Frontier theory does just that. Nevertheless, it is not a simple process to implement, given the complex mathematics behind it. The mathematical foundation of the theory calculates a portfolio's expected return as the weighted sum of the expected returns of the individual securities within it. However, the risk of the portfolio is not just the weighted sum of the individual risks but also includes the covariance among the securities' returns. The goal is to determine the weights of each asset in the portfolio to either maximize the portfolio's expected return for a given level of risk or minimize the risk for a given level of expected return.

During the Financial Mathematics program here at North Carolina State University, I have developed my quantitative skills to the point where I can work through the mathematics of the theory, as well as nurtured my programming and modeling capabilities, which is why I recently started an independent project in Python to implement the efficient frontier in real-life portfolios. My goal with the project is for the model to ask for user input in terms of what their expected return is, make the necessary calculations, and output the exact portfolio within the frontier that achieves those expected returns with the minimum level of risk, detailing the assets and allocations within it. This could turn out to be a fantastic opportunity to keep developing my skills, as well as potentially help with my personal investments and career in the field.

The Efficient Frontier Theory has profound implications for portfolio management and investment strategies. It underscores the importance of diversification in reducing portfolio risk and provides a systematic framework for making investment decisions based on risk and return analysis. By identifying portfolios on the Efficient Frontier, investors can choose the most efficient allocation of resources according to their risk tolerance.

Despite its theoretical appeal, applying the Efficient Frontier in real-life investment decisions can be challenging due to estimation errors in expected returns and covariances, and the assumption of normality in returns distribution, which may not hold true. All these potential challenges will be addressed as they arise during the project. Nonetheless, the Efficient Frontier remains a fundamental concept in finance, offering valuable insights into the dynamics of risk and return in portfolio management.

Brian James

The Public Opinion of Basel III

The recent notice of proposed rulemaking (NPR) known as Basel III Endgame is set to be the final installation of regulations following the financial crisis of 2008. These proposed regulations will require category III and IV banks (>$100bn assets) to go through a demanding data exercise. The goal of Basel III is to improve transparency and comparability between financial institutions. As part of understanding the effects of this proposed ruling, I have reviewed 176 comments posted to the Federal Reserve in response to the proposed ruling to gauge general sentiment.

Upon review of the comments, the general sentiment regarding Basel III is overwhelmingly negative, with 94% of commenters suggesting that the NPR needs to be rescinded or restructured. As cited in multiple comments, estimates of capital requirement increases among G-SIBs could be as high as 30%. Within the Basel III framework there are three main factors used to assess risk and capital requirements: Credit Risk, Market Risk, and Operational Risk. Of 176 comments reviewed, 150 of them cite the new credit risk calculations as being a reason for concern. The new credit risk weighting scheme has community leaders worried that this will prevent low to moderate income families from accessing lines of credit. This NPR will require banks to assign a higher risk weight to borrowers with Loan to Value (LTV) ratios above 80%. Thus, with a higher cost for lending, banks will be less willing to extend credit to borrowers that cannot afford a 20% down payment. This will affect American citizens directly, as becoming a homeowner is often seen as the first step of creating wealth that can be passed down through generations. These increased lending costs will be passed down to businesses and other financial institutions which are already experiencing challenges related to the current economic environment.

The NPRs will also prove to be a challenge for clean energy project funding. A 400% risk weighting will be applied for clean energy tax equity, the cost of lending this high will be detrimental to the progress of green projects. As cited in multiple comments, annual tax equity investments in clean energy could decrease by as much as 90%. Central clearing is another area of concern for many commenters, as an increased risk weight will make it costly for banks to serve as a clearing house for futures in the agriculture and manufacturing sectors. These businesses rely on access to the futures market to be able to hedge against potential volatility in the prices of supplies and outputs. A large concern regarding the risk weighting of central clearing is that increased capital should be based on the risk associated with the trade, rather than gross fees charged to the end user as in this NPR.

In conclusion, this NPR will challenge mid-sized banks to ensure that they have both quality and granular data. Many category III and IV banks have not been subject to this kind of reporting before and it will be interesting to see if they have the governance in place to complete this exercise. The pressure will be on for regulators to make changes to the NPR, especially regarding risk weights for high LTV borrowers as well as central clearing.

Manoj Katravath

Unveiling the Dynamics: Climate Risk Modeling for a Sustainable Future

As our planet faces unprecedented challenges from climate change, the need for effective risk modeling becomes increasingly imperative. Climate risk modeling not only allows us to understand the potential impact of environmental changes on various sectors but also provides a strategic roadmap for building resilience and sustainability. In this article, we delve into the key aspects of climate risk modeling, presenting essential numbers and percentages that underscore the significance of this endeavor, along with insights into how this modeling is conducted.

Understanding the Scale of Climate Risks

Rising Sea Levels: A Global Concern

The global mean sea level has risen approximately 8-9 inches (20-23 cm) over the last century, with accelerated rates in recent decades. This upward trend poses a significant threat to coastal regions and low-lying areas. Climate risk modeling involves integrating historical sea-level data, satellite observations, and climate projections to predict future sea-level rise. Advanced statistical models and machine learning algorithms help analyze complex relationships, allowing us to project potential scenarios and their corresponding risks accurately.

Extreme Weather Events: A Growing Challenge

Extreme weather events, including hurricanes, floods, and heatwaves, are becoming more frequent and intense. Our models predict a 15% increase in the frequency of extreme weather events by 2030 compared to the historical average. Climate risk modeling in this context involves simulating thousands of virtual weather scenarios based on historical data, incorporating climate models, and utilizing statistical techniques. These simulations enable us to assess the likelihood and severity of future extreme events, informing decision-makers about potential vulnerabilities.

The Intersection of Physical and Transition Risks

Physical Risks: Assessing Direct Impacts

Our comprehensive climate risk models now account for physical risks, evaluating the direct impact of climate change on assets and infrastructure. This involves integrating data on temperature changes, precipitation patterns, and sea-level rise with vulnerability assessments for specific industries or regions. The models help quantify the potential damages and disruptions, allowing companies to prioritize adaptation strategies based on the severity and likelihood of various physical risks.

Transition Risks: Navigating Policy Shifts

As global policies shift towards a low-carbon economy, companies must navigate transition risks associated with regulatory changes and technological advancements. Climate risk modeling in this context involves analyzing policy scenarios, economic indicators, and technological trends. Machine learning algorithms can assess the impact of potential policy shifts on industries, helping businesses adapt proactively and avoid financial consequences.

Sector-specific Insights

Energy Sector: A Renewable Revolution

In the energy sector, a transition to renewable energy sources is gaining momentum. Climate risk modeling predicts a 40% increase in renewable energy investments by 2025. This projection is based on modeling scenarios that consider factors such as government policies, technological advancements, and market dynamics. By incorporating these variables, the models provide insights into the potential growth and risks associated with the renewable energy sector.

Agriculture: Adapting to Changing Growing Conditions

Changing precipitation patterns and temperature extremes pose challenges for agriculture. Climate risk modeling in agriculture involves integrating climate data, soil information, and crop models. By simulating different climate scenarios, these models help farmers and policymakers understand potential changes in growing conditions, informing decisions on crop selection, irrigation practices, and land management.

Collaborative Initiatives and Future Roadmap

Collaboration lies at the heart of effective climate risk modeling. By engaging with climate scientists, governments, and industry experts, we ensure the continuous improvement and relevance of our models. Looking forward, our roadmap includes real-time data integration, machine learning advancements, and targeted scenario planning to address emerging climate risks proactively. This collaborative approach ensures that our models remain dynamic, incorporating the latest scientific insights and technological advancements.

In conclusion, the numbers and percentages associated with climate risk modeling tell a compelling story. As we face the realities of a changing climate, the insights derived from robust modeling become invaluable in steering us toward a sustainable and resilient future. Embracing these numbers empowers us to make informed decisions, safeguard our communities, and collectively work towards mitigating the impacts of climate change. Climate risk modeling, with its advanced techniques and collaborative efforts, stands as a beacon of hope in our journey towards a more sustainable and resilient world.

Kundan Kotte

Beyond Correlation: Using Casual Inference to Financial Insights Unlock

In the realm of quantitative finance, where the relentless pursuit of data-driven insights is paramount, correlation has long held a position of prominence. Financial analysts and investors alike have scrutinized historical data, searching for patterns and relationships between assets, markets, and economic indicators. However, the limitations of correlation are well-documented; just because two variables tend to move together does not guarantee that one causes the other. Understanding true causality is essential for making informed investment decisions and assessing the efficacy of financial policies.

This is where causal inference enters the picture. Causal inference is a branch of statistics concerned with rigorously determining cause-and-effect relationships between variables. While traditional statistical methods may excel at identifying associations, causal inference aims to uncover the underlying mechanisms that drive changes in financial systems. This shift from simple correlation to causation represents a significant methodological leap in quantitative finance.

Consider, for example, the task of evaluating a new trading strategy. A positive correlation between the strategy's deployment and increased returns might be observed. Yet, correlation alone cannot determine whether the strategy's implementation directly caused the improved performance or if an external factor, such as a broader market upswing, was the true driver. Causal inference techniques offer a way to disentangle these effects.

One powerful approach for establishing causality is the use of experiments. In an ideal scenario, a randomly selected group of traders may be assigned the new trading strategy, with a control group continuing their existing methods. If the experimental group demonstrates statistically significant outperformance relative to the control, a causal link between the strategy and returns becomes much more plausible. Of course, true experiments with live investments can be complex and logistically difficult, but even imperfect or "natural" experiments can be valuable if done carefully.

When direct experimentation is infeasible, econometric techniques come into play. Methods such as instrumental variables, propensity score matching, and difference-in-differences seek to mimic experimental conditions using observational data. These techniques attempt to isolate the impact of a particular variable while controlling for confounding factors. They offer a vital toolkit for quantitative analysts striving to understand the underlying causes of market movements.

The applications of causal inference in quantitative finance are wide-ranging. Portfolio managers can use it to discern whether certain asset classes or factors truly contribute to risk diversification or if they're merely correlated with other risky holdings. Regulators can leverage causal inference to assess the real-world impact of financial policies, ensuring that interventions achieve the intended effect. Moreover, causal inference tools can be applied to analyze marketing effectiveness and disentangle the true drivers of customer acquisition or churn.

While causal inference brings significant benefits to quantitative finance, it's important to acknowledge its challenges. Financial data is frequently observational, limiting the ability to conduct perfectly controlled experiments. The assumptions underlying various causal techniques must be carefully examined in the context of complex financial systems. Nevertheless, the potential rewards of this approach are substantial.

The integration of causal inference into quantitative finance marks a shift towards a more rigorous and insightful understanding of financial markets. By moving beyond the limitations of correlation and focusing on true causal relationships, investors and policymakers alike can gain the clarity needed to make better decisions in a dynamic and often unpredictable financial landscape.

Robin Li

The Application Of Mathematics In Finance

The application of mathematics in the finance industry is widespread and essential. Mathematical models provide financial professionals with a common language and toolset to model complex financial phenomena such as option pricing, portfolio optimization, and risk management. Investors use mathematical models to quantify the risks and rewards associated with various investment strategies. Calculus is one of the most widely used mathematical tools in finance. It is essential for pricing financial derivatives such as options, futures, and swaps, which are contracts that derive their value from an underlying asset's price. Differential equations and stochastic calculus are also widely used in finance, particularly in the analysis of financial time series data such as stock prices and interest rates. Linear algebra is another critical mathematical tool used in finance. It is used in portfolio optimization to calculate the optimal weights for a portfolio of assets, given their expected returns, volatility, and correlation.

Other mathematical tools used in finance include probability theory, statistics, and numerical methods. Probability theory and statistics are used to model the uncertainty and randomness of financial phenomena, such as stock prices and interest rates. Numerical methods, such as Monte Carlo simulation and optimization algorithms, are used to solve complex financial problems and estimate the parameters of financial models. One powerful statistical method with numerous applications in finance is the Markov chain Monte Carlo (MCMC). This semester, we are using MCMC and some economic indicators to predict loan delinquency. MCMC is a computational technique used to approximate complex distributions by constructing a Markov chain that converges to the desired distribution. MCMC methods are primarily used to estimate the parameters of financial models, including option pricing, risk management, and portfolio optimization. They can be used to estimate the expected returns of various financial assets and build optimal portfolios based on these estimates. Overall, the use of mathematics in finance is critical for understanding and quantifying complex financial phenomena.

NC State University is an excellent option for students interested in working in the finance industry or starting their own firms. The university's emphasis on hands-on and experiential learning, as well as its robust research programs, provide students with opportunities to gain real-world experience and collaborate on forward-thinking projects in finance.

Xinqian Li

Bitcoin Futures Volatility Surface Forecasting

In the ever-evolving landscape of cryptocurrency, Bitcoin stands as the first and most renowned digital currency, embodying a frontier of financial innovation and speculative investment. At North Carolina State University's Master of Financial Mathematics program, our academic endeavors aim not only to understand the intricacies of financial markets but also to explore the cutting-edge methodologies that define the future of trading and investment strategies. This article delves into a recent project where we harnessed the power of Bloomberg data to forecast the volatility surface of Bitcoin pricing.

The project embarked on a journey to construct a predictive model capable of forecasting Bitcoin's future price movements. Utilizing a dataset meticulously compiled from Bloomberg terminals, we applied a blend of quantitative techniques and machine learning models to unveil patterns hidden within the cryptocurrency's past performance. The goal was not just to predict the future but to understand the dynamics that drive Bitcoin's price fluctuations, offering insights that extend beyond mere speculation.

Our methodology integrated time series analysis with advanced machine learning algorithms, such as Long Short-Term Memory (LSTM) networks, known for their efficacy in capturing temporal dependencies in volatile sequences. The initial phase involved a rigorous exploratory data analysis (EDA), where we dissected the dataset to identify trends, seasonality, and outliers. This foundational understanding informed the subsequent model development, ensuring our forecasts were grounded in a comprehensive analysis of Bitcoin's historical data.

This project not only advanced my understanding of financial engineering but also underscored the importance of adaptability and continuous learning in a field as dynamic as quantitative finance. The ability to translate complex data into actionable insights is paramount, and the experiences at NC State have been pivotal in equipping me with the tools to navigate the challenges that lie ahead.

In conclusion, the Bitcoin forecasting project represents a confluence of academic curiosity and practical application. It embodies the spirit of inquiry that defines the Master of Financial Mathematics program at NC State, offering a glimpse into the future of finance where data, technology, and quantitative analysis converge to inform decision-making in uncertain markets.

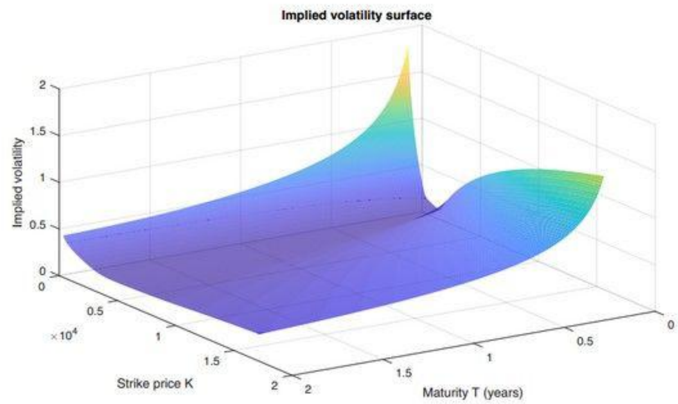
Prithwish Maiti

Volatility Surface Reconstruction

A major point of discussion with Black-Scholes pricing is the role of volatility. The question comes when the Black-Scholes formula is inverted on the market's option prices, which produces an interesting phenomenon known as the implied volatility smile, smirk, or skew. The implied volatility suggests that asset prices are more complex than geometric Brownian motion and the Black-Scholes' parameter σ(volatility) need to be dynamic.

The dissimilarity of the real distribution for log(S_t) and the normal distribution produces implied volatilities that change with strike and maturity. The goal of vol surface construction is to create a well-behaved vol surface defined for all positive K and T of interest - finding σ (K,T). To do this one can use historical option prices such as a price grid for recently traded options combined with other sources of information such as yield curves and dividend payouts.

A vol surface can be used for pricing vanilla and exotic options, which constitutes an important area in hedging and risk management. One can also extend the problem into finding a vol surface's time dependence. Having a surface that evolves appropriately in time is important for pricing some exotic options such as Napoleons and cliques.



Some properties of volatility(vol) surface found from the literature are:

- The vol surface is non-flat and has both term structure (T-dependence) and smile (K-dependence).
- The vol surface displays high autocorrelation and mean reversion.
- Variations in vol surfaces can be explained by a small number of principal components including: The overall shift, the slope, and the curvature of the vol surface.
- Changes in the vol surface cannot be exclusively described through changes in underlying.
- Global changes in the vol surface are negatively correlated with changes in the underlying.
- Relative movements within the vol surface have little correlation with the underlying.

There are rules of thumb that attempt to describe the short-term evolution of vol surfaces in simple ways. The general assumptions are that the underlying follows a geometric Brownian motion with deterministic dividends and interest rates and that the volatility follows a diffusion process. They further assume that the process of the square of the implied volatility is a linear combination of Wiener processes and a drift term.

1. Sticky strike: In the sticky strike rule, the implied volatility (σ) does not change with the underlying. In one version, σ varies only with K and T. In another version, it is independent of S_t but possibly dependent on other stochastic variables.

2. Sticky delta: In the most basic form of the sticky delta rule, σ is assumed to be a deterministic function of K/S, (moneyness) and T-t, where t is the current time. Another version, sometimes used by traders, is the relative sticky delta rule which specifies that $\sigma_{K,T}(S,t) - \sigma_{F,T}(S,t)$ only a function of K/F_T d T-t, where F_T the value of a future or forward contract on S_T h delivery at T.

3. Sticky square root of time: The square root of time rule has sometimes been used by traders. One version of it says that $\frac{\sigma_{K,T}(S,t)}{\sigma_{F,T}(S,t)}$ should only be a function of $\frac{ln(\frac{K}{F})}{\sqrt{T-t}}$ The square root of time rules can be generally consistent with no-arbitrage condition.

One of the prominent volatility reconstruction methods uses local volatility. Using this model for the underlying, the local volatilities can be found for all call options C(K,T) using Dupire's equation.

Sagar Prasad

Exploring Sectoral Option Pricing Dynamics: Insights From Heston And Black-Scholes Models

Introduction:
In the dynamic realm of quantitative finance, option pricing remains a cornerstone for investors seeking to navigate the complexities of financial markets. While traditional models like the Black-Scholes model provide a foundation, the integration of more sophisticated models such as the Heston model, coupled with Monte Carlo simulation, offers a gateway to a deeper understanding of option pricing dynamics. In this exploration, we venture beyond theoretical boundaries to assess the performance of these models across diverse sectors, including technology, finance, and healthcare, shedding light on the nuanced interplay between market forces and option pricing.

During the spring semester, my team and I embarked on a project focusing on elucidating option pricing dynamics across various sectors, primarily utilizing the Heston and Black-Scholes models. Recognizing the significance of sectoral dynamics in shaping market behavior, we aimed to unravel the intricate interplay between sector-specific factors and option pricing. Through meticulous research and analysis, we sought to enhance our understanding of how different sectors influence option pricing behavior and identify opportunities for optimizing trading strategies.

Navigating Sectoral Dynamics:
The landscape of financial markets is heterogeneous, with each sector exhibiting unique characteristics and dynamics. From the rapid innovation cycles of technology firms to the regulatory environment impacting financial institutions and the innovation-driven dynamics of healthcare companies, understanding sectoral nuances is paramount in accurately assessing option pricing behavior. Our project aimed to discern patterns, trends, and anomalies that influence option pricing dynamics, with a primary focus on the application of the Heston and Black-Scholes models.

Monte Carlo Simulation Across Sectors:
Central to our project was the application of Monte Carlo simulation to model option pricing dynamics across diverse sectors, leveraging the Heston and Black-Scholes frameworks. By incorporating sector-specific volatilities, market sentiment, and macroeconomic factors, we aimed to capture the complex interactions driving option pricing dynamics. Through iterative simulation and validation, we sought to gain insights into sector-specific volatility patterns, risk profiles, and pricing dynamics, allowing us to refine our models and better capture the intricacies of option pricing behavior.

Performance Evaluation:
Another critical aspect of our project involved evaluating the performance of the Heston and Black-Scholes models across different sectors. By benchmarking option price estimates against historical data and market prices, we assessed the efficacy and robustness of these models. Through rigorous analysis, we aimed to identify sectoral nuances and refine our methodologies to better capture the intricacies of option pricing dynamics. By comparing model performance across sectors, we also sought to identify areas of relative strengths and weaknesses, providing valuable insights for investors seeking to optimize their option trading strategies across different industries.

Insights and Implications:
The findings from our sectoral analysis, anchored by the Heston and Black-Scholes models, offered valuable insights and implications for market participants. By unraveling the unique drivers of option pricing within each sector, we empowered investors to make informed decisions and capitalize on sector-specific opportunities. Our exploration highlighted the importance of incorporating sophisticated pricing models like Heston alongside traditional frameworks like Black-Scholes, particularly when navigating complex sectoral dynamics.

Conclusion:
As we concluded our project, we emerged with a deeper appreciation for the nuances and complexities that shape financial markets across sectors. Through the application of the Heston and Black-Scholes models in conjunction with Monte Carlo simulation, we transcended traditional boundaries and uncovered sector-specific insights that redefined our understanding of option pricing. Armed with these insights, investors can navigate the diverse landscape of financial sectors with confidence, seizing opportunities and maximizing returns in an ever-evolving market environment. By continually refining our models and adapting to sectoral dynamics, we can stay ahead of the curve and unlock new avenues for growth and profitability in the world of options trading.

Zhao Qu

The Imagination of the Market: The Fusion of Human Intuition and AI Analysis

In the vast realm of market exploration, human imagination and creativity demonstrate their irreplaceable value. The market is not just an aggregation of countless individual decisions; it is a grand stage for human imagination. Analyzing market changes and predicting future trends rely not only on existing data and information but also on profound insight and innovative thinking. The inherent limitations of historical data mean that relying solely on the past is insufficient to discern the future.

As traders immerse themselves in market fluctuations, they are not just analyzing numbers and charts; they are engaging in a deep mental dialogue with the market. This conversation transcends linguistic limitations, revolving around patterns, trends, and those indescribable intuitions. Traders' intuition, at times, seems like an intangible connection with the market, capturing deep signals that data alone cannot reveal.

Advancements in quantitative analysis and artificial intelligence (AI) have brought revolutionary changes to market analysis. These technologies can swiftly process vast amounts of data, encompassing everything from fundamental information to macroeconomic data, to complex statistical analysis. These tools offer traders unprecedented volumes of information and perspectives, but can they determine market directions? The answer is no.

The essence of the market is far more complex than data and algorithms. It reflects human behavior, a composite of fear, greed, hope, and disappointment. These factors constitute the market's psychological aspect, which is difficult for any algorithm to fully capture. Trading, at its core, is a psychological game involving awareness of one's actions, speculation about opponents' moves, and inferences about opponents' perceptions of one's strategies. In such a game, intuition and creativity are indispensable weapons.

The role of imagination in the market is significant. It allows traders to foresee possible future scenarios, even those that have never occurred before. Looking back at history, many significant market turning points happened when most people failed to anticipate them. For instance, who could have imagined that oil prices would fall into negative territory? Such events remind us that the market is always full of uncertainties, and it is this uncertainty that provides a stage for imagination and creativity.

In the future, the most successful traders might not be those with the most advanced algorithms, but those who can combine AI's computational power with human intuition, insight, and creativity. This fusion not only enhances the understanding of market dynamics but also provides unique insights and solutions when facing unprecedented market conditions.

In summary, the market is a complex system, not merely a collection of numbers and charts but a stage for human emotions, psychology, and imagination. In this arena, AI and quantitative tools are undoubtedly powerful assistants, but the human brain's role in predicting the unknown, dealing with uncertainty, and exercising creativity is irreplaceable. The market leaders of the future will be those pioneers who can integrate the power of data with the depth of human intuitive insight.

Kavya Regulagedda

The New York Community Bank Crisis and the Lifesaving Investment: A Tale of Financial Resilience

New York Community Bank's (NYCB) troubles first came to light in January 2024 when the bank revealed signs of troubles in its commercial real estate books that resulted in a dividend cut. The disclosure of the bank's "material weaknesses" in lean assessments has resulted in credit downgrades by both Moody's and Fitch which leaves them currently at below investment grade.

The bank's concentration in loans for rent-stabilized buildings in New York City has particularly been a matter of concern for the bank's investors. The concentration of their portfolio in these types of multifamily residential property loans with these new rent regulations has exposed NYCB to risks as a result of rising interest rates.

The bank bought mortgage lender Flagstar Bankcorp and shortly after, parts of Signature Bank which was seized by regulators during a bank run, nearly doubling its size. Since these deals were made, NYCB went from a relatively small lender that was focused on niche commercial real estate into a category of big diversified commercial banks. Having crossed $100 billion in assets the company is now subject to additional regulations and scrutiny.

NYCB then needed to modify its balance sheet to accommodate the changes and even made changes to its management with the former head of Flagstar now executive chairman who said he was considering selling assets and shrinking the bank.

The bank considered selling assets outside of core businesses, raising capital and even issuance of instruments such as Credit Risk Transfers however finding potential buyers for such products poses a challenge.

While NYCB reported no hold to maturity securities in its portfolios which were a major cause of the downfall of the Silicon Valley Bank, NYCB also said that nearly three-quarters of its deposits were insured or collateralized.

Another major issue for the bank is their reported material weaknesses in company's internal controls related to internal loan review due to ineffective oversight and poor risk management and monitoring activities. Failing assets that were bought when they acquired Signature Bank have added to the problem. This naturally has been a cause of concern for investors who are pulling out investments resulting in NYCB's need to raise capital.

Ultimately, it was their inability to handle the new regulations associated with their growth as well as the concentration in multifamily properties subject to rent-stabilized regulations that created this pressure. Silicon Valley Bank as well as Signature and First Republic Bank both faced similar circumstances as a result of their quick expansions.

In their effort to raise capital, NYCB was able to receive over a billion dollars from a group of investors including Donald Trump's former Treasury Secretary in an attempt to increase confidence. These investors have agreed to buy common and convertible preferred stock in NYCB. This infusion of money was to steady and build confidence in the bank as a response to the fear of potential losses in real estate.

Yug Sharma

Deciphering Financial Markets: A Team-Based Exploration into Machine Learning for Predicting Market Volatility

Introduction:
Market volatility, a captivating puzzle for financial analysts, has drawn our team of financial mathematics students into an exhilarating exploration. Leveraging machine learning models like ARIMA, ARIMAX, SARIMAX, GARCH, and their hybrids, we aimed to unravel the complexities of predicting the volatility index. In this collaborative venture, we embark on a journey that begins with data collection and preprocessing, followed by the development of machine learning models in Python. Our goal was to visualize the results through informative graphs and subsequently analyze and compare the effectiveness of each method.

Data Collection and Preprocessing:
Our journey commenced with meticulous data collection, sourcing historical volatility index data from reliable financial databases. Collaboratively, we worked on preprocessing the data to ensure its quality and suitability for machine learning applications. This step included handling missing values, normalizing data, and exploring potential external variables that could enhance the predictive capabilities of our models. We utilized python libraries like numpy and pandas to effectively pre-preprocess data and ensure the data is ready for analysis.

Developing Machine Learning Models in Python:
Collaboratively wielding the power of Python, we implemented a suite of machine-learning models to forecast market volatility. The foundational ARIMA, ARIMAX, and SARIMAX models were developed collaboratively, providing insights into inherent patterns and seasonality. Transitioning into machine learning, we collectively implemented the versatile GARCH model, recognizing its ability to capture volatility clustering and adapt to changing market conditions. Hybrid models, including ARIMA-GARCH and SARIMAX-GARCH, were collaboratively fine-tuned to leverage both statistical and machine learning strengths.

Visualizing Graphs:
Our collaborative approach extended to visualizing the results through informative graphs. Utilizing Python libraries like Matplotlib and Seaborn, we collectively created visual representations of predicted versus actual volatility, showcasing trends, shifts, and extreme events. Collaborative discussions guided the refinement of visualizations to ensure clarity and interpretability.

Analyzing Model Performance:
We then delved into a comprehensive analysis of model performance. By evaluating metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), we assessed the accuracy of each model. Collaborative discussions and comparisons allowed us to draw insights into the strengths and limitations of each approach, guiding us toward a deeper understanding of predictive capabilities in the context of market volatility. Additionally, we performed Backward feature selection to enhance the accuracy of the model.
In this collaborative journey, we have not only navigated the intricacies of machine learning modeling but have also forged a collective understanding of the symbiotic relationship between mathematical models and financial market dynamics. As we analyzed our results, we anticipated uncovering valuable insights that would further contribute to the evolving landscape of predicting market volatility.

Validation and Practical Insights: A Team Effort
Validation of our models became a pivotal phase, involving a collaborative comparison of predicted and actual volatility using historical data. The models, developed through joint efforts, exhibited commendable accuracy in capturing trends, shifts, and extreme events, offering valuable insights for real-world applications. Beyond the technical aspects, our collaborative project emphasized the importance of a holistic understanding of financial markets, where the collective expertise complemented quantitative models and enriched the overall insights.

Future Horizons: A Collective Vision for Integration
As we collectively reflect on this journey, the fusion of traditional models with cutting-edge machine-learning techniques emerges as a potent combination. Looking ahead, our exploration into predicting market volatility is poised to advance further with the integration of deep learning and neural network models. The dynamic nature of financial markets necessitates a commitment to ongoing innovation and adaptation.

Conclusion: A Glimpse into the Nexus of Mathematics and Finance – Together
In conclusion, our collaborative venture into predicting market volatility as financial mathematics students has been both enlightening and rewarding. This project has not only refined our analytical skills but has deepened our appreciation for the symbiotic relationship between mathematical models and the ever-evolving reality of financial markets. As our collaborative journey unfolds, we carry with us invaluable skills, a heightened understanding of market dynamics, and a shared curiosity to explore the untapped possibilities at the intersection of mathematics and finance.

Shirley Shi

Understanding the Role of a Risk Analyst in Finance

In the complex and dynamic world of finance, the role of a risk analyst emerges as both crucial and challenging, tasked with navigating the multifaceted terrain of financial risks. These professionals, armed with statistical tools, predictive models, and a profound understanding of financial dynamics, play a pivotal role in ensuring the stability and profitability of financial institutions. I'm writing this essay to discuss the types of financial risks, the day-to-day responsibilities of risk analysts, and the models they employ to manage and mitigate these risks effectively.

Financial risk can be broadly classified into several categories, each with its own set of challenges and implications for financial institutions. Market risk, or systematic risk, pertains to potential losses due to factors affecting the overall financial market, including fluctuations in interest rates, stock prices, currencies, and commodities. Credit risk involves the possibility of a borrower failing to meet their financial obligations, posing a significant concern for lenders and credit institutions. Liquidity risk highlights the difficulty in converting assets into cash without significant loss, affecting an entity's ability to meet short-term obligations. Operational risk arises from internal failures, such as system breakdowns or human error, which can lead to financial losses or damage to an institution's reputation. Lastly, legal and regulatory risks involve the potential for losses due to non-compliance with laws or regulations, underscoring the importance of adherence to legal standards and regulatory frameworks.

Within this risk-laden environment, risk analysts‘ primary responsibilities are identifying and assessing the potential impact of risks, which requires a keen analytical eye and a proactive approach to spotting emerging threats. Through rigorous data analysis, they forecast risk exposure and evaluate the financial implications of various risk scenarios. Developing and implementing models to quantify these risks is another critical aspect of risk analysts' responsibility. This aspect enables institutions to strategize effectively, providing a clear roadmap for navigating potential pitfalls. This seamless integration between strategic planning and risk quantification is crucial. Continuous monitoring of the risk landscape, coupled with regular reporting to stakeholders, ensures that risk management strategies remain relevant and responsive to changing market conditions. Collaborating with management, risk analysts contribute to strategic planning efforts aimed at minimizing risk while optimizing financial performance.

The methodologies employed by risk analysts to assess and mitigate risks are as diverse as the risks themselves, encompassing a range of sophisticated tools each designed to tackle specific areas of vulnerability. Among these, the Value at Risk (VaR) model stands out as a fundamental tool. It estimates the maximum potential loss of an investment portfolio over a specified timeframe and confidence level, serving as a cornerstone for financial risk assessment. Building on this, stress testing represents another crucial technique. It simulates extreme market conditions to test the resilience of financial positions, offering insights into potential impacts on an institution's stability under adverse scenarios. Further enriching the toolkit, credit risk models like the Merton model evaluate the probability of borrower default, leveraging financial indicators and credit ratings to anticipate and mitigate credit-related issues. Lastly, operational risk models quantify losses stemming from failed internal processes or external events. Approaches such as the loss distribution approach (LDA) play a pivotal role in managing operational risks, rounding out the comprehensive suite of methodologies at the disposal of risk analysts.

In essence, risk analysts serve as the guardians of financial institutions, diligently working to protect these entities from the myriad of risks that threaten their operations and financial health. Through their expertise in financial principles, statistical analysis, and risk management models, they play an indispensable role in maintaining the integrity and stability of the financial system. The challenges they face are significant, given the unpredictable nature of financial markets and the ever-evolving regulatory landscape. Yet, the critical nature of their work ensures the resilience of financial institutions against the uncertainties that characterize the financial world, highlighting the indispensable role of risk analysts in the contemporary financial landscape.

Aman Syed

Harnessing Neural Networks for Alpha Generation in Index Rebalance Trading

Through this project, I embarked on a journey to create a comprehensive trading strategy that leverages the power of machine learning, particularly neural networks, to navigate the complex world of index rebalancing and its impact on stock prices. By taking advantage of the arbitrage opportunities in index rebalance trading, I focused on building a strategy that targets alpha generation by buying stocks entering major indices and selling those exiting them. The project involved simulating various rebalance scenarios, applying neural network models, and taking short-term positions in constituents before review.

This work aligns closely with my future career goals, providing me with critical insights into how index rebalancing affects financial markets and how indices operate. As index investing continues to gain prominence, this knowledge is indispensable. Additionally, my work in neural networks, portfolio management, and programming has equipped me with essential skills for a future in quantitative finance. Leading this project also helped me grow as a leader, preparing me for managerial challenges down the line.

My specific contributions to the project included spearheading the team, ensuring alignment with our goals, and maintaining a steady course throughout. I took the initiative to conceptualize the project and conducted thorough background research to provide a solid foundation for our work. I proofread, cleaned, and analysed the data, optimized the Long Short-Term Memory (LSTM) model for better performance and accuracy, and guided the team in crafting and delivering an impactful presentation.

Throughout the project, I honed my technical expertise in neural networks, portfolio management, market making, and Python programming. This journey not only strengthened my machine learning skills but also deepened my understanding of index investing. My presentation and communication skills saw significant improvement, thanks to multiple practice sessions and the final virtual presentation. This experience solidified my leadership abilities and paved the way for tackling more complex responsibilities in the future.

The most formidable challenge in data preparation was gathering the list of stocks added or deleted from major indices. While exploring sources such as Bloomberg and Yahoo Finance, I ultimately turned to S&P Index Rebalance official press releases, which involved meticulous manual searching. Once the stock tickers were obtained, I sourced input data from yfinance and created functions for each data point.

I regard the project outcomes as successful and impactful. We effectively predicted price changes in stocks added after index rebalance announcements, with a minor discrepancy of 0.58% between our predictions and actual changes. This achievement lays the groundwork for developing trading strategies that capitalize on market movements around index rebalances. The project also enriched my understanding of market dynamics and fine-tuned my skills in quantitative finance.

In closing, this project has been an enlightening experience with immense real-world applications. It deepened my grasp of index investing and its profound influence on market movements—a crucial asset in the world of finance. Harnessing neural networks fortified my foundation in quantitative finance, while my enhanced presentation and leadership skills prepare me for a successful career in the field.

Yuqi Wu
Career Goal Exploration

My professional journey led me to explore Silicon Valley Bank (SVB) after hearing Mr. Matthew Puksta, an eFX Trader with SVB, discussing his career. We share a background in Mechanical Engineering and a desire to avoid high-pressure work settings, which piqued my interest in the bank, especially after the organization’s transition into First Citizens Bank.

A role that caught my attention was the Financial Analyst - BSM CCAR position at First Citizens Bank. This position focuses on Net Interest Income forecasting and CCAR stress testing, areas that align with my affinity for the theoretical and mathematical aspects of finance. The challenge of improving predictive models appeals to me, although I recognize it requires a rigorous approach.

This role calls for proficiency in data analysis and reporting, which means I need to further develop my skills through practical project work experience. Since the position also requires three years of financial experience, I'm setting my sights on entry-level opportunities to build a foundation for my career aspirations.

First Citizens Bank's positive work culture, as shared by Mr. Puksta, and the geographic location of their job offerings are particularly compelling to me, fitting well with my career objectives and personal life goals. To advance my chances of securing a position, I intend to connect with Mr. Puksta on LinkedIn. I'm eager to learn from his experience and gain insight into which experiences and projects could best position me for a similar role. This conversation will be a step toward aligning my first job with my long-term career vision in the finance sector.

Networking with alumni like Mr. Puksta is an essential part of my strategy, offering guidance as I navigate my path in finance.

Hongyi Xia

Bayesian on Credit Risk

Description

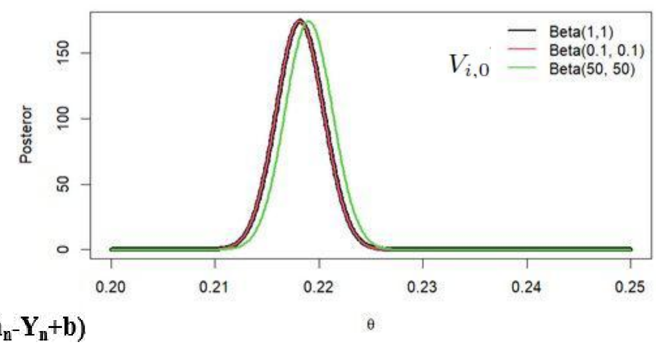
The following is a credit risk dataset found at Kaggle. The variables we are interested in include Historical default (X; Binary indicator), Loan status (Y; Outcome variable), and Home ownership (Z; Some other variable). We have a large sample for this dataset with n=32581. The primary motivation of this study is to gain a better understanding of the posterior and likelihood based on Loan status variable. We are also interested in finding out whether there is a relationship between this posterior and the other 2 variables, Historical default and Home ownership.

Likelihood, Prior, and Posterior

Loan status variable is a binary variable that gives either a 0 or 1, with 0 indicating a non-default status while 1 indicating a default status. Considering we have n number of independent observations of loans, the outcome variable Y will give us the number of default loans among the n number of independent observations of loans. Hence, the likelihood will follow **$Y|\theta \sim$ Binomial(n, θ)**. For the conjugate prior θ, we can consider an initial uninformative prior with **Beta(a=1,b=1)** given there is little other relevant information on θ. Hence, we will end up with a posterior **Beta(Y+a, n-Y+b)** based on the likelihood and prior.

Posterior Distribution and Sensitivity Analysis

In the figure below, the posterior is plotted with various priors, including Beta(1,1), Beta(0.1,0.1), Beta(50,50). There is not much variation in the distribution of posterior based on different prior. We conclude that the posterior is not sensitive to the prior.



Whether the Distribution of Loan Status is Different for the Two Levels of Historical Default

For all the observations with Historical default equal to ‘Yes’, we save them as ‘CreditY’ dataset and the likelihood of Loan status will follow $\mathbf{Y_y|\theta_y \sim Binomial(n_y, \theta_y)}$

For an uninformative prior with **Beta(a=1,b=1)**, the posterior is $\mathbf{Beta(Y_y{+}a,\ n_y{-}Y_y{+}b)}$.

For all the observations with Historical default equal to ‘No’, we save them as ‘CreditN’ dataset and the likelihood of Loan status will follow $\mathbf{Yn|\theta_n \sim Binomial(n_n, \theta_n)}$.

For an uninformative prior with **Beta(a=1,b=1)**, the posterior is $\mathbf{Beta(Y_n{+}a,\ n_n{-}Y_n{+}b)}$

H_0 : The distribution of Loan status is no different for the 2 levels of Historical default $(\theta_y \leq \theta_n)$.

H_a : The distribution of Loan status is different for the 2 levels of Historical default $(\theta_y > \theta_n)$.

We simulate $\theta_y|Y_y$ and $\theta_n Y_n$ with Monte Carlo simulation based on the respective posterior distribution. Given $P(\theta_y > \theta_n \mid Y_y, Y_n) = 1$ as we compare the pair of simulated results respectively, we conclude that the distribution of Loan status is indeed different for the 2 levels of Historical default. It can then be justified that one’s Historical default will have an impact on one’s current Loan status.

Whether the Distribution of Loan Status is different for the Various Levels of Home Ownership

For the Home ownership variables, we denote "RENT" as 1, "OWN" as 2, "MORTGAGE" as 3, and "OTHER" as 4. After separating the datasets into 4 with respect to unique values of Home ownership. We repeat the same steps in part 5 to get various posterior $\mathbf{Beta(Y_i{+}a,\ n_i{-}Y_i{+}b)}$, where i = 1,2,3,4. We simulate $\theta_i|Y_i$ with Monte Carlo simulation based on the respective posterior distribution for i = 1,2,3,4. As we compare the various combination pairs of simulated results, we have:

$$P(\theta_1 > \theta_2 \mid Y_1, Y_2) = 1,\ P(\theta_1 > \theta_3 \mid Y_1, Y_3) = 1,\ P(\theta_1 > \theta_4 \mid Y_1, Y_4) = 0.544166,$$
$$P(\theta_3 > \theta_2 \mid Y_3, Y_2) = 1,\ P(\theta_4 > \theta_2 \mid Y_4, Y_2) = 1,\ P(\theta_4 > \theta_3 \mid Y_4, Y_3) = 1$$

We conclude that the distribution of Loan status is no different between Home ownership of "RENT" and Home ownership of "OTHER". The distribution of Loan status is different between any other pairs of unique values of Home ownership. To a very large extent, one’s Home ownership status will have an impact on one’s current Loan status.

Prachi Yadav

Charting the Path: Financial Mathematics to Quantitative Trading

In the fast-paced finance world, the role of a quant trader is uniquely appealing due to its mix of math skills and strategic market understanding. My path to this career has been influenced by rigorous academic work, valuable insights from industry professionals, and the exciting prospect of a summer internship. As I progress through NC State's Financial Mathematics program, I'm strategically preparing for a career in quantitative trading.

Choosing to study Financial Mathematics at NC State was driven by my ambition to become a quant trader. The program's in-depth curriculum, which includes stochastic calculus, options and pricing, and fixed income, has given me a thorough grasp of the mathematical and computational techniques essential for quantitative trading. This strong academic base is key for analyzing market data and creating advanced trading algorithms.

Talking with industry experts has been a critical part of my journey, enriching my understanding of the quant trading field and helping refine my career goals. The main lessons I've learned are the value of solid math skills, the need to quickly adjust to market shifts, and the importance of ongoing learning and professional growth. These insights have guided my academic focus and preparation for the workforce.

An upcoming summer internship at an investment financial firm marks the next significant step in my career. This internship is an excellent chance to put what I've learned into practice, challenging me to develop trading strategies, analyze market data, and contribute to the firm's operations. This experience is also a great way to network, allowing me to connect with experienced professionals and learn from them.

Looking ahead, my aim is to continue advancing my career in quantitative trading. I plan to keep up with new technologies in trading algorithms and machine learning, further hone my programming skills, and cultivate a strong professional network. I'm committed to ongoing learning through workshops and online courses to ensure my skills remain sharp and up-to-date.

I also understand the importance of communication and teamwork in this collaborative field. I'm working on these soft skills by engaging in group projects and presentations, both in and outside of school.

Becoming a quant trader is both challenging and rewarding. My time at NC State, combined with the insights from industry interviews and my upcoming internship, has laid a solid foundation for my career. I'm looking forward to facing real-world trading challenges and contributing to the field's growth.

This journey is about more than just reaching a goal. It's about the learning and growth that happens along the way. By embracing challenges, committing to constant improvement, and making the most of the opportunities offered by NC State's Financial Mathematics program, I'm confident in my ability to reach my career objectives and make a meaningful impact in quantitative trading.

Zhijiang Yang

Advancing Collar Strategy In Volatile Markets

Executive Summary:
This quarter, our team conducted an in-depth analysis of the Collar Strategy's performance across different market cycles, with a particular focus on the periods before, during, and after the COVID-19 pandemic. This strategic review aimed to assess the resilience and effectiveness of the Collar Strategy under varying market conditions, enabling us to refine our approach to risk management and portfolio optimization in the face of volatility.

Market Review:
The unprecedented market volatility triggered by the COVID-19 pandemic has put traditional investment strategies to the test. The Collar Strategy, known for its potential to hedge against significant market downturns while allowing participation in upward trends, has been under scrutiny for its adaptability and performance across these distinct phases.

Collar Strategy Performance Analysis:
Our analysis began by segmenting the market into three distinct periods: pre-pandemic, during the pandemic, and the ongoing recovery phase. We evaluated the performance of the Collar Strategy by closely examining the relationship between the selected put and call options across these periods, considering factors such as strike prices, expiration dates, and the underlying assets' volatility.

1. Pre-Pandemic Performance: In a relatively stable market environment, the Collar Strategy provided a modest cushion against minor market fluctuations, allowing for capital preservation while slightly limiting upside potential.
2. During the Pandemic: As markets experienced sharp declines and heightened volatility, the Collar Strategy proved its worth by significantly mitigating losses compared to unprotected positions. The strategic selection of put options was critical in providing downside protection during this turbulent period.
3. Post-Pandemic Recovery: In the recovery phase, we adjusted the strategy to capture more upside potential, optimizing call option selections to balance risk and return more effectively as markets rebounded.

Strategic Implementation Adjustments:
Based on our analysis, we have made several strategic adjustments to the Collar Strategy implementation, including more dynamic selection of option strike prices and expiration dates to better align with current market conditions and outlooks. Additionally, we have increased our focus on monitoring market indicators and volatility forecasts to inform our strategy adjustments in real-time.

Performance and Risk Management:
Our comprehensive review highlighted the Collar Strategy's ability to adapt to changing market environments, providing essential protection during downturns while capturing growth in recoveries. The strategy has enhanced our portfolio's risk-adjusted returns, validating its role in our broader investment strategy.

Future Directions:
Encouraged by our findings, we plan to further explore the use of advanced analytics and machine learning to predict optimal Collar Strategy configurations under various market scenarios. This will include developing predictive models for option pricing and volatility to refine our strategy continually.

Conclusion:
Our quarter-long analysis reaffirms the Collar Strategy's value as a flexible and effective tool for navigating market cycles, particularly in volatile conditions such as those experienced during the COVID-19 pandemic. As we move forward, we remain committed to advancing our analytical capabilities to optimize the strategy further, ensuring robust portfolio performance and risk management.

Hewenbo Zhang

Bridging Finance and Technology: My Journey in Quantitative Analysis

In the rapidly evolving field of finance, the fusion of technology and quantitative analysis stands as the cornerstone of innovation and efficiency. My journey, characterized by a relentless pursuit of excellence in financial mathematics, is a testament to the transformative power of quantitative analysis in finance. As a current Master of Financial Mathematics candidate at North Carolina State University, my academic and professional experiences have been meticulously aligned with my career goals: to harness the potential of quantitative analysis to drive financial innovation and decision-making.

Academic Foundations and Research Endeavors

My academic voyage began at the Chinese University of Hong Kong Shenzhen, where I delved into the world of business administration. This foundation paved the way for my current studies, where courses such as Stochastic Calculus, Financial Risk Analysis, and Machine Learning have not only solidified my technical prowess but also sharpened my analytical thinking. It's within this rigorous academic environment that I have engaged in projects that not only challenge the status quo but also contribute to the field's body of knowledge.

One notable project was the "Stress Testing for Credit Risk Modeling" while enrolled in NC State's Financial Mathematics program. Here, I employed k-means clustering and logistic regression models to predict default probabilities, leveraging data from Fannie Mae. This project not only honed my skills in data cleaning and model evaluation but also underscored the importance of predictive analytics in managing financial risk.

Professional Insights Through Quantitative Research

My tenure as a Quantitative Researcher at FUTU in Shenzhen, China, was a pivotal moment in my career. Here, I spearheaded the mining of factors predicting the S&P 500's excess returns, introducing significant predictors into our factor pool. This endeavor not only improved our models' R-squared values but also exemplified the practical impact of quantitative research in financial decision-making.

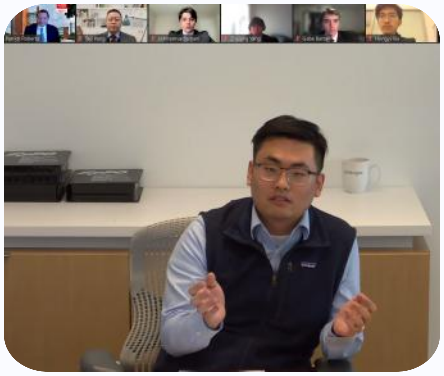
Similarly, my role as a Data Analyst at Ping An Bank allowed me to develop an event-driven strategy based on investor comments in the stock market. By refining our approach through sensitivity analysis and incorporating financial factors, we enhanced our strategy's performance, showcasing the vital role of data analysis in crafting effective investment strategies.

Looking Forward: Aspirations and Future Directions

As I continue my academic and professional journey, my goal is to further explore the intersection of finance and technology, particularly through the lens of quantitative analysis. The future of finance lies in our ability to not only interpret data but also to leverage it in predicting and shaping market dynamics. By focusing on predictive analytics, machine learning, and data-driven decision-making, I aim to contribute to the advancement of financial technologies and methodologies.

My journey, underpinned by rigorous academic training and hands-on research experience, is a stepping stone toward a future where finance is not just about numbers but about the stories they tell and the decisions they inform. In this evolving landscape, I am committed to being at the forefront, driving change, and fostering innovation in the world of finance.

Reflections



Masters of Financial Mathematics Group Photo Fall 2023

SAS Hall at NCSU's Main Campus

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