Volume 2025, Issue 1 - January 2025

Quant Quarterly

NC STATE UNIVERSITY

Financial Mathematics

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Message from the Program Director

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

The Fall 2024 semester continues to be a successful and productive period for the Financial Mathematics Graduate Program.

Our program remains highly ranked, securing the #12 spot in QuantNet's 2025 rankings of the Best Financial Engineering Programs. Notably, we are the highest-ranked program among those with 100% student placement in the U.S. For the sixth consecutive year, our overall student placement rate stands at 100%. Graduates have been successfully placed in prestigious commercial and investment banks, consulting firms, and investment funds.

This fall, we welcomed 23 new students from a diverse range of locations, including California, Iowa, Maryland, North Carolina, New Jersey, New York, and Tennessee, as well as international regions such as India, China, and Barbados. While some students joined the program directly after completing their bachelor's degree, many bring valuable professional experience, and several have pursued certifications such as CFA, FRM, and SOA (Society of Actuaries). Additionally, we are expecting five new students to join us in Spring 2025.

In Summer 2024, we partnered with industry leaders from BlackRock, First Citizens Bank, and Silicon Valley Bank to offer three summer projects for our students. The project topics included: a data-based prepayment model, model risk quantification, and risk models for interest rate derivatives and FX forwards. Over 11 weeks, students worked on these projects, culminating in final presentations on July 26.

This fall, we introduced five special-topic courses in response to evolving industry trends and student demand. These courses covered areas such as fixed income, financial data analytics, machine learning, quantitative trading, and commercial banking risk management. We will continue to offer specialized courses aligned with job market trends.

The year 2024 also marked the 20th anniversary of the Financial Mathematics Program. Over the past two decades, we have graduated approximately 400 students, who are now making an impact across the United States and around the world. To celebrate this milestone, we held an alumni reunion on October 11. The event brought together current students and many alumni, including those from other states and countries. A special highlight was the participation of Mr. Emmanuel Sanchez, a member of the program's first cohort and now Principal Weather Modeler at CarbonPool in Zurich, Switzerland. Mr. Sanchez gave a presentation on climate risk and carbon credit insurance, offering valuable insights to our students.

We are also pleased to announce the selection of our new FM Ambassadors for the Spring 2025 semester. The following students will serve as ambassadors: George Armentrout, Divija Balasankula, Ray (Haozhe) Cui, Zhen He, Dev Kewlani, Sophia (Qiao) Feng, Sanith Rao, and Jingxing Wang. Each of them will lead a student project in Spring 2025. We would also like to express our sincere gratitude to our Fall 2024 ambassadors—Aditya Jagdish Chauhan, Qinyang Huang, Franco Iozzo, Xinqian Li, Sagar Prasad, Kavya Regulagedda, Aman Syed, and Hongyi Xia—who graduated this fall. Their contributions and dedication to the program have been invaluable.

As we move into the new year, we remain committed to supporting our students and helping them succeed in their academic and professional journeys.

Patrick Roberts
Director of Career Services

Top Soft Skills Employers Seek

The field of quantitative finance demands a diverse set of skills, including advanced mathematics, statistics, programming, and a solid understanding of data engineering and financial concepts. While these technical abilities form the foundation, mastering them often takes years and typically requires on-the-job training to fully grasp their practical applications. Employers hiring for entry-level or early-career roles are aware of this and often prioritize a candidate's soft skills over extensive experience with advanced quantitative techniques. These interpersonal and adaptable qualities, as highlighted in a candidate's resume, frequently play a critical role in identifying future hires.

Attributes Employers Seek on a Candidate's Resume

Attribute	% of Respondents	Attribute	% of Respondents
Problem-Solving Skills	88.7%	Interpersonal skills	58.2%
Ability to work in a team	78.9%	Computer skills	54.6%
Communication Skills (written)	72.7%	Leadership	52.1%
Strong work ethic	71.6%	Organizational ability	44.8%
Flexibility/ Adaptability	70.1%	Strategic planning skills	34.5%
Communication skills (verbal)	67.5%	Friendly/outgoing personality	25.8%
Technical skills	67.0%	Creativity	21.6%
Analytic/ quantitative skills	66.0%	Tactfulness	21.1%
Initiative	65.5%	Entrepreneurial skills/risk-taker	18.6%
Detail-oriented	61.3%	Fluency in a foreign language	5.2%

NACE National Association of Colleges and Employers

Source: Job Outlook 2024, National Association of Colleges and Employers

The National Association of Colleges and Employers (NACE) is a professional association that connects college career services professionals, university relations and recruiting professionals, and is recognized as a leading source of information about the employment of college graduates, including hiring trends, best practices, and starting salaries. Each year NACE releases the Job Outlook report, a yearly survey that forecasts hiring intentions of employers regarding new college graduates, essentially providing insight into the anticipated job market for recent graduates across different industries and degree levels. Included within this report are the top attributes employers seek on candidate's resumes.

This year, the top characteristics employers seek on candidate resumes include problem-solving, ability to work in a team, communication (written), strong work ethic, and flexibility/adaptability. Many of these skills can be gained through coursework, projects, and extracurricular activities including participating in competitions, student clubs, or volunteerism. Much like the technical skills required, these attributes are seen as foundational for recent graduates and are strong indication of future success within organizations.

One interesting skill highlighted by the Job Outlook Survey was strong work ethic at almost 72% of respondents indicating that they seek this skill on candidate resumes. A recent guest speaker emphasized this characteristic further by saying that they "look for the experiences on your resume that were not required." This could include outside of the classroom activities, student leadership roles, and participating in independent projects. In addition to recent guest speakers, the Financial Mathematics alumni board and advisory board members also echoed more emphasis on soft skills when they evaluate potential hires, further stressing the need for both technical and soft skill development while seeking employment.

As students within the Financial Mathematics program, finding ways to communicate these skills on your resume will make you a stronger candidate when seeking both internships and full-time positions. There are many opportunities at NC State, nationally, virtually, and even globally to gain more experience and enhance your skills while enrolled in the graduate school. If you would like to discuss additional opportunities to develop your skills or how to translate past experiences on your resume, you can contact Career Services Director, Mr. Patrick Roberts at probert2@ncsu.edu to schedule an appointment

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George Armentrout

Interest Rate Modeling with Monte Carlo Simulations

One of the primary forms of risk in finance is found in interest rate fluctuation. As borrowing and lending rates fluctuate, inherent value in cash flows is impacted. For example, one could lend a dollar out today, and given an annual interest rate of 5%, the value of that dollar would grow to $1.05 in a year's time. To extend this, if expecting a payment at some point in the future, one can discount that cash value to determine the present value of the payment. As such, changes in interest rates can greatly impact the value of assets and portfolios that include future cash payments.

Therefore, an important aspect of interest rate risk management is developing and implementing models to predict future interest rates to make predictions about future cash flow values. Although there are a variety of different approaches to interest rate modeling, there is a shared intuition among several methodologies. In this approach, there is a specific value that the interest rate migrates towards over time, a speed at which the interest rate reverts to said value, and an additional amount of randomness that emulates market volatility. The Vasicek model, the Cox-Ingersoll-Ross (CIR) model, and the Hull-White model all employ this general method, however the exact values for each of the terms varies.

Vasicek Model $$dr_t = a\left(b - r_t\right)dt + c\,dW_t$$

The Vasicek model has constant values for the long-term mean (b), constant mean reversion rate (a), and constant volatility sensitivity (c). The first expression in the sum denotes the portion of the model that is deterministic, scaling linearly with change in time, while the second expression denotes a Wiener process, a normally distributed value, that scales by the specified sensitivity (c). This model is one of the least complex, allowing for easier implementation. However, this ease of use comes at a cost of nuance, being simpler than other models.

Cox-Ingersoll-Ross Model $$dr_t = a\left(b - r_t\right)dt + c\sqrt{r_t}\,dW_t$$

The CIR model is very similar to the Vasicek model; however, the volatility also scales with respect to the square root of the current interest rate. As such, the implementation is still relatively simple, however the additional nuance in the market volatility is helpful. Generally, an increased interest rate implies higher market volatility. Also, this model does not allow for negative interest rates, a convention that is generally held in most markets.

Hull-White Model $$dr_t = b(t) - a(t)r_t\,dt + c(t)\,dW_t$$

The Hull-White model is more complex than the others discussed so far. Rather than have constant values, the long-term average, reversion rate, and market volatility are all time dependent, or functions of time. This model can account for much more nuance as these values are no longer constant, however this does drastically increase complexity. Now, instead of choosing or finding the optimal number for each of these parameters, one must make decisions regarding different functions to try and employ or develop a system to discern an optimal function to utilize.

Monte Carlo Simulations

With any of these interest rate models, an element of randomness is employed. As such, only iterating through the model once may not yield interest rates that are the most useful; flipping a coin once and getting heads is not indicative of every coin flip being heads. Therefore, one must take steps to ensure that simulated interest rates in these models are reflective of the specified parameters. The primary approach to ensure this is to employ Monte Carlo simulations. Monte Carlo simulations are a way in which, by simulating a random process many times, the aggregate of these iterations reflects the distribution of the process. To extend the coin example: flipping a fair coin once either yields heads or tails, indicating a 100% chance of the specific outcome; flipping 1000 coins one could expect closer to a 50/50 split. As such, when implementing these interest rate models, it is necessary to run Monte Carlo simulations to gain true insight into the possible outcomes of interest rates given the specified model.

Divija Balasankula

Beyond Basic Forecasting: Comparing Two Powerful Time Series Techniques

We explore two advanced statistical methods for time series analysis: Cross-Correlation Function (CCF) with Lasso regression, and SARIMAX-GARCH model. These approaches provide powerful tools for understanding complex time series data. The choice between them should be guided by data characteristics, the presence of seasonality and volatility clustering, and the specific goals of the analysis. In some cases, combining both methods may be advantageous, allowing for a more comprehensive modeling approach that leverages the strengths of each technique.

Method 1: Cross-Correlation Function (CCF) with Lasso Regression

Cross-Correlation Function (CCF)
The CCF is used to identify relationships between two time series at different time lags. It measures the similarity between a reference time series and lagged versions of another time series.

Mathematically, the CCF between two time series x_t and y_t is defined as:

$$CCF_{xy}(k) = \frac{\sum_{t=1}^{n-k}(x_t - \bar{x})(y_{t+k} - \bar{y})}{\sqrt{\sum_{t=1}^{n}(x_t - \bar{x})^2 \sum_{t=1}^{n}(y_t - \bar{y})^2}}$$

Where k is the lag, and $\bar{x}$ and $\bar{y}$ are the means of respective series.

Lasso Regression
Lasso regression performs both regularization and feature selection. This approach adds a penalty term to the ordinary least squares objective function:

$$\min_{\theta} \frac{1}{2n}\|y - X\theta\|_2^2 + \lambda\|\theta\|_1$$

Where y is the target variable, X is the feature matrix, θ are the model coefficients, λ is the regularization parameter, and $\|\theta\|_1$ is the $\mathrm{L}1$ norm of the coefficients.

Implementation Approach
1. Compute CCF between target and predictor variables
2. Identify significant lags for each predictor
3. Create lagged features based on CCF results
4. Apply Lasso regression to the lagged features

Method 2: SARIMAX-GARCH Model

SARIMAX
SARIMAX incorporates seasonality and exogenous variables into the ARIMA model. This method is useful for time series data with recurring patterns and external influences.

The SARIMAX model can be represented as:

$$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D y_t = \theta_q(B)\Theta_Q(B^s)\epsilon_t + \beta X_t$$

Where B is the backshift operator, $\Phi_P, \phi_p, \theta_q, \Theta_Q$ are polynomial functions of the backshift operator, d and D are orders of differencing, s is the seasonal period, X_t are exogenous variables, and ϵ_t is the error term.

GARCH
GARCH models handle heteroskedasticity in time series data. The GARCH(p,q) model is defined as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

Where σ_t^2 is the conditional variance at time t, $\omega, \alpha_i, \beta_j$ are parameters to be estimated, and ϵ_t s the error term.

Implementation Approach
1. Perform stationarity tests on the time series data
2. Identify SARIMAX order using ACF and PACF plots or information criteria
3. Fit SARIMAX model to the data
4. Apply GARCH modeling to SARIMAX residuals

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Divija Balasankula

Beyond Basic Forecasting: Comparing Two Powerful Time Series Techniques

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Comparison of Approaches

CCF with Lasso

Strengths:
- Effective for identifying lagged relationships
- Provides automatic feature selection
- Handles high-dimensional data well

Limitations:
- May not capture complex seasonal patterns effectively
- Assumes linear relationships between variables

SARIMAX-GARCH

Strengths:
- Captures both seasonal and non-seasonal patterns
- Accounts for time-varying volatility
- Can incorporate exogenous variables

Limitations:
- More complex to implement and interpret
- May require larger datasets for accurate estimation

The choice between these methods depends on the specific characteristics of the time series data and analysis objectives. CCF with Lasso is useful for multiple potential predictors and when feature selection is crucial. It excels in identifying important lagged relationships and creating a parsimonious model.

SARIMAX-GARCH is more suitable for time series with clear seasonal patterns and volatility clustering. It provides a comprehensive framework for modeling both the mean and variance of the time series, making it valuable for financial time series and datasets with changing volatility.

In terms of implementation, CCF with Lasso is generally simpler and more straightforward. SARIMAX-GARCH, while more complex, offers a more integrated approach to modeling both time series structure and volatility.

Both methods require careful model selection and validation. For CCF with Lasso, this involves choosing an appropriate regularization parameter and potentially cross-validation. For SARIMAX- GARCH, it requires selecting appropriate orders for the SARIMAX and GARCH components, often using information criteria or diagnostic plots

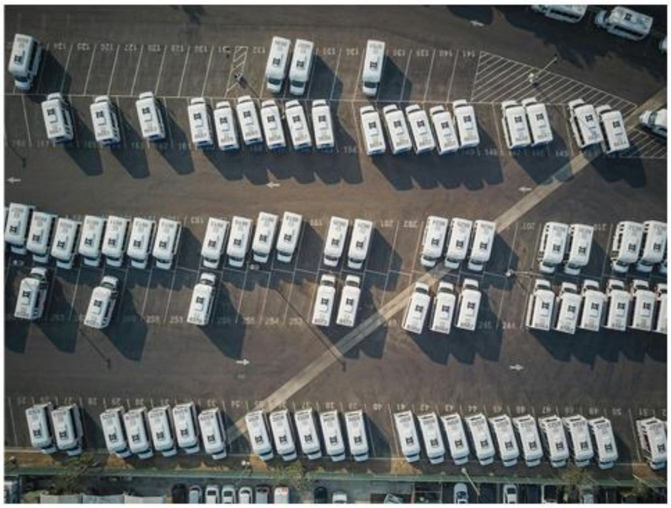
Thaddeus Creech

Alternative Data: A Double-Edged Sword

In their article, *Does Alternative Data Improve Financial Forecasting? The Horizon Effect*, Olivier Dessaint, Thierry Foucault, and Laurent Fresard explore how incorporating unconventional data sources—such as satellite imaging, social media sentiment analysis, and other non-traditional metrics—can affect financial forecasting in both the short- and long-term. When I first came across this article, I thought that it felt particularly pertinent. With the rapid adoption of large-language models, and other forms of machine learning, data, and sometimes alternative data, has become both more prevalent and more relevant than ever before. Additionally, as markets become more and more complex, we are witnessing a shift in the financial landscape where “thinking outside the box” has become essential for portfolio managers and investors seeking to locate alpha in increasingly competitive markets. An analogy that once resonated with me, and partially inspired me to pursue a career in quantitative finance, likens the markets to the earth and alpha to rare, valuable materials like gold. The idea is that, as time goes on and investors develop ever more creative and complex ways to uncover alpha, it becomes more elusive and challenging to find. To me, this is the beauty of the field: the perpetual need for innovation will always drive the industry forward.

Reading this article, I was genuinely fascinated by some of the alternative data sources the authors proposed. Some seemed more straightforward, such as social media sentiment analysis, while others had a far more distanced linkage to financial markets than one would expect such as geolocation and satellite imagery. However, what I found most interesting was the conclusions the authors made regarding its limitations. The authors warned that while the inclusion of this data seemed to help short-term financial forecasting, it negatively impacted forecasting in the long-term. Therefore, investors interested in incorporating this data into their strategies should be weary depending on their investment horizon. This brings an interesting dichotomy when it comes to understanding how to use this data as many investment strategies blend both short and long term performance of equities to attain returns that are necessitated by the firm. Therefore, a firm looking to incorporate this data into their strategy could find itself in a precarious position as there are obvious trade-offs. For example, incorporating this data and focusing your forecasting efforts on the short-term could shift valuable resources away from development of long-term forecasts. More broadly, the incorporation of this data also might have trade-offs in the industry at large. For example, if more and more investment firms stress this data, companies could shift focus to bettering their “alternative data” rather than bettering their financial fundamentals to receive a short-term boost in share price.

Incorporation of alternative data is undoubtedly a game changer in financial forecasting, but as the article by Dessaint, Foucault, and Fresard shows, it does not come without significant trade-offs. While this approach can provide valuable insights, the long-term impacts of such methods are much more nuanced and deserve careful consideration. This raises an important question: how do we use alternative data effectively and ethically? It’s clear that the incorporation of this data requires a delicate balance, both at the firm level and across the broader financial landscape. At the end of the day, I think this, and similar issues illustrate the beauty of the field of quantitative finance. This being that the need for innovation, discipline, and foresight will always remain at the heart of the pursuit for alpha.



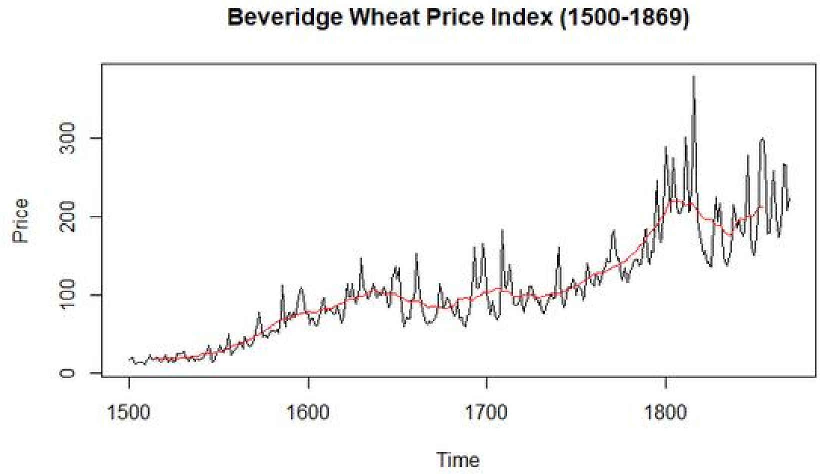
Source: DESSAINT, O., FOUCAULT, T. and FRESARD, L. (2024), Does Alternative Data Improve Financial Forecasting? The Horizon Effect. J Finance, 79: 2237-2287. https://doi.org/10.1111/jofi.13323

Haozhe Cui

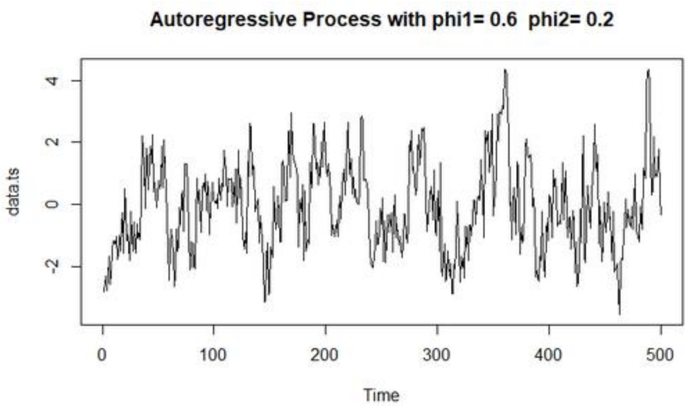
Introduction to Time-Series Analysis

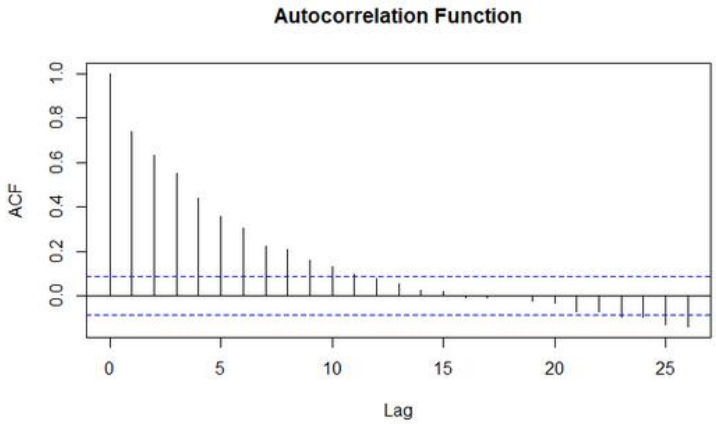
Time series analysis is a critical statistical technique used to analyze data points collected or recorded at specific time intervals. Its primary objective is to identify patterns, trends, and seasonal effects within the data, which can then be leveraged to make informed forecasts and decisions. Central to this analysis are the Autoregressive (AR) and Moving Average (MA) processes, each addressing different aspects of the data's behavior. The AR process focuses on the relationship between an observation and a number of lagged observations, essentially capturing the momentum or mean-reversion tendencies within the series. Mathematically, an AR model of order p (AR(p)) expresses the current value as a linear combination of the previous ppp values plus a stochastic error term. This allows the model to account for the persistence of past values influencing future ones, making it particularly useful in scenarios where past performance is indicative of future behavior.

On the other hand, the Moving Average (MA) process emphasizes the relationship between the current observation and past error terms or shocks. An MA model of order q (MA(q)) represents the current value as a linear combination of the current and past qqq error terms. This component is adept at modeling the noise or random fluctuations within the data, effectively smoothing out short-term irregularities and capturing the impact of recent unexpected events on the series. By integrating both AR and MA components, the ARIMA model becomes a powerful tool capable of handling a wide array of time series data exhibiting both autoregressive and moving average characteristics.



The interplay between AR and MA processes within the ARIMA model facilitates a comprehensive approach to modeling and forecasting. While the AR component accounts for the inherent dependence on past values, the MA component adjusts for the randomness and shocks that may disrupt the series. This combination ensures that the model not only reflects the underlying trends and patterns but also remains robust against irregularities and sudden changes in the data. Additionally, the integration aspect of ARIMA, which involves differencing the data to achieve stationarity, further enhances the model's applicability by addressing non-stationary behaviors such as trends and seasonality, thereby stabilizing the mean and variance of the series..





In practice, selecting the appropriate orders of AR and MA (denoted by p and q respectively) is crucial for the model's accuracy and effectiveness. Techniques such as the Box-Jenkins methodology provide systematic guidelines for identifying these parameters through diagnostic checks and iterative model fitting. Once the parameters are aptly determined, the ARIMA model can deliver precise short-term forecasts by leveraging both past values and past errors, offering a nuanced understanding of the time series dynamics.

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Haozhe Cui

Introduction to Time-Series Analysis

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However, it is important to acknowledge the limitations inherent in ARIMA models. The requirement for stationarity necessitates careful preprocessing of the data, which can sometimes complicate the modeling process. Moreover, the model's sensitivity to parameter selection demands meticulous estimation to avoid overfitting or underfitting. While ARIMA excels in modeling time series with clear autocorrelation patterns, it may fall short in capturing more complex behaviors such as long-term trends or seasonal effects, which require extensions like Seasonal ARIMA (SARIMA).

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plot(data, main='ARMA(1,1) Time Series: phi1=0.7, theta=0.2', xlim=c(0, 400))
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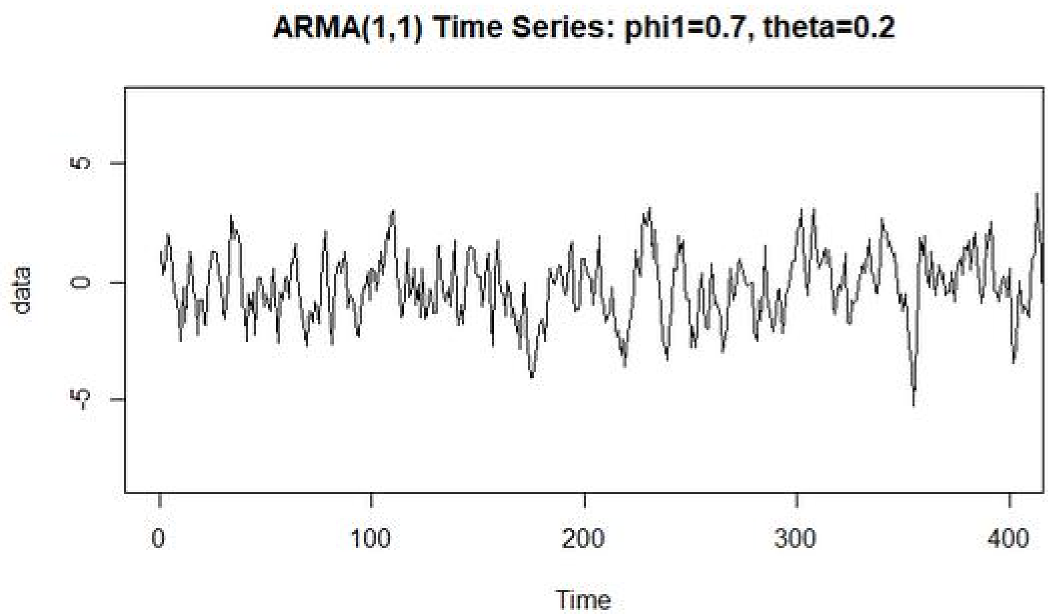

In the realm of volatility forecasting, ARIMA serves as a valuable alternative or complement to traditional models like GARCH. By modeling the variance of error terms through squared or absolute returns, ARIMA can provide insights into future volatility trends. Nevertheless, financial time series often exhibit characteristics like volatility clustering and abrupt shifts, which ARIMA may not fully capture due to its reliance on historical data and linear relationships. Despite these challenges, ARIMA remains a fundamental tool in the analyst's arsenal, offering simplicity and effectiveness for a wide range of forecasting applications. Its ability to integrate past values and errors into predictions ensures that, when properly applied, ARIMA can yield meaningful and actionable forecasts, making it an enduringly relevant model in the evolving landscape of time series analysis and financial forecasting.

Jacob Dolan

Crypto Boom Under Trump?

Following the election of Donald Trump as the 47th president of the United States, cryptocurrency prices have soared. On November 4th, 2024, the range of prices that Bitcoin traded at was $66,803-$69,433. On the same day, Ethereum prices spanned $2,359-$2,488 and Solana prices spanned $155-$164. On Friday, November 15, Bitcoin touched as high as $91,765, Ethereum as high as $3,154, and Solana as high as $220. Evidently, the election of Donald Trump has sparked the strongest cryptocurrency bear market we've seen since 2021. The question is, will this trend continue during his tenure in the oval office?

There are many reasons that cryptocurrency investors are hopeful for a multi-year bull run following Trump's return to the White House. One large cause for the enthusiasm in this space is not unique to cryptocurrency. Equity markets are simultaneously experiencing a period of euphoria, and it appears that equity and cryptocurrency investors alike are anticipating continued appreciation in their holdings, and stocks, although being outperformed by crypto this month, equity investors are also experiencing significant gains across the board this month, with the S&P 500 even hitting new record highs. Rates have remained high for the past couple of years, and the combination of the Federal Reserve hinting at continued rate cuts as inflation calms as well as Trump's criticism of government spending and appointment of individuals like Elon Musk to reduce government inefficiencies give investors hope that we may have a period of both decreasing inflation and decreasing rates. The benefit of lower rates is more evident on equity valuations, but cryptocurrency tends to follow equity markets during bull runs, and lower rates means companies may be more willing to spend on risky projects such as those involving cryptocurrencies. Trump is also a proponent of lower tax rates for business, even proposing to cut them all together and replace them for tariffs, which would strengthen balance sheets for American businesses of all kinds.

Perhaps the biggest reason for cryptocurrency enthusiasm under Donald Trump is his pro-cryptocurrency, anti-regulation stance. Trump is very against government regulations, particularly in business and banking. This may result in investors and businesses feeling more comfortable transacting in and holding cryptocurrencies without fear of regulatory hurdles. A reduction in federal government oversight of crypto, including scaling back requirements around anti-money laundering and know-your-customer policies, would result in more cryptocurrency investment products being readily and easily available to customers. There has also been a concern that the United States Government and the Central Reserve Bank would create their own central bank digital currency as an alternative to cryptocurrencies such as Bitcoin, Ethereum, and Solana. This is appealing to governments and central banks as it affords many of the benefits of decentralized cryptocurrencies while simultaneously allowing for control of supply and monitoring of transactions. Investors and crypto enthusiasts who favor these assets due to their decentralized nature, however, are staunchly against central bank digital currencies as it eliminates the key features of fixed supply, decentralized digital currencies such as inflation protection and anonymity. Trump has stated that he is opposed to central bank digital currencies, leaving an opening for other cryptocurrencies to serve a legitimate purpose in business and finance. In fact, he has even voiced support for US companies to integrate existing cryptocurrencies into their financial ecosystems, and would like to see the US as the world leader in crypto.

It is far too early to tell how much of what Trump hopes to accomplish as president will come to fruition as we are still two months away from his swearing in, but investors are certainly showing confidence that what he does accomplish will be beneficial to cryptocurrency. There are many uncertainties in financial markets both in the US and across the globe, and this could position cryptocurrency to finally take on a legitimate role in finance beyond its current role as a speculative asset. Given Trump's stance on regulation and crypto, investor enthusiasm in the space seems justified thus far, and it will be very interesting to see how it plays out over the course of his presidency.

Kristen Epperly

The Value of Curiosity in Interviews

How do I stand out from other applicants to an interviewer? What skills do they want me to have? How do I convince them that I have these skills? These are just a few of the most imperative questions to answer when trying to secure a position at your desired company. In my limited experience, I have discovered what I believe to be the “golden trait” that could separate a candidate from someone else with the same qualifications.

I am a student enrolled in the Accelerated Bachelor’s/Master’s Program of Financial Mathematics at North Carolina State University. I have completed an internship in Business Intelligence, and I have successfully secured an internship in Finance for the upcoming summer. During my job search over the last two years, I have submitted over 100 internship applications. Out of those 100, I have been given two face-to-face interviews. I will let that soak in for a second. I have completed two face-to-face interviews and have secured two internships. In both scenarios, there was one trait that I attempted to convey to the interviewers above all else: curiosity.

It is easy to talk about the information that you know, but how do you address topics that you do not know when asked about them in an interview setting? I think that it is important to be transparent about what you do not know while simultaneously convincing the interviewer that you want to know. No amount of academic experience can entirely prepare you for a job, and interviewers know this. That is why they want to be sure that you will be able to learn and apply new skills while working for them, but more importantly that you have a desire to learn these new skills. It is no fun trying to teach an uninterested student.

During one of my interviews, I was asked “What do you hope to get out of this internship?” I used this as an opportunity to be honest about my skill set and my goals to learn and improve my knowledge. I explained that I have a strong background in mathematics, statistics, and data analytics, but my finance knowledge is limited. Being that this interview was for a finance position, I was a bit nervous saying I am not experienced on financial topics. However, I explained that I have a strong desire to learn how I can apply my analytical skills to the finance industry. I gave examples of such fields that I would like to learn more about and mentioned some analytical strategies, such as forecasting, that I have experience with. This experience can easily be transferred to financial data, and I knew that working for this company would assist me in expanding my understanding of broad financial topics and industries. I was able to convince the interviewers that I am eager to learn and that I am curious about their field. I believe that this helped separate me from other candidates and led to me securing an offer.

In my experience, if you can convince an employer that you are eager and able to learn about the field at hand while sharing skills that are transferable to said field, you will greatly improve your chances of securing a job offer. Always remember, people love talking about themselves and this extends to their jobs. I am confident that convincing an interviewer that you have great curiosity about their industry and the willpower to soak in new information necessary to do the job will go a very long way in securing an offer.

Sophia Feng

Quantitative Investment Model Using NLP and ML Methods

Introduction

As the market economy develops, the financial market's role has become increasingly significant. Market fluctuations not only impact investors but also pose challenges to regulation. News is a key driver of market changes. This study leverages the TF-IDF model to vectorize news related to industry indices and employs two machine learning classifiers, SVM and MLP, to explore the relationship between news and future industry index fluctuations. The model predicted the 10-day frequency rate of change for industry indices in a simulation year, demonstrating its ability to capture textual features and predict market fluctuations. Additionally, a news-driven portfolio strategy was developed, achieving robust excess returns.

Data Mining

This study utilizes industry news as its dataset, focusing on sectors like finance, pharmaceuticals, real estate, and telecommunications. Data was collected from the Tonghuashun website, consisting of 81,485 pieces of news across 77 industries, which provides a solid foundation for analysis.

TF-IDF Model

The text data was divided into training and test sets based on dates. For each industry and trading day, all news headlines were recorded. After obtaining industry news panel data, the TF-IDF model transformed the textual data into computable matrices. The text data underwent tokenization and stop-word removal. The TF-IDF model was applied to the training set to calculate a weight matrix for the top 300 most frequent words. For the test set, the same 300 words from the training set were used to generate the vectorized data.

Industry market data was used to calculate the rate of change in the opening prices of industry indices over different time intervals (1-day, 3-day, 5-day, 10-day, 30-day, and 60-day) as the dependent variable in the regression model. For each industry, daily vectorized news text was paired with the corresponding future rate of change in the index. Data for the feature matrix was standardized using Z-score normalization.

To simplify model complexity, numerical data for industry index movements was converted to categorical data. The 25th and 75th percentiles of the rate of change data for each frequency were used to classify the data into three categories: values above the 75th percentile were labeled as 1, below the 25th percentile as -1, and the rest as 0.

Machine Learning Models

Two machine learning models were constructed: SVM and MLP. For the SVM model, the kernel function was set to linear, with a maximum of 10,000 iterations and a regularization parameter C = 0.1. However, the classification results did not converge, likely due to the large data size and complexity.

Thus, we focused on the MLP model, setting the convolution kernel size equal to the input weight vector. Two hidden layers with 400 and 100 neurons were used, and the activation function was $f(x) = \max(0, x)$. The random gradient optimizer was selected with a regularization parameter of 0.01 and a maximum of 300 iterations.

The study tested different methods (SVM, MLP) across various frequencies (1-day, 3-day, 5-day, 10-day, 30-day, 60-day). The MLP model with a 10-day frequency outperformed others, achieving average accuracies of 0.87 for the training set and 0.54 for the test set. In contrast, the SVM model performed poorly, with an average accuracy of 0.29 for both the training and test sets.

Trading Strategy

Given the MLP's superior performance with 10-day frequency data, an investment strategy was devised with rebalancing every ten days. The MLP model's vectorized text data was used to predict index movement rate groupings. Group 1 represents a predicted price change above the 25th percentile, group -1 represents a predicted price change below the 75th percentile, and group 0 represents changes between the two. Based on these predictions, target securities were bought, and others were sold.

Over the simulated year, the portfolio return for group 1 was 14.4%, for group -1 it was -7.1%, and the long-short portfolio return was 21.5%, with a Sharpe ratio of 2.39.

Isaac Gohn

Using Machine Learning to Predict Mortgage Defaults

Just as machine learning systems are used in credit card approvals, they are also used in mortgage applications. These systems streamline the approval process by evaluating applicants based on a variety of data points and features, such as credit scores, income stability, debt-to-income ratio, and even alternative data like spending patterns and savings behavior. By leveraging advanced algorithms, these systems can process large volumes of applications in real-time, providing quicker decisions while maintaining consistent standards.

During this fall semester, my group has embarked on a project to build predictive models aimed at assessing mortgage loan default risk, helping lenders identify high-risk loans more effectively. Our objective is to develop two straightforward yet effective binary classification models: one using logistic regression and the other employing random forests. In the industry, model performance is typically measured using metrics like AUC (Area Under the Curve) scores, with standard benchmarks ranging from 0.6 to 0.7. Our goal is to not only surpass this benchmark but also to achieve notable improvements in other key performance metrics such as Recall, Precision, and the F1 score.

In our project, one of my key responsibilities is to clean and preprocess the dataset, which was sourced from the Freddie Mac Single-Family Home Loan Dataset. This dataset included features such as credit scores, original unpaid principal balance (UPB), and debt-to-income ratio, among others. I have employed various techniques to identify and retain the most important features, drawing on methods I have learned in my Machine Learning class this semester. These techniques included Principal Component Analysis (PCA), forward and backward feature selection, and feature correlation analysis to remove redundant variables. This process reinforced the critical importance to me of data cleaning and preparation, as the quality of a model's output is inherently tied to the quality of the data it is built upon—emphasizing the truth behind the adage, "garbage in, garbage out."

I’ve also been responsible for building the logistic regression model for our application. Since our dataset is highly imbalanced, I utilized SMOTE (Synthetic Minority Oversampling Technique) to generate synthetic samples for the default class, aiming to improve the model's performance. A couple of challenges I have faced include determining the optimal ratio for SMOTE oversampling and selecting the appropriate decision threshold for the logistic regression model. While there are several approaches to address these issues, the most straightforward and effective method is to iterate through various values for both parameters and compare the model's performance across key metrics such as the F1 score, Precision, Recall, ROC curves, and more.

This project has been very fun to work on with my teammates and has strengthened my abilities in building models and data science in general. It’s been exciting to work on a real-world problem with tangible implications, as mortgage default risk assessment is a critical issue in the lending industry.

Zhen He

Analysis of the impact of the Russia-Ukraine conflict on fats and oils prices

The Russia-Ukraine war is one of the most important geopolitical events in recent years, with far-reaching impacts on the global economy and commodity markets. In 2022 Russia launched a full-scale military operation against Ukraine, which directly led to dramatic fluctuations in the market for fats and oils and other commodities. As the world's leading exporter of oils and fats, the conflict between Russia and Ukraine disrupted the supply chain of products such as sunflower oil, which in turn affected the international market.

Russia and Ukraine together accounted for 70-80% of global sunflower oil exports, and the conflict led to the closure of ports in the Black Sea region, disruption of supply, and a sharp rise in prices as the international edible vegetable oil stock-to-consumption ratio fell to a low level. At the same time, the surge in international energy prices also exacerbated the volatility of oil and grease prices. During the conflict, the price of crude oil exceeded US$100 per barrel, and the rise in energy costs pushed up the demand for energizing oilseeds such as corn and soybean oil, especially the production and consumption of biodiesel, which further expanded, leading to an intensification of the contradiction between supply and demand in the oil and grease market. In addition, the spread of the food crisis has also indirectly pushed up the uncertainty of oil and fat prices.

Based on the data from September 2014 to May 2023, this paper constructs the Russian-Ukrainian Conflict Risk Intensity Index (RUCR), then selecting the price volatility of rapeseed, palm oil, soybean oil, corn, and sunflower seeds and empirically analyzes it in combination with macroeconomic variables such as Russia's export share, CBOE volatility index, and the federal funds rate. It is found that RUCR significantly and positively affects the volatility risk of the oil and grease market. Each rise in the intensity of the conflict exacerbates market uncertainty, suggesting that geopolitical risk is an important driver of market volatility.

The study also finds that a rise in the share of Russian export commodities helps to mitigate market volatility, suggesting that Russia's stable exports as a major supplier has a buffering effect on the market. Fluctuations in other economic variables such as the CBOE volatility index and the federal funds rate significantly exacerbate market volatility.

The control variable analysis shows that the US dollar index has no significant effect on the volatility of oil and grease prices, while the increase in the effective exchange rate of the Russian ruble can significantly mitigate the market volatility. This may be related to the fact that Russia reduces currency depreciation pressure through policies such as pegging the ruble to gold. In addition, although the financial stress index floats higher, its impact on the oil and grease market is not significant.

From a policy perspective, the research in this paper shows that supply chain stability is crucial to counter geopolitical risks. Countries should diversify their sources of supply and reduce their dependence on a single exporter. Meanwhile, a moderate increase in military spending can mitigate market volatility and provide an important reference for governments to cope with conflict risks. In addition, the construction of the RUCR index provides a new tool for measuring and predicting geopolitical risks, with potential for wide application.

Although the study reveals the association between the Russo-Ukrainian conflict and oil and grease market volatility, there are still limitations, such as the variable selection is not comprehensive enough and the model does not adequately capture the nonlinear relationship. Future research could combine more geopolitical variables or utilize techniques such as machine learning to enhance the depth of analysis.

Feature Importance

	Model 1		Model 2	
RUCR	0.006	***	0.000	***
	(0.0017516)		(0.0038063)	
Trade	0.091	*	0.095	*
	(0.0000249)		(0.0000281)	
VIX	0.062	*	0.051	*
	(0.0000348)		(0.0000917)	
FFR	0.004	***	0.002	***
	(0.0056752)		(0.0059311)	
FXreserve	0.000	***	0.000	***
	(0.0084725)		(0.0080385)	
ME	0.009	***	0.009	***
	(-0.094213)		(-0.0213035)	
USdollar			0.193	
			(-0.0001915)	
Ruble			0.000	***
			(-0.0001602)	
FS			0.227	
			(-0.0001126)	

Note: ***, **, * denote significance at the 1%, 5%, and 10% level of significance, respectively, with coefficients in parentheses and p-values in nonparentheses.

In conclusion, the Russia-Ukraine conflict significantly affected the global oil and grease market, exacerbating volatility through mechanisms such as supply chain disruptions, energy price transmission, and market sentiment. The study provides new perspectives for understanding how geopolitical risks affect commodity markets and provides a scientific basis for policymaking and market regulation

Chance Humiston

Application Of Arima Modeling To Predicting Bitcoin Price

Introduction

Bitcoin often makes financial headlines with its price changes. This is the cryptocurrency with the highest trading volume, and is known for its volatility. This makes the closing price of Bitcoin an excellent subject for time series modeling. This report details a project I worked on to build an Autoregressive Integrated Moving Average (ARIMA) model for the closing price of bitcoin. The data used for this project was the daily BTC closing price obtained from Bloomberg Terminal and spanned from January 2020 through June 2024. Data from the third quarter of 2024 was also pulled and used as a holdout set to test the final model. This project was written in Python using Jupyter Notebooks. Pandas and Numpy were used to organize and transform the data. SciPy and Statsmodels were used to conduct the time series analysis and Statsmodels was used to fit the ARIMA model.

Building the Model

The first issue to consider in developing the ARIMA model was stationarity. Bitcoin has gone on a famous bull run in the timeframe this project was looking at, so the series did not have constant mean. The first method used to address this was a standard differencing of the data per the Integrated component of ARIMA. This result achieved stationarity in the series as assessed by ADF and KPSS tests. Another modification to the data that was explored as a means of addressing nonstationary was using daily returns rather than closing price. The calculation for returns still involves differencing the data but also scales the difference by dividing by the previous day's closing price. This transformation also achieved stationarity, but has the added benefit of being a more useful set of information. For the purpose of an investment portfolio, the actual price change of an asset doesn't matter nearly as much as the percent change. Since an investor is going to buy a certain dollar amount of an asset rather than a set number of units, the daily returns are really the data of most interest. Because the returns are not normally distributed, a box-cox transformation with lambda equal to 1.78 was applied to the return data.

The next step was determining the Autoregressive and Moving Average parameters to use in the model. Plots of the autocorrelation function and partial autocorrelation function were used to assess initiation values for these parameters respectively. Neither plot showed any obvious lag to use for these parameters, but both had a small rise at four lags. Using the box-cox transformed daily return data, an ARIMA (4, 0, 4) model was initiated. The Integrated parameter is zero here because the differencing was done prior to feeding the data in. Two attempts were made to optimize the parameters. The first used AIC selection to find the optimal model parameters. The second used brute force to test every model up to 10 lags for both the autoregressive and moving average parameters. Both attempts yielded the same result that the original ARIMA (4, 0, 4) was the best fit.

Testing on Holdout Data

The model was trained and validated on data from the beginning of 2020 through the middle of 2024. Data from the third quarter of 2024 was held out to be used as a test set for the final model. The same transformation was applied to closing price so the model input was the box-cox transformed daily return. The model was used to make next-day predictions for every data point in Q3 based on the real data up to that point. The prediction was then transformed back into a percent return. The result was that our model achieved an RMSE of 2.66%.

Conclusion

This project has successfully built a model to make predictions for Bitcoin return and could also be a jumping-off point for more advanced models that incorporate more factors beyond the univariate time series used here. Perhaps most significantly, this project has yielded some valuable insights about the power of ARIMA as a prediction tool. With the rise of machine learning techniques, it is important to remember that more traditional, and interpretable, statistical tools still have a place in the financial sector.

Vidyul Jain

Building My Path: Lessons And Growth In Nc State's Mfm Program

The journey to pursue a Master of Financial Mathematics (MFM) at NC State has been a transformative experience. From overcoming challenges during the application process to expanding my knowledge through coursework and projects, this program has shaped my career goals and opened doors to incredible opportunities.

My decision to apply to NC State's MFM program stems from a deep love for mathematics and its applications in the financial industry. During my undergraduate studies, I realized how quantitative tools could solve complex financial problems and wanted to pursue a program that combined these fields.

The application process was challenging. Coming from a middle-class background, I had limited guidance and resources. Determined to succeed, I sought advice from alumni, reached out to mentors, and carefully tailored my application materials. What drew me to NC State was its unique blend of theory and real-world application, as well as its reputation for producing professionals ready to take on the financial industry. When I received my acceptance, it felt like the beginning of an exciting journey.

One of the most impactful experiences in the program has been my Fixed Income Products and Analytics class with Dr. Richard Ellson. The course covered essential concepts such as bond pricing, yield curves, and duration, but what set it apart was the way it bridges the gap between theory and practice. Dr. Ellson's wealth of industry experience made every lecture engaging and insightful.

This class expanded my understanding of the fixed-income market and prepared me for professional opportunities. During internship interviews, I found myself confidently discussing topics like interest rate risks and bond portfolio strategies. Recruiters appreciated my ability to connect academic theories with real-world scenarios—a skill I owe largely to this course.

In addition to coursework, hands-on projects have been instrumental in my growth. One project that stands out is the Fixed Income Forecasting initiative as part of the career development class. Working in a team, we analyzed historical interest rate data and used models like Vasicek, CIR, and Hull-White to forecast interest rate movements.

This project taught me more than just technical skills—it honed my ability to collaborate, analyse data critically, and present findings effectively. Presenting our results to peers and professors gave me the confidence to explain complex ideas clearly, a skill that proved invaluable during interviews.

The MFM program has provided numerous opportunities to connect with professionals and alumni, helping me bridge the gap between academics and industry. One memorable experience was a call with an alum now working as a risk modeler at Capital One. We discussed how the MFM coursework prepared them for the demands of their role, as well as tips for securing internships and full-time opportunities.

Additionally, participating in career fairs and networking events has broadened my professional network. These experiences have given me a clearer sense of how to align my skills with industry needs, particularly in areas like portfolio management and risk analysis.

My time at NC State has been filled with challenges, growth, and new opportunities. The combination of rigorous coursework, practical projects, and professional guidance has prepared me for a future in finance. I hope to apply the knowledge and skills I've gained to roles in portfolio management, quantitative research, or risk analysis, where I can contribute to solving complex financial challenges.

Reflecting on this journey, I am deeply grateful for the supportive faculty, the engaging curriculum, and the chance to grow both personally and professionally. NC State's MFM program has not only shaped my career path but also given me the confidence to navigate the dynamic world of finance..

Joseph Jonasson

Portfolio Optimization as a Mutli-armed Bandit Problem

The term “Multi-armed Bandit” refers to the hypothetical experience of attempting to maximize winnings at a casino full of slot machines, which are often called “one-armed bandits.” In this theoretical casino, gamblers can choose which arm they want to pull, freely switching between pulls as they aim to decipher which arms will yield the best return, even as the expected return for each machine varies as the gambler plays additional rounds. Generally, this framework can describe any situation where a person chooses between multiple actions that may have varying rewards or “payouts.”

Considering the complexity of portfolio optimization, it is helpful to use simplified situations like the multi-armed bandit problem to help establish intelligent decision-making for managing a portfolio of financial investments. Like the hypothetical slot machines, investment returns change over time, but investors are limited to observable information about the investments. Future returns are always unknown, so portfolio managers use historical data to predict future values, ultimately informing how the portfolio should be constructed. Similarly, when a gambler begins their risk-taking adventure, there is no information on how the machines perform. There must be a period of exploration where the gambler collects data on how each machine performs, and this data is then used to inform what machines to gamble on for the remainder of their casino experience.

A portfolio optimizer’s objective may be to maximize return, minimize risk, or achieve some combination of low risk and high return. Assuming a portfolio manager can somewhat accurately predict future trends, they can use the Markowitz model to minimize risk, where it is straightforward to develop a minimum variance portfolio as a function of the covariance matrix of assets being invested in. More specifically, if π is a vector where each term represents the fraction of wealth invested in each asset,

$$\pi_{min} = \frac{1_d C^{-1}}{1_d C^{-1} 1_d^T} \text{ where } 1_d = (1, 1, ...1) \in \mathbb{R}^d$$

gives the portfolio with minimum variance where C is the covariance matrix of the assets. Since an investor does not have to invest in every asset, there is a minimum variance portfolio for each subset of assets.

Although this strategy is simple and easily implemented, it may not always be the most effective. Regarding the multi-armed bandit problem, each portfolio choice can represent an “arm.” We can refine the problem more by only considering minimum variance portfolios. Then, for each subset of assets, there is an arm that can be pulled, which represents using the associated minimum variance portfolio as our investment strategy. Each machine becomes slightly more predictable as we gather more data, but the exact returns are unknown.

With this new perspective on the portfolio optimization problem, the goal becomes devising a strategy for which minimum variance portfolios to choose. At this point, well-known solutions to the multi-armed bandit problem can be implemented. For example, we can use the ∈-greedy strategy, which involves picking the portfolio with the best expected return with probability, meaning we choose to randomly “explore” other portfolios with probability 1 - . The portfolio with the best expected return may change as we gain more information, but the strategy remains the same. Another solution is the upper confidence bound strategy, which considers the uncertainty associated with each choice when deciding on portfolio strategies. Each choice has an expected return based on known data and a confidence interval dependent on the variance of the chosen assets. The upper confidence bound strategy says to select the portfolio whose upper bound of the confidence interval is the largest.

Regardless of the chosen strategy, the decisions become more informed as more data is collected. It is beneficial to reframe problems like this in finance to include aspects of mathematics and statistics rather than relying on financial intuition, which often introduces harmful biases. It should also be acknowledged that many of the best portfolio managers rely heavily on finance knowledge, but they often combine their expertise with intelligent data analysis. Even though it is helpful to use the multi-armed bandit problem to clarify some aspects of portfolio optimization, it should only be used as a piece of a portfolio manager’s collection of research

Sarang Kansara

Volatility, Vision, And Value: My Road To Becoming A Portfolio Manager

Introduction

Aspiring to make a significant impact in finance, I am pursuing a Master's degree in Financial Mathematics at NC State University. My goal is to build a career as a portfolio manager, and my time at NC State has equipped me with both the theoretical foundation and practical skills needed to excel in this role. This article highlights my current academic pursuits, my interview experiences, and the reasons I chose NC State as the launchpad for my career in finance.

Career Goals

As I envision my future, the role of a portfolio manager stands out as my ultimate career destination. This role appeals to me because of its dynamic nature and the opportunity it offers to make impactful, data-driven investment decisions. Building and managing portfolios requires a strong command of financial markets, risk management, and quantitative analysis, and I am excited to shape my career trajectory toward this goal. Every project I undertake, every tool I master, and each industry connection I build is a step toward becoming proficient in asset allocation, risk analysis, and performance optimization.

Current Academic Project: Forecasting the Monthly VIX

In my current academic project, I am working on forecasting the monthly VIX, which reflects market volatility and investor sentiment. This project has been intellectually stimulating and allows me to leverage both traditional time series models and advanced machine learning techniques. I am utilizing time series models like ARIMA, SARIMA, SARIMAX, and GARCH to analyze historical patterns and forecast future volatility levels. In addition, I am incorporating machine learning models, including random forest, LSTM, and XGBoost, to capture non-linear relationships and complex patterns in the data.

The project has been instrumental in deepening my understanding of model selection and evaluation. Each model has unique assumptions and strengths, and learning how to assess their effectiveness in a forecasting context has provided me with invaluable insights into quantitative finance. This experience is sharpening my skills in using predictive analytics and programming tools, which will be crucial as I move forward in my career.

Interview Experiences

Throughout my academic journey, I have interviewed with several firms, primarily for roles within the risk domain. These interviews have provided valuable insights into industry expectations and required skills. Questions have spanned a diverse array of topics, including Python programming, SQL, model risk management, and regulatory frameworks such as CECL (Current Expected Credit Loss) and CCAR (Comprehensive Capital Analysis and Review). I have also fielded questions on fixed-income products, derivatives, and mortgage insurance, as well as on my academic projects. These interviews have been both challenging and enlightening, helping me identify areas for further growth and deepening my understanding of the technical knowledge needed to succeed in financial risk management.

Why I Chose NC State

Choosing NC State for my master's program was an easy decision, as it offered a unique blend of rigorous academics, personalized career support, and a vibrant professional community. The reasons for my choice include:

- Small Cohort: The program's small cohort size allows for personalized guidance and mentorship from professors, and the focused environment has been essential for my career development.
- Academic Flexibility: Students can select courses from diverse fields such as finance, computer science, statistics, and the MBA program. This flexibility has enabled me to tailor my coursework to align with my interests in quantitative finance and risk management.
- Program Ranking: NC State's Financial Mathematics program is well-ranked and recognized for its emphasis on applied mathematics in finance. This reputation aligns with my goals and provides a competitive edge in the job market.
- Strong Alumni Network: The strong alumni foundation has been invaluable for networking and mentorship, allowing me to connect with former students who are now leaders in the finance industry, helping me gain insights and guidance on navigating my career path.
- Guest Lecture Series: Every Friday, the FinMath program hosts guest lectures featuring industry professionals who share their experiences and insights on finance and analytics. These sessions have been both informative and inspiring, providing a glimpse into the real-world applications of the concepts we learn in class.
- Strategic Location: Located in the Research Triangle, NC State offers access to numerous internship and job opportunities in the finance sector. The region's vibrant professional landscape has provided me with invaluable exposure to the industry and the chance to attend various networking events.

Conclusion

My experience at NC State has been transformative. The program's challenging curriculum, supportive faculty, and extensive industry connections have provided me with the skills and confidence to pursue a career as a portfolio manager. With a solid foundation in quantitative finance and a clear career path ahead, I am excited about the journey and eager to contribute to the finance industry.

Dev Kewlani

From Theory to Practice: Exploring Advanced Volatility Metrics in Options Trading

As a Financial Mathematics graduate student at NC State University, my journey into the depths of market volatility analysis began during my tenure at NX Block Trades. What started as a curiosity about market behaviour evolved into a research project that would fundamentally change my understanding of options trading.

The Quest for Better Volatility Prediction

The challenge was clear: develop more accurate predictors of market volatility for Indian indexes (Nifty and Bank nifty). Traditional volatility measures often fall short in capturing the complete picture of market dynamics, especially in rapidly changing markets. My approach involved analyzing five years of historical data through multiple lenses, each offering unique insights into market behaviour.

The research began with implementing classical volatility estimators, including Parkinson and Garman-Klass models. The Parkinson model, assuming continuous Brownian motion, leverages high-low price ranges to estimate volatility. While effective, it didn't capture the full spectrum of market behaviour. This led to exploring the more sophisticated Garman-Klass estimator, which incorporates open-close returns to account for intraday price movements.

Breaking New Ground

1. Advanced Volatility Estimators: The Yang-Zhang volatility model proved particularly valuable, as it separately analyzed overnight and intraday volatility components. This distinction was crucial for markets like India, where overnight gaps can significantly impact trading strategies.
2. Market Sentiment Indicators: By analyzing implied volatility metrics (IV rank and percentile) across different strike prices, I gained insights into market sentiment that historical volatility alone couldn't provide. The volatility smile and skew analysis became powerful tools for predicting potential market movements.
3. Feature Engineering: Perhaps the most ambitious part of the project was creating a library of over 400 technical indicators and their derivatives. Through careful correlation analysis, I identified the most predictive features for volatility forecasting.

Real-World Impact

The practical implementation of this research led to remarkable results. By incorporating these advanced volatility metrics into our trading strategies, I achieved:

- A Sharpe Ratio of 2.4 in backtesting
- 45% cumulative profit with -8% maximum drawdown in backtesting

Looking Forward

As I continue my studies at NC State, I'm expanding upon this research by exploring machine learning applications in volatility prediction. The combination of traditional financial mathematics with modern computational methods opens exciting possibilities for more sophisticated trading strategies.

This project not only enhanced my technical skills but also deepened my appreciation for the complexities of financial markets. It demonstrated that successful trading strategies require a delicate balance of theoretical understanding and practical application, a principle that continues to guide my academic and professional development.

The experience reinforced my belief that the future of quantitative finance lies in the intersection of traditional financial theory and innovative computational methods. As markets become increasingly complex, the ability to develop and implement sophisticated analytical tools becomes ever more crucial.

William Lanzoni

How The Election Has Created An Economic Surge

This past week has been filled with people personally expressing their thoughts on the United States elected government officials, and specifically, the election of President Trump. While everyone is entitled to their own opinions on his policies, there is no denying the fact that the U.S. stock market has already seen the effects of President Trump's re-election.

The S&P 500, widely used as a general market measure, has recently seen a $300 jump after the election results, and more specifically, Tesla stock (TSLA) saw an almost 50% increase in just over a week. In the case of Tesla, this was most likely a result of the large public endorsements their CEO Elon Musk had for President Trump.

However, I wanted to dive deep into why the market reacted in the way it did, due to the election results.

There are a few main reasons why economists believe that the election has positively affected the U.S. stock market. Primarily, economists believe the surge was due to President Trump's anticipated tax cuts and deregulation, which would largely affect larger corporations and banks.

President Biden's policies put a halt to potential large mergers between corporations and acquisitions between large and small businesses. President Trump has promised to lift some of these regulations, making it easier for large corporations to grow and expand.

Potential tax cuts would also positively affect companies, as they would be able to retain more of their revenues, positively affecting their earnings reports and shareholder payoffs.

President Trump, throughout his campaign, has emphasized specific sectors in the economy that he plans to expand and focus on during his second presidency. Energy stocks, specifically fossil fuels and small caps, are most likely going to see a large jump due to Trump's reduction in energy sector incentives and a shift in focus to oil and drilling.

Although the overall market outlook is positive, it is important to consider some potential plans that could negatively affect the economy and the stock market. One of the main issues with Trump's economic plan is his willingness to impose tariffs on imported goods, specifically from China. Although this could be beneficial for creating jobs for Americans, as large corporations would have to start building production plants in the United States, this process could take much longer than expected. As a result, these corporations will have to find ways to maintain their profit margins while paying the tariffs.

Companies will have to counteract this by potentially increasing their sales price or “biting the bullet” and accepting smaller profit margins, which might affect their stock price.

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William Lanzoni

How The Election Has Created An Economic Surge

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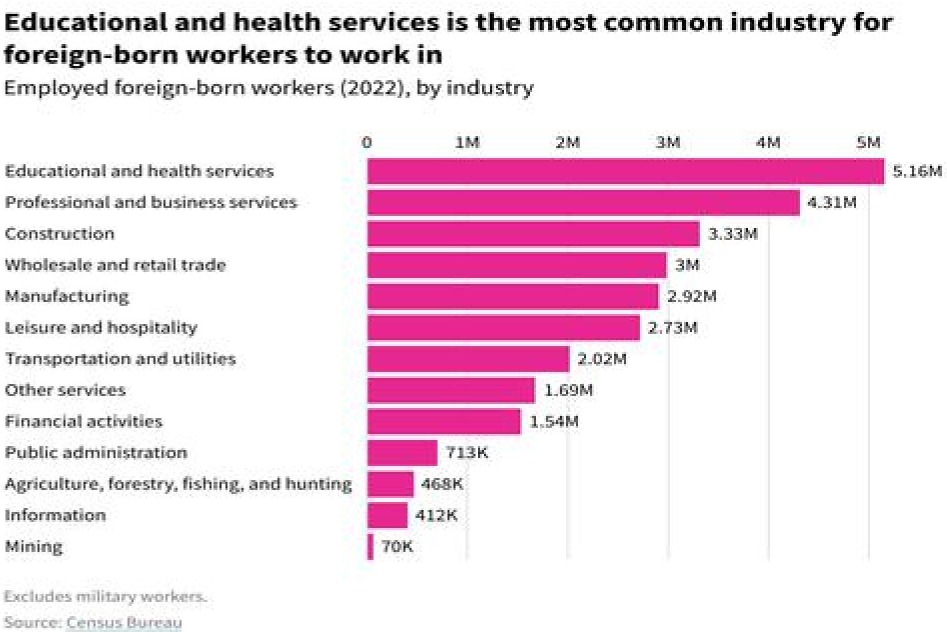
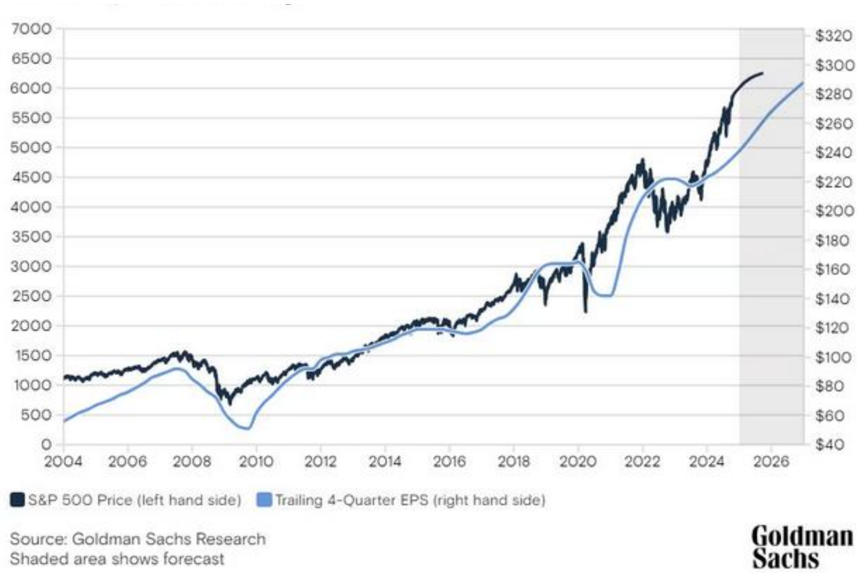
Another point to consider is the immigration laws that President Trump plans to put into effect and how these might alter certain industries. Below is a chart from 2022 that shows the industries with the highest migrant working population:



As shown in the bar chart, some industries such as educational and healthcare services, as well as the construction industry, are among the most popular industries for migrant workers. Although it might take some time to affect these industries, it is important to closely monitor large and small-cap companies within these industries throughout Trump's presidency.

As previously stated, the U.S. economy has experienced a recent surge after the election of President Donald Trump. Most of the surge was due to the positive outlook that Donald Trump has on the economy. Although expected to slow down in the upcoming weeks, Goldman Sachs analysts project the S&P 500 index to increase by over 9% in the coming year due to the anticipated increase in large corporations' earnings.

It has been interesting seeing the market react as it did to a political event, and one can only wonder what it may have looked like if Kamala Harris had won the election. I am personally interested to see how Donald Trump and the Federal Reserve will navigate reducing and controlling inflation through policy and altering interest rates.



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Tharun Mandadi

Machine Learning In Financial Risk Management: Key Techniques And Applications

Introduction

Machine learning (ML) has become a crucial tool in financial risk management (FRM) due to its ability to model complex financial systems and predict uncertain outcomes. Traditional risk management techniques often fall short in capturing the full complexity of dynamic and data-rich financial markets. ML allows for more accurate predictions, optimized risk mitigation strategies, and better decision-making by uncovering hidden patterns in large, unstructured datasets. This article outlines the main ML techniques used in FRM and their applications, strengths, and challenges.

Supervised Learning in Financial Risk Management

Supervised learning trains models using labeled data, where both input features and outcomes are known, enabling the model to predict outcomes for new data.

- Classification: Used for tasks like credit scoring and bankruptcy prediction. The model classifies financial entities based on risk levels (e.g., high, medium, low), essential for assessing creditworthiness and preventing defaults.
- Regression: Predicts continuous outcomes, such as forecasting stock volatility or insurance claim frequency. These models help estimate risk exposure and potential losses.

Supervised learning is ideal for structured data with historical labels, making it effective in fraud detection, volatility forecasting, and credit scoring.

Unsupervised Learning in Financial Risk Management

Unsupervised learning uncovers hidden patterns in data without predefined labels. It is useful for analyzing complex datasets where outcomes are not known.

- Clustering: Groups similar financial entities, such as credit applicants or investment portfolios, allowing for tailored risk management strategies.
- Anomaly Detection: Helps detect unusual activities, such as fraud, by analyzing transaction data and flagging irregularities without prior knowledge of fraudulent behavior.
- Dimensionality Reduction: Techniques like Principal Component Analysis (PCA) reduce complex datasets to the most significant variables, helping in insurance underwriting and mortality modeling.

Unsupervised learning is valuable for discovering unknown patterns and relationships, especially when labeled data is limited.

Reinforcement Learning in Financial Risk Management

Reinforcement learning (RL) trains an agent to make decisions by interacting with its environment and receiving feedback through rewards or penalties. This approach helps optimize long-term outcomes.

- Dynamic Portfolio Allocation: RL is particularly powerful in portfolio optimization, where models adjust asset allocations in real time to maximize risk-adjusted returns, adapting to changing market conditions.

RL's ability to optimize decisions over time makes it a valuable tool for financial institutions managing volatility and market dynamics.

Semi-Supervised Learning for Risk Modeling

Semi-supervised learning combines labeled and unlabeled data, enabling accurate predictions even when labeled data is scarce or expensive to acquire.

- Monte Carlo Simulation Approximation: Semi-supervised learning enhances Monte Carlo simulations, which assess portfolio risk and insurance pricing. By combining labeled and unlabeled data, these models speed up complex simulations.

This method is especially useful when acquiring labeled data is costly, improving the efficiency of risk modeling.

Continue Next Page

Tharun Mandadi

Machine Learning In Financial Risk Management: Key Techniques And Applications

Continued From Previous Page

Deep Learning in Financial Risk Management

Deep learning, which uses multi-layered neural networks, excels at capturing complex, non-linear relationships in financial data. These models are powerful for tasks involving large volumes of unstructured data.

- Convolutional Neural Networks (CNNs): Applied in fraud detection, volatility forecasting, and predicting credit defaults, CNNs identify intricate patterns in financial data.
- Recurrent Neural Networks (RNNs): Used for time-series forecasting, such as stock price predictions and economic forecasting. These models capture temporal dependencies in financial data.
- Deep Reinforcement Learning: Combines deep learning and RL to optimize portfolio management and risk mitigation by adapting strategies based on real-time market data.
- Graph Neural Networks: Represent financial entities and relationships as graphs, helping model systemic risks and interdependencies among financial institutions.

Deep learning techniques provide accurate forecasting and decision-making, making them vital for managing financial risk.

Challenges and Future Directions

Despite its potential, ML in financial risk management faces several challenges:

- Data Quality and Availability: Financial data can be noisy or incomplete, impacting model performance. Ensuring high-quality, reliable data is essential for effective risk modeling.
- Interpretability: Many ML models, especially deep learning models, are difficult to interpret. In regulated industries like finance, understanding how models arrive at their decisions is crucial for transparency and compliance.
- Overfitting and Generalization: Financial markets are volatile and constantly changing. Models trained on historical data may overfit to past trends, failing to generalize to new conditions. Ensuring that models adapt to evolving market dynamics is essential.
- Regulatory Compliance: Financial institutions must ensure that ML models comply with regulations. Models need to be transparent, interpretable, and fair to meet legal and ethical standards.

The future of ML in FRM will focus on improving model transparency, data quality, and generalization to ensure robustness in dynamic financial environments.

Conclusion

Machine learning holds transformative potential for financial risk management by improving predictive accuracy, optimizing decision-making, and adapting to changing market conditions. Supervised, unsupervised, reinforcement, semi-supervised, and deep learning techniques each offer unique strengths in tackling the complex challenges of FRM. While challenges such as data quality, interpretability, and regulatory compliance remain, ML’s ability to revolutionize risk management strategies is immense. As the field continues to evolve, financial institutions will increasingly rely on advanced ML models to navigate the complexities of global financial markets.

Chelsea Niles

Interviewing and Networking: A Learning Experience

When I began my journey at NC State University, I expected to learn in-depth about financial mathematics and the technical concepts central to the field. What came as a surprise to me was the learning opportunities that came from my career development journey. The program not only improved my technical knowledge but also provided excellent career mentoring that has led me down a path of interviewing and networking.

Career mentoring began even before the program had started. During the summer, I received advice on tailoring my resume and refining my interview skills. This early support gave me a head start, and I was able to secure job interviews soon after my classes began. This allowed me to take meaningful steps toward my career goal of becoming an actuary.

Walking into my first actuarial interview, I felt both a mix of excitement and nerves. What I thought was just a chance to secure an internship became an opportunity to showcase my skills, learn from seasoned professionals, and gain valuable insights into the actuarial world. This interview experience consisted of two rounds: an initial 30-minute phone screen with a junior actuary, who had been in my position not long ago, and a second round where I met individually with three actuaries at different career stages, ranging from seven to over 20 years of experience.

This experience was a way for me to learn more about the field from multiple professionals at varying career stages. I ended each conversation with questions about their current projects and recent trends they were observing. A recurring topic in these conversations was the increasing impact of climate change on insurance models and the rising damages they were seeing from disasters like Hurricane Helene. These discussions solidified my interest in the field and reinforced how interesting and dynamic it could be.

These discussions left me wanting to hear more about the field, and I began networking with other professionals. I connected with and reached out to actuarial professionals, including alumni of this program, and I had the chance to learn about the different roles within the field, the programs and technologies most commonly used by actuaries, and how to make myself stand out as a candidate. One conversation in particular that stood out to me involved combining new AI techniques with actuarial modeling, sparking my interest in exploring this intersection further. These interactions gave me clarity on the roles that align with my interests while also building my confidence in professional settings.

Jinjia Peng

Advancing My Career in Quantitative Finance: An Enriching Journey at NC State's MFM Program

As I reflect on my journey so far, the decision to join the Master of Financial Mathematics (MFM) program at North Carolina State University (NCSU) stands out as a turning point that aligns perfectly with my passion for quantitative finance and risk management. With a strong foundation in mathematics and business from my undergraduate years at the University of California, Irvine, I have been able to integrate my analytical skills with the rigorous training provided by the MFM program, opening doors to a career at the intersection of finance, data science, and quantitative analytics.

My Academic Foundation: Merging Mathematics and Finance

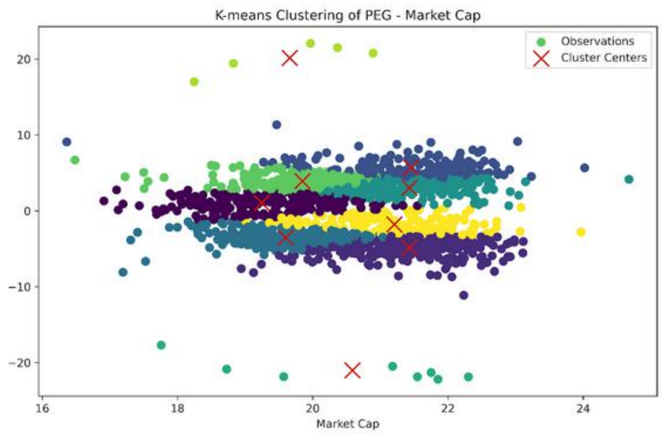
During my undergraduate studies, I earned dual degrees, a Bachelor of Science in Mathematics and a Bachelor of Arts in Business Administration with an emphasis in Finance. This academic combination laid the groundwork for my fascination with quantitative finance. Courses such as Partial Differential Equations, Fixed Income Products, and Advanced Statistics sparked my interest in understanding the mathematical models that drive financial markets.

This strong foundation proved invaluable when I joined the MFM program at NCSU, where the coursework focuses on applying mathematical concepts to solve real-world financial problems. The MFM program's focus on practical applications in areas such as Machine Learning in Finance, Risk Management, and Derivatives Pricing has further solidified my commitment to pursuing a career in quantitative analysis and mathematical modeling.

Applying Machine Learning in Real Estate and Stock Analysis

Beyond academic research, I have actively sought opportunities to apply my skills in diverse projects. For instance, in a recent project focused on predicting Iowa house prices, our team cleaned and standardized the dataset, experimented with Ridge and LASSO regression models, and fine-tuned parameters using RandomizedSearchCV. By the end of the project, we achieved an R^2 score of 0.9 on the test set, with a prediction error of around 10%, which underscores the model's effectiveness in estimating housing costs in the current market.

In another academic project at NCSU, I delved into stock classification using machine learning techniques. Our team focused on clustering companies within the Russell 2000 index using K-Means, leveraging metrics such as market capitalization and price-to-. earnings growth (PEG). We created nine clusters and compared them against Morningstar ratings to assess how our clusters aligned with traditional market classifications. To further enhance our analysis, we applied K-Nearest Neighbors (KNN) for stock classification. By training the KNN model with the clusters generated from K-means, we were able to classify new stocks based on their market cap and PEG values, demonstrating a practical application of machine learning in stock analysis.



The graph of the K-Means grouping of Russell 2000 stocks

Looking Ahead: Career Aspirations in Quantitative Finance

As I near the completion of my master's degree, my career goals are becoming clearer. I am excited about the prospect of working in quantitative financial analysis, including the area of risk and trading, particularly within financial institutions where I can leverage my expertise in machine learning and statistical modeling. The ability to forecast market trends, optimize trading strategies, and manage financial risks using data-driven techniques is a challenge that I am eager to embrace.

Choosing NC State's MFM program was a significant step toward achieving these goals. The program has provided me with not only technical knowledge but also the confidence to tackle complex financial challenges. With graduation approaching in December 2025, I am enthusiastic about applying the skills I have gained to contribute meaningfully to the world of finance.

In conclusion, the journey through the MFM program has been transformative, enabling me to merge my academic interests with practical applications in finance. As I continue to build my career, I am grateful for the experiences that have shaped me and excited for the opportunities that lie ahead.

Sanith Rao

Optimizing For Success: Building A Portfolio Optimization Tool

Optimizing for Success: Building a Portfolio Optimization Tool

As a graduate student in Financial Mathematics at NC State, I'm constantly looking for opportunities to apply theoretical concepts to practical problems. One such opportunity arose during my first semester when I undertook a project to design a portfolio optimization tool. This project became a defining moment in my academic journey, combining mathematical rigor, programming expertise, and a deep understanding of financial principles.

The Project's Motivation

The foundation of this project was rooted in modern portfolio theory, introduced by Harry Markowitz. The idea is straightforward yet powerful: maximize returns for a given level of risk, or equivalently, minimize risk for a desired return. I wanted to create a tool that could apply these principles in a practical setting, empowering investors to construct more efficient portfolios.

To achieve this, I chose C++ as the programming language, leveraging its speed and flexibility. Libraries like Boost, Eigen, and QuantLib allowed me to handle complex numerical computations, including matrix algebra and financial modeling.

Bringing Theory to Life

The project started with gathering historical price data for a set of assets. Using this data, I calculated expected returns, variances, and covariances, laying the groundwork for the optimization process. One of the key challenges was ensuring the covariance matrix was positive definite, a requirement for stable optimization. Eigen's numerical capabilities were instrumental in addressing this.

Next, I implemented a quadratic programming algorithm to solve the optimization problem. This process required balancing computational efficiency with accuracy, especially as I added real-world constraints such as limits on individual asset weights and minimum diversification requirements.

The final product was a user-friendly tool capable of optimizing portfolios based on user-defined risk and return preferences. During backtesting, it demonstrated an 18% improvement in returns compared to simple equal-weight strategies, showcasing the practical value of quantitative finance.

Lessons Learned

This project was not without its challenges, but each hurdle offered valuable lessons:

1. Bridging the Gap: Translating theoretical models into code highlighted the nuances that exist between academic frameworks and practical implementation.
2. Iterative Improvement: Debugging and refining the algorithm required patience and a structured approach, skills that are essential for tackling complex financial problems.
3. Risk-Return Dynamics: Exploring how risk interacts with return deepened my understanding of portfolio management and the importance of diversification.

Quantitative Finance in Action

This project was more than just an academic exercise—it exemplified the real-world impact of quantitative techniques in finance. By enabling investors to make data-driven decisions, tools like this one provide a competitive edge in an increasingly complex and volatile market environment.

Career Aspirations in Quant Trading

Developing this portfolio optimization tool has significantly shaped my career aspirations. As someone deeply interested in quant trading, I see this project as a foundational experience. Quant trading relies on data-driven decision-making, where tools like portfolio optimization play a critical role in risk management and strategy design.

The skills I honed, mathematical modeling, algorithmic implementation, and problem-solving under constraints, are directly transferable to the fast-paced, high-stakes world of quant trading. Whether designing trading algorithms or optimizing risk exposure in portfolios, this project has prepared me to tackle the challenges of the field with confidence and creativity.

Vismit Rekhan

My Journey with the MFM Program at NC State

Starting the Master of Financial Management (MFM) program at NC State has been one of the most rewarding decisions of my academic journey. From setting clear career goals to engaging in meaningful projects, this program has equipped me with the skills and confidence needed to thrive in the finance industry.

When deciding where to pursue my MFM, NC State stood out for several reasons. The university's strong reputation in this field and its vibrant community were major factors. I wanted a place that not only offered excellent academic resources but also fostered a supportive and collaborative environment. NC State delivered on both fronts, making it the ideal choice for my graduate studies.

One of the main reasons I joined the MFM program was to become a financial analyst specializing in risk, quant and investment strategies. The curriculum is designed to provide a deep understanding of financial markets, risk management, and investment analysis. Courses like Advanced Investments and Statistics for Researchers have been instrumental in building my technical expertise. These classes have taught me how to analyze market trends, assess financial risks, and develop effective investment portfolios.

Projects have been a significant part of my MFM experience. I worked on a project optimizing portfolio by introducing momentum and rebalancing aspects. This project not only sharpened my analytical skills but also taught me the importance of data driven decision making in finance. Collaborating with classmates and seniors on such a project has been incredibly enriching, allowing me to learn from diverse perspectives.

Another memorable project involved simulating a portfolio management scenario. Our team had to allocate assets based on different market conditions, which helped me understand the complexities of diversification and strategic asset allocation. Applying theoretical knowledge to real world scenarios through these projects has been invaluable in preparing me for the challenges of the finance industry.

The MFM program places a strong emphasis on professional networking, which has been a highlight of my time at NC State. Attending seminars, workshops, and networking events has allowed me to connect with industry professionals and alumni. These interactions have provided insights into various career paths and opened doors to potential internship opportunities. Building these connections has been crucial in shaping my career aspirations and guiding my professional journey.

Balancing rigorous coursework with personal commitments has been challenging, but it has taught me important lessons in time management and resilience. There were times when juggling multiple deadlines felt overwhelming, but with effective planning and support from peers and faculty, I was able to stay on track. These experiences have strengthened my ability to handle high-pressure situations, a skill that is essential in the fast-paced world of finance.

Beyond academics, NC State offered a welcoming and inclusive community. The diverse student body and collaborative culture made it easy to form meaningful connections and friendships. Additionally, the university's commitment to innovation and practical learning aligns perfectly with my personal values and career goals. Choosing NC State has not only enhanced my financial knowledge but also contributed to my personal growth and development.

As I look forward, I feel well-prepared to enter the financial industry. The comprehensive education and hands-on experiences have laid a solid foundation for my career. I am excited about the opportunities that lie ahead and confident that the skills and knowledge gained at NC State will help me achieve my professional goals.

Reflecting on my time in the MFM program at NC State, I am grateful for the growth and learning I have experienced. The program has not only equipped me with essential financial skills but also shaped me into a more confident and capable individual. I look forward to leveraging these experiences as I embark on my career in finance, knowing that NC State has prepared me well for the challenges and opportunities that await.

Jingxing Wang

Deep Hedging in Asian Options

Asian options, which base their payouts on the average price of an underlying asset over a specific period, are widely traded due to their reduced sensitivity to short-term market fluctuations. However, their path-dependent nature makes effective hedging a significant challenge. Traditional methods like Monte Carlo simulations are computationally expensive and often unreliable, particularly near critical price levels where the option's payoff structure changes. To overcome these limitations, I applied deep learning techniques to develop a dynamic and efficient hedging framework for Asian options.

This project employed the deep hedging framework, which integrates machine learning into risk management. I designed a model using recurrent neural networks (RNNs), specifically Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). These architectures are well-suited for handling the sequential data and path dependencies inherent in Asian options. Unlike traditional methods that calculate delta statically, the RNN-based approach dynamically adjusts hedging strategies by learning patterns from historical data and adapting to evolving market conditions.

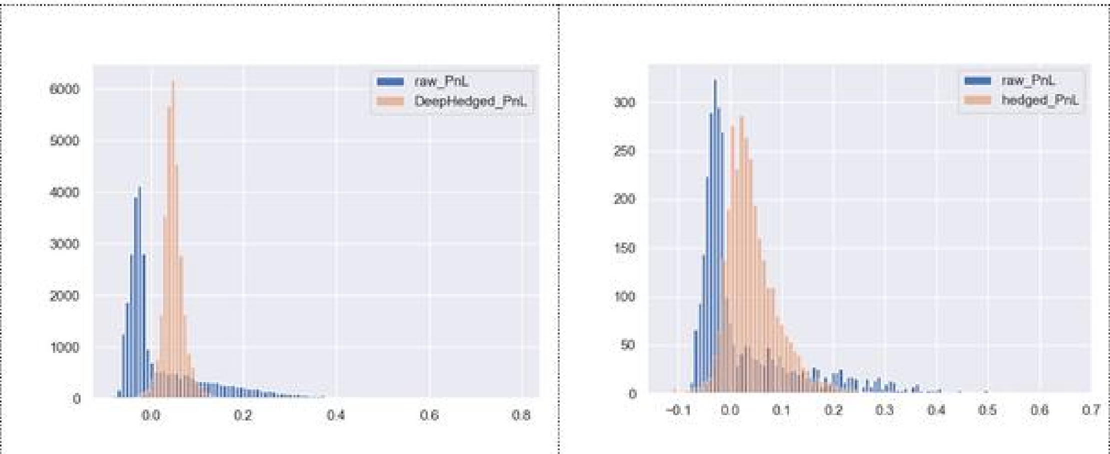
The dataset for this research included daily CSI 500 Index data from 2013 to 2024. To ensure robustness and realism, I used advanced preprocessing techniques such as fat-tailed distribution modeling to account for extreme market events, AR-GARCH processes for volatility clustering, and segmented bootstrapping to simulate diverse market scenarios. These methods created a high-quality dataset that allowed the model to capture the intricate behaviors of Asian options effectively.

Empirical results demonstrated the RNN model's superiority over traditional Monte Carlo methods. The variance of profit and loss (P&L) after hedging was reduced to just 5% of the pre-hedging level, compared to 20% achieved by Monte Carlo simulations. The RNN model also addressed key limitations of Monte Carlo methods, such as poor convergence near critical price levels, and was computationally more efficient due to its ability to leverage learned patterns rather than recalculating delta for each simulation.

This research showcases the transformative potential of machine learning in quantitative finance. By addressing the inefficiencies of traditional hedging methods, the deep hedging framework provided a scalable and adaptive solution for managing the risks associated with Asian options. The success of the RNN model in improving hedging precision and efficiency highlights how advanced machine learning techniques can enhance traditional financial models.

Beyond its technical achievements, this project was a defining moment in my academic journey. As a student in NC State's Master of Financial Mathematics program, I applied theoretical knowledge to a practical challenge, blending financial modeling, machine learning, and programming. The experience deepened my understanding of interdisciplinary problem-solving and reinforced my passion for leveraging innovation to tackle complex challenges in finance.

In conclusion, the application of deep learning to Asian option hedging represents a significant advancement in financial mathematics. This research not only underscores the value of innovative approaches in addressing industry challenges but also highlights the potential for machine learning to transform risk management practices. As the financial industry continues to evolve, I am eager to contribute to its growth by exploring new applications of advanced quantitative techniques.



(a) Deep Hedging PnL | (b) Delta Hedging PnL

Yu Wang

Fixed Income Trade Ideas: Harnessing Rate Cuts and Market Trends

US Credit Market Outlook

A positive medium-term outlook on credit markets is driven by strong fundamentals, a favorable macroeconomic environment, and improving technical factors. The recent Fed rate cuts, combined with stable data (e.g., retail sales, jobless claims), support tighter spreads for investment-grade bonds and loans, and stable spreads for high-yield. BB-rated and short-dated investment-grade bonds offer defensive catch-up opportunities after lagging during the recent rally.

With improving fundamentals, increasing demand, and modest supply, tight spreads are justified. We can refer to the mid-1990s soft landing, which showed that credit spreads reached their tightest levels in recent years while the Fed maintained restrictive policies.

Fed Rate Cut Implication

The Fed's larger-than-expected 50 basis point rate cut in September, as well as the 25 basis point rate cut in November, signaling the beginning of an easing cycle, has eased the investors' concern that the Fed might fall behind the curve. A steeper yield curve will boost credit demand. Declining cash rates are expected to attract more fund flows into credit, especially for riskier assets.

Nevertheless, data dependency remains critical. Weak labor market data could bring back the concerns, while stable data could boost market confidence.

Navigating Market Uncertainty

Despite positive rate-cut effects, uncertainty persists due to weak labor market data. Markets recently reacted to soft payroll numbers in July and August, emphasizing the sensitivity of tight spreads to even small economic shifts.

Current spreads for investment-grade (IG) and high-yield (HY) suggest limited near-term compression opportunities, while structured products like Agency Mortgage-Backed Securities offer better risk-adjusted returns.

Asia Credit at a Turning Point

Asia credit faces challenges like high economic, sector, and issuer concentration, and lower risk-adjusted returns, particularly due to defaults in China's high-yield property sector. Improvements in diversification and risk management are necessary to enhance Asia credit. Key issues include high issuer and sector concentration and reliance on specific economies like China.

Potential strategies for Asia credit investors include diversifying portfolios, focusing on sectors like banking, and considering investments in other countries such as Japan to mitigate concentration risks.

Investment Strategies

Defensive sectors such as investment-grade bonds, agency MBS, and structured products are preferred in the near term due to tighter spreads.

CCC-rated high-yield bonds have significantly outperformed, while BBs have lagged but are expected to rebound once market stabilization occurs.

Diversification guidelines recommend limiting issuer, sector, and economy weights to avoid concentration risks and improve risk-adjusted returns.

Jinyi Yang

Loss Severity Analysis

During the Fall 2024 semester, I had the opportunity to work on a team project focused on loss severity modeling, also known as Loss Given Default (LGD) modeling. The primary objective was to develop a comprehensive LGD model to predict potential losses for loans in default. LGD models are widely used in the financial industry, as they enable institutions to better assess potential losses and allocate capital for reserves more effectively.

For our analysis, we collected data on single-family residential mortgage loans from Fannie Mae, which included monthly data spanning from 2003 to 2017. Additionally, we gathered macroeconomic data from Bloomberg and the Federal Housing Finance Agency, including metrics such as the Consumer Price Index (CPI), unemployment rate, and Housing Price Index (HPI). We merged these macroeconomic variables with the loan data based on the loans' zero balance dates and origination dates. It was crucial to estimate loss indicators, which are components used to compute LGD, such as foreclosure costs. However, we could not use these components directly due to the risk of forward bias. Instead, we employed state-level averages of these components from the training dataset as estimators.

In our feature analysis, we identified significant features and visualized their relationships with LGD. For example, loans with mortgage insurance coverage tended to exhibit lower LGD, as the insurance aids in recovering losses during defaults. To capture this relationship, we used one-hot encoding to generate dummy variables as features for our regression models.

For model construction, we implemented a rolling window method to train our models. We began by sorting the loan data by zero balance date to create a time series dataset. Next, we iteratively established a testing set within a rolling window, using all data prior to the testing set as the training set. This methodology reflects real-world scenarios, where we rely solely on historical loan data to build our model.

We selected linear regression and XGBoost as our modeling approaches. Our results showed an R-squared value of 0.39 for linear regression and 0.50 for XGBoost, indicating that LGD may have complex non-linear relationships with the selected features. Analyzing the SHAP values from XGBoost revealed that CPI was a significant factor in modeling LGD, while linear regression indicated that CPI was not a significant factor. This discrepancy suggests that CPI's relationship with LGD is likely non-linear.

Although XGBoost outperformed linear regression in our analysis, this does not imply that linearity is an inadequate assumption for LGD. It is important to note that the calculation of LGD inherently involves linear combinations of costs and proceeds, indicating that some linear relationships are indeed present. In future analyses, we may consider integrating both linear and non-linear methods to enhance our LGD modeling.

This project allowed me to apply the knowledge I gained in the classroom to build a model based on real data, while also exposing me to the field of quantitative risk modeling. As a result of this experience, I feel more confident pursuing a career in this area and aspire to make a meaningful impact by leveraging my skills.

Nick Zehnle

Takeaways and Future Testing from my Undergraduate Thesis

The aim of my undergraduate thesis was to evaluate which model, GARCH(1,1) or COGARCH(1,2), is more effective in estimating variance swaps. In essence, I set out to determine whether a discrete-time model or continuous-time model would produce better results. Using three-year contracts, it was discovered that the COGARCH(1,2) model well outperformed the GARCH(1,1) model in most regards. However, the strict assumptions of the COGARCH(p,q) model pose a concern in terms of reliability. Out of the assumptions, the requirement of the data to be stationary proved to be the most hindering. This caused only 54.33% of the intended simulations to generate valid variance estimates, i.e. estimates greater than zero. That said, the GARCH(1,1) variance swap estimates were generally ineffective with considerable differences between V (annualized variance) and K_{var} (estimated fair strike). Thus, despite the number of erroneous estimates provided by COGARCH(1,2), it appears to be the superior model in estimating variance swap payoffs.

Overall, the COGARCH(1,2) model displayed promising results in variance swap estimation. Yet, it is salient to note that COGARCH(1,2) did not function properly with less than roughly three years of data; hence, the decision to analyze three-year contracts. An investigation of short-term payoff forecasting using COGARCH(1,2) should be conducted following our results. For instance, the payoffs of three-year contracts should be forecasted one day before expiration and then compared to the realized payoffs. It is possible that COGARCH(1,2) could be used to hedge losses in underperforming variance swap contracts. Four-year contracts would be a suitable next candidate for testing with perhaps a different underlying asset. Additionally, although stock prices cannot oftentimes be expressed as stationary, the extraneous variable of COVID-19 seemed to affect the dataset analyzed. Choosing a period of time not substantially influenced by an extraneous variable may produce different results.

Reflections





20th Anniversary & Alumni Reunion
October 2024






Financial Mathematics Class of 2025

SAS Hall at NCSU's Main Campus

NC STATE UNIVERSITY

Financial Mathematics Graduate Program

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