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NC STATE UNIVERSITY

Financial Mathematics

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Message from the Director

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

As we wrap up the spring semester, I am glad to share with you that our students continue to perform strongly on the job market. We continue to maintain the perfect 100% placement rate (6 months within graduation) for the class of December 2022. All our graduates who were actively looking for full-time jobs have received full time job offers. The employers include Goldman Sachs, JP Morgan Chase, Blackstone, Fidelity, Bank of America, Wells Fargo, Truist, etc. with an average starting compensation of $130,000 (base salary plus bonus) reflecting an increase of more than 10% from last year. Our student internship placement is also very strong. More than two thirds of our students have secured summer internships at companies such as Morgan Stanley, Citi, Truist, etc., while some of our remaining students are still actively earning interviews.

This summer, students who don't plan to do any summer internships will be working on three industry originated projects. These include interest rate derivative models; consumer and small business credit risk; and quarterly forecasting models. Our industry mentors have backgrounds in commercial banking, investment banking and financial services.

The high quality of our graduates is not only reflected in those strong placement records but is also recognized by the industry. Please refer to the message from our career services director, Mr. Patrick Roberts, for more details.

In fall 2023, we look forward to hosting a *Women in Finance* symposium on Friday, September 15, 2023, at the McKimmon Center here at North Carolina State University. This symposium is funded by NC State University together with our Financial Mathematics program. Industry leaders will be invited to share their path to success and the future career opportunities available for women within the field of finance.

In addition, the 7th Eastern Conference on Mathematical Finance will be hosted at NC State University on Oct. 20-22, 2023. Researchers and students from other top universities will come to Raleigh to share their research results and ideas. Students from the Financial Mathematics Program are strongly encouraged to attend.

I wish everyone a great summer!

NC State Financial Mathematics Is Highlighted

Patrick Roberts
Director of Career Services

The NC State Master of Financial Mathematics (MFM) program was recently highlighted in an article published by the globally known leading financial services career website efinancialcareers.com.

The article discusses the value and return on investment of master's degree programs in financial engineering (MFE) or financial mathematics as an alternative to traditional master's programs in finance. The authors utilized the latest graduation data from publicly available employment reports to compare outcomes of specialized master's programs like the MFM program at NC State. As stated in the article "MFE graduate salaries rose at all colleges in the past two years. The largest jump in base salary was at NC State University, with the current average of $118k up $31k on two years ago." This is an impressive 35% increase in base salary secured by NC State graduates within this two-year span.

In addition to an increase in base salary, NC State also consistently maintains a 100% full-time employment rate of graduates up to 6 months following graduation, including the recent graduating class of 2022.

The MFM Program at NC State is proud to be cited by this internationally recognized news source and be included on a list of prestigious universities such as NYU, Berkley, Carnegie Mellon, Columbia, and Georgia Tech.

NC State MFM program director, Dr. Tao Pang said "I am thrilled to see that more and more companies recognize the value of our students. We will continue to maintain an updated curriculum and meet the market demands. I am confident that our students at NC State will have continued success and be competitive in the job market."

Click here to view the complete article. For more information regarding the MFM program at NC State, please contact program director, Dr. Tao Pang at tpang@ncsu.edu.

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Nidhay Acharekar

The Downfall of Credit Suisse: A Series of Scandals and Risk Management Failures

Credit Suisse, the second largest bank in Switzerland, has been acquired by UBS Group AG for $3.3 billion in an effort to prevent its collapse and the potential devastation it could cause to the global financial system. The bank was one of the 30 globally systematically important banks, meaning its collapse could have severe consequences.

What led to the downfall of this once-prominent institution in the finance industry? In recent years, Credit Suisse has faced multiple management shifts due to a series of scandals and significant financial losses. One such scandal was the spying controversy in 2019, which led to the resignation of CEO Tidjane Thiam. In addition, the bank's wealth management head Iqbal Khan left for UBS and was placed under surveillance through a private contractor, as he was accused of poaching clients. However, the most significant event that led to the fall of Credit Suisse was the collapse of two major financial firms, Archegos Capital and Greensill Capital, which caused the bank to lose approximately $1 billion in 2021.

After the Archegos collapse, Credit Suisse's CEO and Chief Risk and Compliance Officer resigned. An independent investigation revealed that the bank had failed to manage its risk effectively, although there was no evidence of fraudulent or illegal conduct. The bank's troubles continued when chairman Antonio Horta-Osorio resigned in January 2022 over a scandal related to breaching Swiss and British COVID-19 quarantine protocols. Later that year, a rumor about Credit Suisse facing impending failure led to clients withdrawing around $119 billion of funds in the last quarter of 2022, causing the bank's stock to decline almost 70% in the same year.

To boost liquidity and investor confidence, Credit Suisse announced plans in early 2023 to borrow $55 billion. However, its top-backer, Saudi National Bank, declined to lend any more money due to regulatory barriers. The final blow came with the collapse of US-based Silicon Valley Bank and Signature Bank, which sparked fear throughout the global banking system. The US government promised depositors that funds would be available for withdrawal, but the fear led to UBS' purchase of Credit Suisse.

In summary, Credit Suisse's downfall was a result of a series of scandals and risk management failures, causing significant financial losses and ultimately leading to the bank's acquisition by UBS Group AG.

Rushikesh Amode

Aletheia: Shedding Light Inside the Black Box

Interpretability of black box models is a critical issue in the field of machine learning and artificial intelligence. Black box models are models whose internal workings are not transparent, making it difficult for users to understand how they arrive at their predictions or decisions. This lack of transparency can limit the trust that users have in these models, as well as their ability to diagnose errors or biases.

The paper "Interpretability of Deep ReLU Neural Networks using Aletheia" proposes a novel method for interpreting the behavior of deep neural networks with rectified linear unit (ReLU) activation functions, which are commonly used in deep learning.

The method, called Aletheia, is based on the idea of approximating the behavior of the neural network using a set of piecewise linear functions. These linear functions capture the local behavior of the network around each point in the input space and can be used to identify the regions where the network is most sensitive to changes in the input.

To generate these piecewise linear functions, Aletheia uses a combination of gradient descent and random sampling. First, the method randomly samples a set of points from the input space and computes the gradients of the network with respect to each input variable at each point. This technique then uses these gradients to perform a series of gradient descent steps, which converge to a set of piecewise linear functions that approximate the behavior of the network around each point.

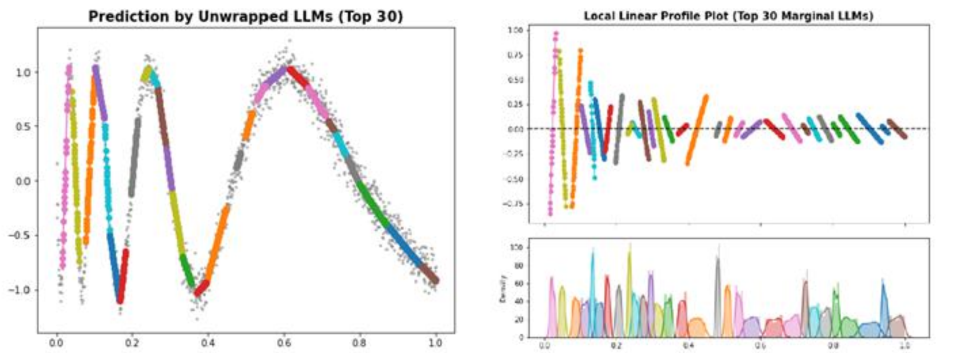


Figure 4: DNN prediction and local linear profile plot (Data: ChirpWave; ReLU Net: [40]*4)

The authors demonstrate the effectiveness of Aletheia on several benchmark datasets, showing that it can accurately identify the regions where the network is most sensitive to changes in the input, and can identify which input variables are most important for making predictions. They also show that Aletheia can be used to identify adversarial examples, which are inputs that have been intentionally crafted to fool the neural network into making incorrect predictions.

In regression problems, the goal is to predict a continuous output variable given a set of input variables. The Aletheia method can be used to identify the regions in the input space where the network is most sensitive to changes in the input variables, and to identify which input variables are most important for making accurate predictions. This can help to understand the relationship between the input variables and the output variable, and to identify any non-linear interactions between them.

In classification problems, the goal is to predict a categorical output variable given a set of input variables. The Aletheia method can be used to identify the regions in the input space where the network is most sensitive to changes in the input variables for each class, and to identify which input variables are most important for distinguishing between different classes. This can help to understand the decision boundaries of the neural network and to identify any features or combinations of features that are particularly important for classifying different instances.

Figure 5: Local linear models unwrapped from pre-trained ReLU net, the corresponding activation regions, and the local linear profile plot (Data: CoCircles; ReLU Net: [40]*4)

Overall, the paper presents a promising new approach to interpreting the behavior of deep neural networks with ReLU activation functions and demonstrates its effectiveness on several benchmark datasets.

Colson Chen

Credit Risk Analysis Under State Transition Framework

A state transition framework for the study of credit risk and other time-series-based events comes in handy in estimating future events. The project that my team is working on this semester focuses on the comparison of the performance of different classification models under the state transition framework and we also touch a bit on the simulation method for long-term prediction as the concluding part of our project.

In this project, we study the performance, measured in Area Under the Receiver Operating Characteristic(AUROC), Area Under the Precision-Recall Curve(PRAUC), and Multiclass Brier Score, of various multiclass-classification models. The empirical probability model would be used as a baseline model and we explore models ranging from a generalized linear model to a neural network to conduct a comprehensive comparison. The implemented models include Deep Neural Networks, Multinomial Logistics Regression, Support Vector Machine, Linear Discriminant Analysis, and CatBoost Tree-based Model so that we have at least a representative from each class of models and thus we could determine the best model concerning the prediction of future credit risk.

In the first half of the semester, we paid more attention to building up a streamlined data pre-processing procedure which enables us to scale up our model fitting at a later stage. Specifically speaking, we collected mortgage performance data from Fannie Mae, property price data from the Federal Housing Finance Agency, benchmark mortgage rate data from Freddie Mac, unemployment rate data from the Bureau of Labor Statistics, and other supplementary data such as judicial information for each state. After merging and synchronizing the data from multiple data sources, we follow the standard procedure to detect and handle missingness issues, outlier issues, and other abnormal entries with imputation and filtering. For the machine learning model, we adopt the Z-score method for standardization and one-hot encoding for the categorical variables if necessary.

Cross-validation and common train test split techniques are utilized when we are training the model. For specific neural networks and gradient boosting models, parameter tuning and grid searching routines are utilized to figure out the setting that yields the best prediction performance. To ensure the fairness of comparison we use the same sample proportion of performance data and the same test set for all proposed models.

One of the biggest challenges we have encountered is the limitation of computing resources. A task like training an extremely large dataset with multiple training iterations could easily overwhelm and crush our local machine which only has very limited RAM and a poor cooling system. To resolve this problem we try to revise and improve our program efficiency, seek help from external experts, and try to transport our project to cloud-based computing platforms such as Amazon AWS and Google Colab which could further scale up our model training and fitting process utilizing the parallel computing and cloud computing features. University's high-performance computing units would be another resource that we are applying for which could also help us out.

The conclusion is not yet drawn and we will focus on the simulation process for the coming months before we could finally compare the accuracy of all proposed models on individual loan level and portfolio level. We acknowledge two approaches, Markov Chain simulation and Monte Carlo simulation that are commonly adopted together to verify the convergence which we will implement shortly.

Chieh-hsi Cheng

My Second Semester in NC State

Being in the second semester at NC State University, I think I've gotten accustomed to life here. Owing to last semester's workload, I selected less courses than last semester and also focused more on the risk field.

In my educational phase now, I think I'm still exploring which field might fit best to me. For the first semester, I tried different data science courses and projects, including Credit Card Default Prediction and Crime Rates Analysis, it's a great attempt and I also feel interested in processing those data. This semester, I focused more on the risk field, I chose risk electives, which is Financial Risk Analysis, and risk project, which is Comparison of VaR with parametric method and EVT. I also scheduled meetings with Dr. Pang and Mr. Robert many times. They give me a lot of support in setting up a career path, adjusting my resume and cover letters, and searching for a Summer Internship.

For the start of this semester, I applied to almost three hundred interns but did not get any interviews from any companies. However, after getting some suggestions from classmates and professors, I started to adjust my strategy in applying for an internship. I focused more on the job description in each job and customized my resume and cover letter. And because I narrowed down my own career path, I can now select the positions I'm truly interested in. Recently, I just got two interview opportunities from a bank and a technology company. In the first round, I talked to a manager and a leader from a small team and there were just some behavioral questions asked from them. However, there was a question I thought was funny. They asked me what kinds of animals I would choose to represent myself, and they also shared their own representations to me. I found that during this type of interview, we were more like friends, sharing our thoughts and trying to get to know each other. It's a pretty great experience in this interview. During another interview, done by phone, I felt more nervous because I couldn't see their reactions. And my interviewer was more likely a HR representative than an expert in the field. There were also some behavior questions but most of the interview was focused on asking questions about their company and the position. No matter how I behave in these interviews, I learn a lot from these experiences. It's just a great start!

Last semester, I attended our school's mentor and mentee program. I've been assigned an undergrad student who is an applied math major. He was interested in the financial mathematics program and wanted to know more. So, I spent time with him and shared my own experience in the program. Fortunately, this semester we are both in the Monte Carlo class in Financial Mathematics and we work in the same team. He also applied to our program and has been recently admitted - I'm proud of him and really appreciate our friendship right now.

This is a fast paced program and I feel like I want to stay here for a longer time. I really like the life here. However, because of my goal of entering into this program, I need to put more effort into finding an Internship or even full-time job in the future. I learned a lot from this program and if anyone wants to know more about the financial mathematics field, I would definitely recommend this program!

GV Gundepudi

Monte Carlo Methods for Finance: Implementing Python

Monte Carlo simulations are a powerful tool used in finance to model various scenarios and predict potential outcomes. These simulations can be used to estimate the probability of different outcomes occurring and to assess the risk associated with investment decisions.
In finance, Monte Carlo simulations are often used to model the behavior of financial assets such as stocks, bonds, and derivatives. These simulations are typically based on a set of assumptions about the underlying asset and the market in which it trades. The simulations can then be used to generate a range of possible outcomes for the asset, including its expected return and its volatility.

Python is a popular programming language used in finance and is well-suited for Monte Carlo simulations. There are several libraries available in Python, such as NumPy and SciPy, that provide the necessary tools for generating random numbers and performing statistical analyses.
To illustrate the use of Monte Carlo simulations in finance, let's consider an example of a simple stock price model. We will assume that the stock price follows a geometric Brownian motion, which is a common model used to describe the behavior of stock prices over time. This model assumes that the rate of return on the stock is normally distributed with a constant mean and variance.

To simulate this model in Python, we will use the NumPy library to generate a set of random numbers that follow a normal distribution. We will then use these random numbers to generate a set of simulated stock prices over a given time horizon.

Here is some example code that illustrates how this can be done:

```
import numpy as np

# Define the model parameters
S0 = 100 # initial stock price
mu = 0.05 # expected return
sigma = 0.2 # volatility
T = 1 # time horizon in years
N = 252 # number of time steps

# Generate a set of random numbers
dt = T / N
t = np.linspace(0, T, N+1)
dW = np.random.normal(0, np.sqrt(dt), N)

# Generate a set of simulated stock prices
S = np.zeros(N+1)
S[0] = S0
for i in range(1, N+1):

 S[i] = S[i-1] * np.exp((mu - 0.5 * sigma**2) * dt + sigma * dW[i-1])

print(S)
```

In this example, we first define the model parameters such as the initial stock price, expected return, volatility, time horizon, and number of time steps. We then use NumPy to generate a set of random numbers dW that follow a normal distribution with mean zero and standard deviation sqrt(dt).

We then use these random numbers to generate a set of simulated stock prices S over the time horizon T. The simulated stock prices are calculated using the formula for geometric Brownian motion, which takes into account the expected return, volatility, and time step. Once we have generated a set of simulated stock prices, we can use these prices to estimate various statistics such as the expected return and volatility of the stock. We can also use these prices to estimate the probability of different outcomes occurring, such as the probability of the stock price exceeding a certain threshold or the probability of the stock price declining by a certain amount.
Monte Carlo simulations can also be used to model more complex financial instruments such as options and derivatives. These instruments often have nonlinear payoffs that depend on the underlying asset price, and Monte Carlo simulations can be used to estimate the expected payoff and associated risk.

In conclusion, Monte Carlo simulations are a powerful tool used in finance to model various scenarios and predict potential outcomes. Python is a popular programming language for performing Monte Carlo simulations, and there are several libraries available that provide the necessary tools for generating simulations.

Sachin Iyengar
Financial Math: My Road to a PhD

As someone who has always been curious in the way businesses operate, I have been interested in pursuing a PhD in Business Management - Accounting for a long time. However, the path to obtaining a PhD is not linear in the same way as K-12 and undergraduate programs. After finishing my undergraduate degree, in the beginning of the pandemic, I quickly started my Masters in Accounting program. I was halfway through completing my degree, when I realized that my skill set was designed for working in the industry. The PhD programs I wanted to apply to all required background knowledge in statistics, programming, math, and economics. Finding myself lacking in these skills is what led me to apply to the Financial Mathematics (FIM) program at NCSU.

The program at NCSU was ideal for me. While I had developed some general knowledge in accounting, I needed to work on my quantitative skills and the FIM program had the perfect list of courses to set me up for a PhD. In fact, the program even had a specific track for prospective PhD students! During the program, I communicated with Dr. Tao Pang every step of the way to make sure the courses I were taking would have a direct impact on my future goals. I made changes such as substituting statistics courses where another course may not have been as directly applicable. These minute details are what really helped set me up for my PhD applications. With that said, the program itself is set up well for any goal that you may have, whether in academia or in industry.

I am currently in the process of applying to the PhD programs and I could not be more grateful to the FIM program for setting me up well to apply. The programming and quantitative skills I have developed will be invaluable in my pursuit of research. I already have been given opportunities to put my skills to use during my interviews such as the questions related to my projects. Over the many interviews I have had over the past few months, I have found that interviewers love to see and discuss the projects that I have worked on. I am often asked about my project involving venture capitalist expectations and valuation of their pre and post IPO company.

As a future PhD student, I have had to narrow my interests in accounting to corporate governance, the opportunities/effects of fraud, and the economic, social, and environmental consequences of corporate policies. There are so many different avenues for research and topics are very broad. While it is important for researchers to consider the stakeholders, I believe the footprint that a company makes must also be considered when looking at research topics. I hope to make an impact by researching ways to help the system hold itself more accountable.

Rohit Jain

Getting to Know About IV Regression

IV regression, also known as instrumental variable regression, is a statistical technique used to estimate the causal effect of an independent variable on a dependent variable when there is a problem of endogeneity. Endogeneity occurs when the independent variable is correlated with the error term in the regression equation, leading to biased estimates of the causal effect. IV regression solves this problem by introducing an instrument variable that is correlated with the independent variable but not with the error term, thus providing a valid estimation of the causal effect.

The instrument variable must satisfy two conditions: relevance and exogeneity. The relevance condition requires that the instrument variable is correlated with the independent variable, while the exogeneity condition requires that the instrument variable is uncorrelated with the error term in the regression equation. Violation of either of these conditions may lead to biased estimates of the causal effect.

IV regression can be used in various fields, such as economics, finance, and public health. For example, in economics, IV regression can be used to estimate the effect of education on income, while controlling for endogeneity due to unobserved factors that affect both education and income, such as innate ability or family background. In finance, IV regression can be used to estimate the effect of a firm's investment on its stock price, while controlling for endogeneity due to factors such as market conditions or management decisions.

There are several methods for estimating IV regression, such as two-stage least squares (2SLS), three-stage least squares (3SLS), and limited information maximum likelihood (LIML). The 2SLS method is the most widely used and involves two stages. In the first stage, the instrument variable is regressed on the independent variable to obtain the predicted values of the independent variable. In the second stage, the predicted values of the independent variable are used as the regressor in the regression equation, along with the instrument variable and other control variables, to estimate the causal effect of the independent variable on the dependent variable.

The 3SLS method is similar to 2SLS but involves an additional stage for estimating the covariance matrix of the error terms in the first two stages. The LIML method is a more efficient method that uses a combination of 2SLS and maximum likelihood estimation to obtain consistent estimates of the causal effect.

IV regression has several advantages over ordinary least squares (OLS) regression, which is the most commonly used method for estimating regression equations. First, IV regression provides unbiased estimates of the causal effect even when there is endogeneity in the regression equation. OLS regression, on the other hand, may provide biased estimates of the causal effect when there is endogeneity, leading to incorrect inferences about the relationship between the independent and dependent variables.

Second, IV regression can handle situations where the independent variable is not directly observable or is subject to measurement error. In such cases, IV regression can use an instrument variable that is correlated with the unobservable or mismeasured independent variable to estimate the causal effect.

However, IV regression also has some limitations. First, it requires a valid instrument variable that satisfies the relevance and exogeneity conditions. Finding such an instrument variable may be difficult or impossible in some cases, which limits the applicability of IV regression.
Second, IV regression may lead to reduced precision and statistical power compared to OLS regression, especially when the sample size is small or the instrument variable is weakly correlated with the independent variable.

In conclusion, IV regression is a useful statistical technique for estimating the causal effect of an independent variable on a dependent variable when there is a problem of endogeneity. It is widely used in various fields to control for endogeneity and obtain unbiased estimates of the causal effect. Overall, IV regression is a valuable tool for researchers and practitioners in various fields who seek to estimate causal relationships while controlling for endogeneity.

Abhilash Kalapatapu

Silicon Valley Bank Goes Down The Valley

Silicon Valley bank was founded in 1983. They specialized in banking and finance for young businesses with venture capital backing, mostly in the technology sector. Around half of all venture-backed technology and healthcare startups in the United States received funding from SVB. It was a favoured bank for the technology sector because they backed new businesses that other banks wouldn't accept owing to higher risks. This could be seen in the bank's rising deposits, which by the end of 2021 had increased to $189.2 billion from $49 billion in 2018. Most of these deposits were invested by the bank, as banks frequently do. When consumers spent a lot of money on electronics and digital services during the pandemic in 2020, this was a hot market for tech companies. The services of SVB were required during this period for tech companies to hold their funds for operational costs like payroll.

Silicon Valley Bank's failure may have been mostly caused by these three elements, namely: regulation rollbacks during the Trump administration, poor risk management at the bank, and sudden interest rate increases following a decade of extremely cheap borrowing rates.
The Economic Growth, Regulatory Relief, and Consumer Protection Act was approved by Trump in 2018. It made the case that regional and community banks' capital, liquidity, and stress requirements would be bad for the economy. The asset threshold for companies designated as "systemically important financial institutions" was raised by legislators from $50 billion to $250 billion. The Federal Reserve restricted its stress testing to banks and bank holding companies with assets of at least $100 billion. These revisions increased the likelihood that a large financial firm with assets of between $100bn and $250bn would fail.

A Fed review of the bank in 2021 uncovered significant flaws in the way it was managing risks. They raised the concern that the company was not doing a good enough job of guaranteeing its solvency in the event of crisis. Yet, the bank did not address these issues. By the second half of 2022, the bank was subject to a supervisory review, and the Fed realized that the company was using bad models to predict how its operations would fare as the Fed raised interest rates. Its executives had believed that higher interest income would significantly improve their financial situation as rates rose, but this assumption was not supported by the facts. Additionally, the bank didn't have a chief risk officer for a portion of 2022, a claim that the Federal Reserve is currently reviewing.

A large percentage of the bank's deposits were not covered by federal insurance, which increased the likelihood that consumers would leave the company at the first indication of trouble. A large portion of the bank's depositors came from the IT industry, which has recently faced difficulties because of rising interest rates that have hurt the company. In addition, Silicon Valley Bank owned a significant amount of long-term debt that had lost market value because of the Fed's increase in interest rates to combat inflation. As a result, the bank suffered significant losses when they had to sell those securities to raise money to handle a surge in consumer withdrawals. With the sell-off, the bank reported losses of $1.8 billion, alarming the public of a capital shortage. Rapidly spreading panic resulted in billions of dollars in withdrawals. The bank was taken over by the regulators in a matter of days.

The collapse of the Silicon Valley Bank is viewed as the biggest financial crisis since 2008. It serves as a classic example of the consequences of risk mismanagement in the banking industry and emphasizes the importance of effectively managing risk.

Although we cannot predict how it would affect the entire economy, a recession in the coming year is now more likely.

Eby Kannamkara

The Bank Run of Silicon Valley Bank (SVB)

In 2008, the financial crisis caused a wave of bank failures and massive losses. One bank that was hit hard was Silicon Valley Bank (SVB), a bank that specialized in lending to tech start-ups in Silicon Valley. The bank was considered one of the most successful banks in the industry, but it was not immune to the financial crisis. In the fall of 2008, the financial crisis was at its peak. Lehman Brothers had just collapsed, and investors were panicking. As the panic spread, investors started to withdraw their funds from SVB, causing a bank run.

The bank run was caused by a lack of confidence in the banking system, as well as concerns over the health of SVB. Investors feared that the bank would not survive the crisis, and they wanted to withdraw their funds before it was too late. SVB was hit hard by the bank run. The bank had to use its own funds to meet the withdrawal requests, which caused a liquidity crisis. The bank was forced to cut back on its lending to start-ups, which had a ripple effect on the Silicon Valley tech industry.

SVB was able to survive the bank run, but it was a wake-up call for the bank and the tech industry. The bank realized that it needed to be more transparent with its investors and provide more information about its financial health. The tech industry also realized that it was not immune to the financial crisis, and it needed to be more cautious with its investments.
In the years since the bank run, SVB has made changes to its business model to reduce its risk exposure. The bank has also become more transparent with its investors, providing more information about its financial health and risk exposure.

The bank run of SVB was a reminder that no bank or industry is immune to a financial crisis. It was also a reminder of the importance of transparency and risk management. SVB and the tech industry learned valuable lessons from the bank run, and they have emerged stronger and more resilient as a result.

Shivani Kohade
Sustainable Investing

Sustainable investing, also known as socially responsible investing (SRI) or environmental, social, and governance (ESG) investing, has been gaining in popularity in recent years as investors seek to align their investments with their values.

What is sustainable investing?

Sustainable investing is an investment approach that seeks to consider environmental, social, and governance (ESG) factors in addition to traditional financial metrics when making investment decisions. Sustainable investors believe that companies that prioritize ESG factors are more likely to be financially sustainable over the long term and create positive social and environmental impacts.

ESG factors can include a wide range of issues such as climate change, labor standards, diversity and inclusion, human rights, and corporate governance. Sustainable investors evaluate companies based on these ESG factors and use this information to make investment decisions.

Why is sustainable investing becoming more popular?

There are several reasons why sustainable investing is becoming more popular:

1. Values alignment: Sustainable investing allows investors to align their investments with their personal values and beliefs. Many investors want their investments to have a positive impact on society and the environment, and sustainable investing provides a way to do so.
2. Financial performance: There is growing evidence that companies that prioritize ESG factors are more likely to be financially sustainable over the long term. This is because companies that manage ESG risks effectively are better positioned to withstand market disruptions and regulatory changes, and are more likely to attract and retain customers, employees, and investors.
3. Regulatory and societal pressures: Governments, regulators, and civil society are increasingly demanding that companies address ESG risks and opportunities. Sustainable investing allows investors to support companies that are making progress on ESG issues and encourage others to do the same.
4. Investment opportunities: Sustainable investing is no longer a niche investment approach. There is now a wide range of investment products and strategies that incorporate ESG factors, making sustainable investing accessible to investors of all types and sizes.

There are several types of sustainable investing strategies, including:

1. Negative screening: Excluding companies or industries that do not meet certain ESG criteria, such as those involved in tobacco, weapons, or fossil fuels.
2. Positive screening: Investing in companies that meet certain ESG criteria, such as those with strong environmental practices or diverse and inclusive workforces.
3. Impact investing: Investing in companies or projects that have a specific social or environmental impact, such as renewable energy or affordable housing.
4. Engagement: Using shareholder activism or other forms of engagement to encourage companies to improve their ESG practices.

Conclusion:
Sustainable investing is a growing investment approach that allows investors to align their investments with their values while also potentially achieving strong financial returns. There is a range of investment products and strategies available for sustainable investing, making it accessible to investors of all types and sizes. As with any investment approach, investors should carefully evaluate their options and consult with a financial advisor before making any investment decisions.

Olivia Li
Credit Card Default Prediction Project

During the fall 2022 semester, my group built 5 machine learning models to facilitate decision-making regarding the release of credit to customers. The goal of this project is to utilize algorithms and identify features to predict whether a customer will default. This is a classic classification problem and a common problem in data science. This project can help me build knowledge on a data science project, get in touch with a real data science project and know the flow of building a model.

In our project, my work was mainly focused on data preprocessing and using a support vector machine to predict whether credit card users will default in the next month. After this process was complete, my job was focused on mode important on, such as comparing model's performance using different kinds of scores, creating feature importance plot, and interpreting their business meaning. I had a lot of fun in those processes. Every dataset has its characteristic, and it can always give me some insights into data science during those processes.

In this project, I utilized a support vector machine to predict and used hyperparameter to get the best parameter for the model. This was a technique that I learned before, and this project gave me an opportunity to use this method in an actual project.
As for the new knowledge that I learned during this project, I learned several confusion matrixes that I never had previous experience, such as recall score, AUC score, ROC curve. These can help us easily choose a model from a specific aspect. For example, in our project, we wanted our model to pay more attention to predicting the positives out of actual positives, which means the actual defaulters out of predicted defaulters. So, we choose to use recall score to hyperparameter. This was a new concept for me, especially ROC curve which refers to a trade-off between true positive rate to false positive rate. I think all the new concepts that I learned here will help me build my knowledge of data science.

I think the biggest challenge was dealing with multicollinearity. There are several ways to deal with multicollinearity, such as dropping variables that have high VIF value, using PCA to decrease dimension. This process took a while to decide which technique to use. There is never a best way to deal with a problem. Every technique has its own pros and cons. In the end, I choose to drop variables that are highly correlated since it can have better performance compared with using PCA and dropping variables is easier compared with using PCA.

As for me, the most important effect of this project is to put myself into a real-life data science project and get in touch with the whole process of building a model, conducting feature engineering, and comparing all the models. I think our project did very well in these aspects. I think this was a good project because I had the opportunity to utilize techniques that I learned previously and learn some new data anaylsis methods. So, I think our project was a successful and useful project.

Robin Li

The Application of Mathematics in Finance

The application of mathematics in the finance industry is widespread and essential. Mathematical models provide financial professionals with a common language and toolset to model complex financial phenomena such as option pricing, portfolio optimization, and risk management. Investors use mathematical models to quantify the risks and rewards associated with various investment strategies.

Calculus is one of the most widely used mathematical tools in finance. This is essential for pricing financial derivatives such as options, futures, and swaps, which are contracts that derive their value from an underlying asset's price. Differential equations and stochastic calculus are also widely used in finance, particularly in the analysis of financial time series data such as stock prices and interest rates. Linear algebra is another critical mathematical tool used in finance. This concept is used in portfolio optimization to calculate the optimal weights for a portfolio of assets, given their expected returns, volatility, and correlation.

Other mathematical tools used in finance include probability theory, statistics, and numerical methods. Probability theory and statistics are used to model the uncertainty and randomness of financial phenomena, such as stock prices and interest rates. Numerical methods, such as Monte Carlo simulation and optimization algorithms, are used to solve complex financial problems and estimate the parameters of financial models.

One powerful statistical method with numerous applications in finance is the Markov chain Monte Carlo (MCMC). This semester, we are using MCMC and some economic indicators to predict loan delinquency. MCMC is a computational technique used to approximate complex distributions by constructing a Markov chain that converges to the desired distribution. MCMC methods are primarily used to estimate the parameters of financial models, including option pricing, risk management, and portfolio optimization. They can be used to estimate the expected returns of various financial assets and build optimal portfolios based on these estimates.

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

Parth Mahajan
Silicon Valley Bank's Collapse: Lessons in Risk Management

A tale of ambition and poor management is the demise of Silicon Valley Bank. It started off as a tiny community bank that catered to budding IT companies and developed into the beating core of what we now refer to as the innovation economy. However, the bank had recently been caught off guard by a fast shifting economic landscape and had waited until the very last minute to try to escape its doom. The financial stability of Silicon Valley Bank was in trouble, and its bonds faced the possibility of being downgraded to junk, notwithstanding the arrogant, confident manner of its CEO, Gregory Becker. More than a dozen small and midsize banks' stocks fell as a result of the bank's failure, and by March 25, 2023, the bank was no more.

As Silicon Valley Bank launched a botched excursion into real estate lending in the early 1990s, difficulties started to arise. Following that, the bank went back to its roots by promoting its services to quickly expanding but often unsuccessful IT firms during the internet boom. After joining the company in 1993 and taking over as CEO in 2011, Mr. Becker expanded its operations to dozens of cities both domestically and abroad. He intended to be the driving force behind what is now known as the innovation economy and saw an opportunity to attract start-ups and venture investors with innovative offers. He was successful in his goal since "Silicon Valley Bank was involved in everything that happened in the Valley."

But poor risk management ultimately hurt the bank's ability to succeed. Mr. Becker and his lieutenants spent so much time talking about innovation and the future that they neglected to focus adequately on the routine but vital work of risk management and maintaining financial responsibility. The bank acted too late in attempting to try to avoid its fate after being caught off guard in a fast shifting economic environment.

Danny Moses, an investor at Moses Ventures known for his role in predicting the 2008 financial crisis in the book and movie "The Big Short," said, "It's just bad risk management. It was complete and utter bad risk management on the part of SVB." The bank's failure sent the stocks of more than a dozen small and midsize banks reeling on Monday, March 27, 2023, but they rebounded on Tuesday. However, the rebound remains small compared to the scale of the losses inflicted in recent days.

Sachin Margam

Machine Learning: Revolutionizing Risk Management

Risk management is an important aspect of running any business. It involves recognizing, evaluating, and prioritizing potential risks to reduce their impact on the organization's goals. In today's world, we have access to vast amounts of data and advanced computing capabilities, which has made machine learning a valuable tool in risk management.

There are several ways in which machine learning can be applied to risk management. One common application is credit risk assessment, where banks and financial institutions use ML algorithms to evaluate the creditworthiness of their clients. The algorithms analyze factors such as credit history, income, employment status, and other relevant data. This helps banks make informed lending decisions and reduces the default risk.

Another area where machine learning can be helpful is fraud detection. Criminals are becoming more sophisticated in their methods, and traditional rule-based systems may not be able to keep up. Machine learning algorithms can analyze patterns in the data and identify suspicious behavior that may indicate fraud. This can help financial institutions detect unusual spending patterns on credit cards or identify fake accounts created for fraudulent purposes.

Operational risk management is another area where machine learning can be applied. Operational risks are those associated with inadequate or failed internal processes, people, systems, or external events. Machine learning can help analyze data from various sources, such as log files, customer complaints, and system errors, to identify potential risks. ML algorithms can also predict the likelihood of an operational risk event occurring and help organizations take preventative measures.

Finally, machine learning can be used in market risk management. Market risk refers to the potential loss due to changes in market conditions, such as fluctuations in interest rates, exchange rates, and stock prices. Machine learning can analyze historical market data and identify patterns that may indicate future market trends. This can help organizations make informed decisions about their investments and reduce the risk of losses due to market fluctuations.

In conclusion, machine learning has become an essential tool in risk management. It can help organizations make informed decisions about lending, fraud detection, operational risk management, and market risk management. With the increasing availability of data and computing power, machine learning will continue to play a critical role in risk management in the years to come.

Sauvik Mittra

A Professional Networking Experience

In my pursuit of a career in portfolio management and risk management, I connected with one of the quant risk managers at Prudential PLC through LinkedIn. In my introductory message, I provided a brief overview of my background, work experience, and motivation for pursuing financial mathematics at NC State University. I also expressed my interest in learning more about the US markets and the skills required for individuals interested in this field.

Fortunately, the risk manager responded to my message, and we scheduled a call to discuss his work in the quantitative modeling group. Our interaction was incredibly informative, and he provided valuable insights into the day-to-day activities of his team. He explained that his team looked at different risk measures and monitored and reported them to senior management regularly. Additionally, he discussed how they utilized Principal Component Analysis to decompose fixed income components into 6-8 relevant components.

The risk manager also emphasized the importance of stress testing, which is a crucial aspect of any risk management team. At Prudential, they build a correlation matrix to assess what shocks in the market could look like given the present-day scenario. The company's research is fundamentally driven, but they also rely on quantitative analysis on the risk side. They use Python, Tableau, and SQL daily to assist in their analysis.

After assessing risk and building models, the risk management team communicates with their portfolio managers to decide on which trades would be most beneficial. Through our conversation, I gained a better understanding of the risk management team within Prudential and the work they do.

The risk manager encouraged me to stay in touch and reach out if I came across any relevant roles within Prudential PLC. I believe that my previous work experience, current coursework, and understanding of the markets enabled me to hold a meaningful conversation with the risk manager.

Overall, my networking experience with the quant risk manager at Prudential PLC was both informative and encouraging. By connecting with professionals in the field, I have gained valuable insights and knowledge, which will help me in my career journey. I am grateful for the opportunity to have spoken with him and look forward to future conversations with professionals in the field.

Hemanth Pinnamaraju

From Riches to Rumbles: The Fall of Credit Suisse

In addition to its stunning natural scenery, which draws travelers from all over the world, Switzerland is also renowned for its outstanding banking services and track record of financial stability. But it may soon lose this title, the latter of course.

Credit Suisse, one of the premier Swiss Banks is now in the news for all the wrong reasons. While many attribute its downfall to the ongoing banking crisis in the USA, a closer look paints a different picture. From its previous peak in 2007, right before the financial crisis, the Swiss giant has lost close to 99% of its share price.

Credit Suisse' main revenues were split into 4 streams with Wealth Management at 37%, Commercial Banking at 32%, and the rest coming from Asset Management and Investment Banking. The seeds of the decline were sowed in much before, thanks to its more than fair share of scandals. From the Bulgarian drug money laundering, enabling tax evasion in USA, the spying scandal, the bank ended up spending a fortune in legal and arbitration fees. The bank was still able to pay these enormous fines since there was still trust from their customers and their strong balance sheet.

Things however took a downturn when the bank also lost about $5bn during the Archegos blowout and was one of the worst hit banks. In addition to this the Greensil Capital debacle brought about mistrust among its customers after FINMA, the Swiss regulator declared that Credit Suisse did not perform its duties as the asset managers. The low customer confidence meant that throughout 2022 clients started pulling their money out from the bank and it saw the AUM drop from CHF740bn to CHF540bn in just 4 quarters with about CHF93bn being pulled out in just the last quarter of 2022. This meant that after adjusting for litigation fees, the bank's pre-tax loss increased from CHF600m in 2021 to CHF3.3bn in 2022.

While this was happening, the CDS rate of Credit Suisse's bonds were increasing in value and it rose to 500 bps in November 2022 and from 67 bps in May 2022. By March 2023 it was over 3000 bps, implying the riskiness of the bank, since anything above 1000 bps basically means a high probability of default. After this panic the Swiss bank gave a credit line of $54bn to guarantee that there would be no default, this move was done since the bank was an integral part of the Swiss economy and that its default would pave the way for many unwanted externalities.

Having done this, the bank was sold to UBS Group, the largest bank of Switzerland. UBS took great advantage of this situation and bought its former rival for just $3bn, in what can be termed as the steal of the century. Now the Swiss National Bank has offered $100bn liquidity assistance to UBS, secondly if UBS encounters losses on the purchased assets, the Swiss National bank pledged an additional 9bn francs for the same. In addition to this sale, the regulators wrote off 16bn francs worth of AT1 bonds, an unprecedented move. This pretty much concluded the fall of Credit Suisse, often claimed as "Too Big to Fail".

While this Swiss banking crisis has had one winner in the form of UBS group, the losers were clearly many, including individuals, mostly wealthy, businesses and of course the AT1 bond holders not to mention the panic and turmoil this has caused world-wide.

Ritu Sharma

Words Of A Quant

Skilled in Quant, a skill to flaunt

A bit of Finance and Maths, add-on of some Stats

Spend sometime on Cox-Ingersol-Ross, way to impress your boss

Aspiring to manage risks in banks, hire us before your portfolio tanks

Predicting the economic inflation, experts in model validation

Why all the fuss? When there is so much fun in Stochastic Calculus

Heartbeat skips with every interest rate hike of 500 Bps

Despite the market volatility, not losing faith in your ability

Equity, fixed income or in derivatives are you investing? Summer internship is all that we are manifesting

Coding-paralysis? How will you do quantitative analysis?

Put some effort to learn, definitely in future well you will earn!

Palak Sinha

Bankruptcy of FTX

One of the most significant cryptocurrency exchanges in the world, FTX, just announced bankruptcy, shocking the whole industry. Many people were surprised by the statement because they thought FTX was a very popular and lucrative business. We shall examine the causes of FTX's bankruptcy and its effects on the larger cryptocurrency market in this post.

It's crucial to remember that FTX's bankruptcy was not brought on by a decline in interest or demand for bitcoin trading. Contrarily, the cryptocurrency sector has experienced unheard-of expansion in recent years, with the value of Bitcoin and other digital assets reaching record highs. One of the exchanges in the market with the fastest rate of expansion was FTX, which processed trades worth billions of dollars and drew millions of users. But FTX's quick growth might have eventually been a factor in its demise. The exchange was renowned for its aggressive marketing strategies and large sign-up bonuses and no-fee trading for new members. The exchange's finances were put under pressure even though these tactics were successful in bringing in new consumers.

Moreover, FTX's efforts to broaden its product line may have been overly ambitious. Throughout the past year, the exchange has introduced a number of new products, including a decentralized exchange and a number of leveraged coins. Although these products were unique and attracted the attention of traders, they also needed a lot of money and resources to keep up. Finally, outside influences like regulatory restrictions and market instability may have made FTX's bankruptcy worse. Countries have very diverse cryptocurrency laws, therefore FTX might have had trouble adhering to all of the different regulations. Also infamous for its dramatic and unpredictable price swings is the bitcoin market. As a result, managing risk and upholding stable financial conditions may be challenging for exchanges.

The wider cryptocurrency market is expected to be significantly impacted by FTX's bankruptcy. First of all, it emphasizes the dangers and difficulties that even the most prosperous and well-funded exchanges face. In the fiercely competitive and quickly changing world of cryptocurrency trading, even the smallest slip-up or error in judgment can have disastrous results.

Second, additional oversight and regulation of bitcoin exchanges may result from FTX's insolvency. The bitcoin sector is still mostly unregulated, so regulators and policymakers are debating how to do so. Calls for stronger oversight and regulation, particularly in respect to financial stability and investor protection, may be sparked by the failure of a significant exchange like FTX. FTX's bankruptcy may also have broader effects on the economy as a whole. Major institutions and investors are investing billions of dollars in the cryptocurrency market, which is leading to cryptocurrencies being considered as a legitimate asset class. Investor confidence could be shaken and a broader market downturn could be sparked by the failure of a significant exchange like FTX.

Finally, the FTX bankruptcy serves as a sobering reminder of the dangers and difficulties the cryptocurrency business faces. The market is still a turbulent and unpredictable area even as it grows and draws more customers and investors. Exchanges and other market participants must be aware of these dangers and take precautions to responsibly manage their finances and business operations. Regulators and policymakers must simultaneously find a balance between fostering innovation and safeguarding investors and the financial system. We can only ensure that the bitcoin market grows and changes in a sustainable and responsible way by cooperating.

Zitao Song

Time Series Volatility Models

The time series model can be written into two parts: deterministic and stochastic. Let Y_t be a time series, and it can be written as shown (Formula 1), where D_t is the deterministic trend and W_t is the stochastic trend. The deterministic part removes any deterministic trend or seasonality contained in the data. Techniques like regression are normally used to fit this part. For example, if the deterministic part shows a constant increase or decrease, D_t can be modeled using standard linear regression, and it can be written as shown (Formula 2).

Formula 1

$$Y_t = D_t + W_t$$

Formula 2

$$D_t = \beta_0 + \beta_1 t$$

After fitting the deterministic part, the stochastic part or residuals can be obtained. In most cases, these residuals are expected to meet a few assumptions: normality, constant variance, and independence. When the assumption of independence is not met, the stochastic part can be modeled using time series models. For example, the stochastic part can be modeled using the ARMA model, and it can be written as shown below:

$$W_t = \phi_1 W_{t-1} + \phi_2 W_{t-2} + \dots + \phi_p W_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}$$

Residual analysis is also required after the stochastic fitting; the assumptions are normal distributed, mean of 0, constant variance, and independence needed to be satisfied. If the residual analysis fails, it is either because the selection of the model went wrong, or the stochastic part is not stationary, and it is caused by non-constant variance and dependence. GARCH model now can be introduced to explain heteroskedasticity.

Generalized Autoregressive Conditional Heteroskedasticity, or GARCH, is an extended version of the ARCH model. GARCH has two components: moving average and autoregressive. Each component has an order. The order of the moving average part is denoted by q, and the order of the autoregressive part is denoted by p. GARCH (p, q) would be a p order and q order, model, and it can be denoted as shown (Formula 4), where r_t is the stochastic part, or normally residuals from the mean function, σ_t^2 is the conditional variance, $\varepsilon_t \sim i.i.d.\, N(0,\ 1)$ is the error term, and ω is a constant. Furthermore, the order of the moving average part, or q, represents the number of lags in squared residuals in the GARCH model, and the order of the autoregressive part, or p, is the number of lags in squared conditional variance in the GARCH model. Similar approaches like ACF and PACF are used for determining orders in the GARCH model. After the fitting, residuals are supposed to be normally distributed with a mean of 0 and a variance of 1, and independent of each other.

Formula 4

$$r_t = \sigma_t \varepsilon_t$$

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

There are many known variations of the GARCH model. For example, EGARCH, TGARCH, and GJR-GARCH. However, the methodology I applied mainly focuses on GARCH and its simple variations. Four models are been used: ARMA (p, q) + GARCH (p, q), Weighted GARCH (p, q), GARCH (p, q) with an exogenous variable, Seasonal GARCH (p, q). ARMA (1, 1) + GARCH (1, 1) can be written as shown (Formula 5), where Y_t is the return for a stock at time r_t is the residual from ARMA(1,1) at time t, and σ_t^2 is the conditional variance, that is, the volatility of a stock at time t.

Formula 5

$$Y_t = \phi_1 Y_{t-1} + r_t - \theta_1 r_{t-1}$$

$$r_t = \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha_1 r_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Weighted GARCH (1, 1) can be written as shown (Formula 6), where w_t is a weighted factor at time t. In this case, I chose the trading volume of a stock as the weighted factor. For a good amount of stocks, the trading volume is correlated with volatility. Weighing returns by a correlated factor, which is trading volume, can emphasize the variances of return so that the volatility would have a better capture of volatility when it is significantly changing. Normally, a weighted factor is in percentage, so I applied normalization by dividing the mean of the trading volume in a selected period.

Formula 6

$$r_t = \frac{1}{w_t} \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha_1 r_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

GARCH (1, 1) with a exogenous variable can be denoted as shown (Formula 7), where x_{t-1} is an external variable. In this model, I also applied the trading volume, which means x_{t-1} is the daily trading volume of a stock at time t-1. Since the exogenous variable is independent of the conditional variance, I used the ARIMA model to forecast. Instead of weighing returns, the trading volume is directly modeled into the volatility as an external variable in the GARCH model.

Formula 7

$$r_t = \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha_1 r_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \beta_1 x_{t-1}$$

Seasonality is another potential co-factor of the volatility in a relatively short time window. Seasonal GARCH (1, 1) with the cosine trends can be written as shown (Formula 8), where f is the frequency, and β_1, β_2 are amplitudes.

Formula 8

$$r_t = \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha_1 r_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \beta_1 \cos\cos(2\pi f t) + \beta_2 \sin\sin(2\pi f t)$$

Ameya Tembhekar

Value At Risk Vs Expected Shortfall

Value at Risk (VaR) can be defined as the maximum value of the portfolio (V) which can be lost with a certain confidence level (X%) during a given time period (T). This concept was pioneered by JP Morgan in the 1990s in order to simplify reporting of the risk metrics and has been used widely ever since. VaR can be calculated by using the probability distribution of losses or gains during a given time period. For instance, when T is 10 days and X is 96%, when looking at the distribution of loss, VaR can be said as the loss on the 96th percentile of the distribution. Conversely, for the distribution of gains, VaR will be the loss on the (100 – 96 =) 4th percentile on the distribution.

VaR serves its purpose of easily explaining the extent of loss to a lay person. But while implementing the VaR in real life, there could be a scenario where there is a much higher loss beyond the confidence threshold. For instance, if some portfolio has been positioned such that there is a 98% chance of a loss of $5 million and 2% chance of a loss of $50 million. This will mean that even though the portfolio might satisfy the risk thresholds set by the organization, there are significant risks being taken albeit with a less probability. This can be considered as a drawback for using VaR as a measure of risk.

Expected Shortfall (ES) can produce a better outcome as compared to VaR as it asks the more important question “Given that things go south, what will be the expected loss?”. ES, like VaR, is also dependent on the time period (T) and the confidence level (X). ES can be said as the expected loss given that the loss is greater than VaR during T. This said, to arrive at ES, we need to calculate VaR first. For instance, for a 3 day period when the VaR is $1 million with a confidence interval of 99%, the ES will be the average over a 3 day period assuming that the loss exceeds $1 million.

VaR and ES both satisfy the conditions of Monotonicity (higher risk measure for worse performing portfolio), Translation Invariance (addition of cash reduces risk measures by the amount of cash added) and Homogeneity (scaling the size of the portfolio by a constant factor will scale the risk measure by the same factor). But, ES has an additional property called Subadditivity (the combined risk measure of two portfolios is less than or equal to the risk measure of the sum of risk measures of individual portfolios). VaR sometimes fails to satisfy this condition.

Thus, using ES also captures the tail cases which might be ignored by the VaR. This is why ES is also referred to as “expected tail loss” or “conditional tail expectation”. But on the other hand, the simplicity of VaR is difficult to beat as ES might not be as intuitive as VaR to a lay person. Also, it is difficult to back-test the ES calculation methodology as compared to VaR and hence the reliability of accurate measurement on historical data can be questioned.

Source: *Risk Management and Financial Institutions* - John C. Hull

Zhong Tian
Being a Quantitative Risk Analyst

I aimed to be a quantitative risk analyst after graduation from the financial math program. There are a number of different career paths that a quantitative risk analyst might pursue. One might work in industries such as finance, insurance, or healthcare, where risk management is particularly important. Alternatively, one might work for consulting firms, where the analyst can help a range of different clients to identify and manage risks.

As a quantitative risk analyst, I need to use statistical and mathematical tools to analyze complex data sets and build predictive models that can help organizations make informed decisions. The first step in the quantitative risk analysis process is to identify potential risks. This can include anything that might impact an organization's ability to achieve its goals, such as natural disasters, economic downturns, technological failures, and cybersecurity threats. Once risks have been identified, the next step is to assess their likelihood and impact. To do this, quantitative risk analysts use a variety of statistical and mathematical techniques.

Another key skill required for a quantitative risk analyst is the ability to communicate complex data and analysis to stakeholders who may not have a technical background. This means being able to translate statistical models and mathematical concepts into language that is accessible and understandable to non-experts.

To become a quantitative risk analyst, I typically need a strong background in mathematics, statistics, and computer science. Many employers will also require a master degree in a related field such financial math or financial engineering. I also need to have experience working with large data sets and be proficient in programming languages such as Python or R.

Harshil Zaveri

Becoming a Quantitative Analyst

Beyond my education in Financial Mathematics at North Carolina State University, I see myself working as a Quantitative Analyst working for a leading financial institution. What is Quantitative analytics? Quantitative analytics involves the use of mathematical and statistical techniques to analyse and interpret data. This can be done in a variety of fields, including finance, healthcare, marketing, and technology. The goal of quantitative analytics is to provide insights and recommendations based on data, which can help organizations make informed decisions and improve their overall performance.

To succeed in this career, I have developed programming skills in Python, R and SAS. My master's degree has given me a strong foundation in a variety of statistics and mathematical concepts such as linear algebra, calculus, and probability theory. Apart from my technical skills, through my projects in Financial Mathematics, I have gained strong analytical and problem-solving skills. I had taken Financial Data Analytics as a minor during my undergraduate degree. Before enrolling for my Master's program, my knowledge in Finance was very limited. Through my courses in "Derivatives Pricing', 'Fixed Income', 'Monte Carlo Simulation' and 'Financial Risk Analysis' I have broadened my knowledge in Finance.

My journey so far has been on track with my career path and with excellent career services at NC State I think I will be able to achieve my career goal of becoming a Quantitative Analyst.

Ruikang Zhang

Why Consulting is Important for Financial Mangement

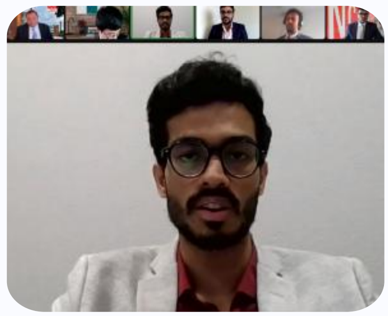
Financial management is a crucial aspect of any business, as it involves the planning, organizing, and controlling of financial resources in order to achieve the goals of the organization. Consulting plays a critical role in the success of financial management by providing expert advice, support, and guidance to organizations in managing their finances. In this essay, we will explore the reasons why consulting is more important for financial management.

Consulting also provides organizations with access to the latest financial tools and technologies. The financial management landscape is constantly evolving, and new technologies and tools are being developed all the time. Consulting firms invest heavily in the latest financial tools and technologies, and they provide their clients with access to these tools. This enables organizations to perform complex financial analyses and calculations quickly and efficiently, which helps them to make more informed financial decisions.

Furthermore, consulting helps organizations to manage financial risks. Financial management involves managing a range of risks, including credit risk, market risk, and liquidity risk. Consulting firms employ experts who are skilled in identifying, assessing, and managing financial risks. These experts can help organizations to develop effective risk management strategies that mitigate the impact of financial risks on their operations. This can help organizations to avoid financial losses and to achieve their financial goals and objectives.

In conclusion, consulting is more important for financial management for a variety of reasons. It provides organizations with access to expert financial advice, the latest financial tools and technologies, and valuable insights into financial performance. It also helps organizations to manage financial risks, learn from the experience of others, and develop more effective financial management strategies. Consulting firms provide an objective perspective on financial management practices, which can help organizations to make more informed decisions that are based on evidence and data.

Reflections



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