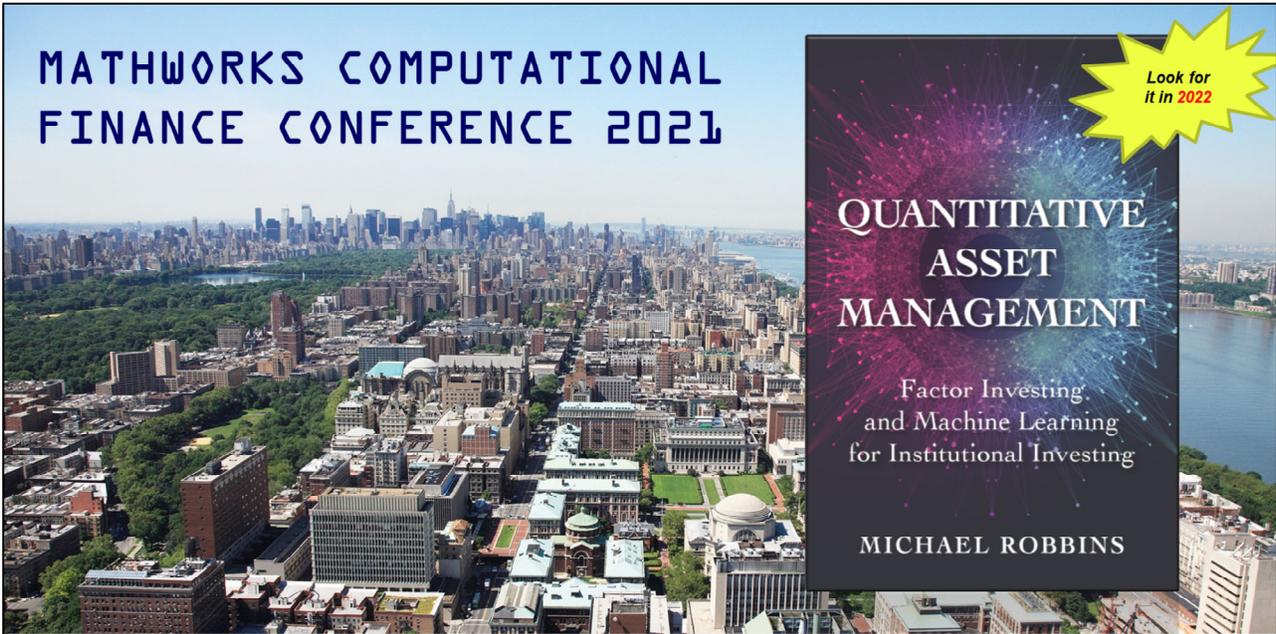


MATHWORKS COMPUTATIONAL FINANCE CONFERENCE 2021



QUANTITATIVE ASSET MANAGEMENT

Factor Investing
and Machine Learning
for Institutional Investing

MICHAEL ROBBINS

Look for
it in 2022



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Speakers



Michael Robbins
Columbia University
Professor

**Overview of Columbia Classes
and Case Studies from My Book**

Michael Robbins has been the Chief Investment Officer of 5 large investment firms, including a bank with 8½ million clients, and was the Chief Risk Officer for the State of Utah's systems. He is a professor at Columbia University. Look for Michael's new book, *Quantitative Asset Management* in 2022. Published by *McGraw-Hill*.



Yao Shang
Columbia University
Master's Class of 2021

**Backtesting and Performance Attribution
of 101 External Managers**

Yao Shang graduated from Columbia University with a Masters in Operations Research. She has worked with wealth managers at Morgan Stanley using deep learning techniques and holds several degrees from Rensselaer Polytechnic Institute. Yao is now working as a data scientist for one of the Big Four accounting firms.



Malin Ortenblad
Columbia University
Master's Class of 2020

**ESG and GTAA for a fund
with 193 Employees in 7 Offices**

Malin Ortenblad graduated from Columbia University with a Master's in Business Analytics. Malin has expertise in healthcare strategy consulting including machine learning during a cancer research project for Frederick National Laboratories, a hospital in the National Institutes of Health and Cancer Research Institutes systems. She is now working as a consultant in healthcare.



Richard Wang
Columbia University
Master's Class of 2022

**Order Book, Tax-Loss Harvesting,
and Transaction Cost Forecasting**

Richard Wang will graduate from Columbia University with a Masters in Management Science. He has worked as a data analyst in industry and at banks, including Citi and CITIC. He holds a Bachelor of Science in Business and Managerial Economics from University of California, Davis with a 3.89/4.00 average.



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- Malin and Yao have been students and CAs for my courses and have made significant contributions. Richard is currently researching tax-loss harvesting strategies.
- I have been the Chief Investment Officer of 5 large investment firms, including a bank with 8½ million clients, and was the Chief Risk Officer for the State of Utah's systems. I teach at Columbia University and my new book, *Quantitative Asset Management* will be published by McGraw-Hill next year.
- Malin Ortenblad graduated from Columbia University with a Master's in Business Analytics. Malin has expertise in healthcare strategy consulting including machine learning during a cancer research project for Frederick National Laboratories, a hospital in the National Institutes of Health and Cancer Research Institutes systems. She is now working as a consultant in healthcare.
- Yao Shang graduated from Columbia University with a Masters in Operations Research. She has worked with wealth managers at Morgan Stanley using deep learning techniques and holds several degrees from Rensselaer Polytechnic Institute. Yao is now working as a data scientist for one of the Big Four accounting firms.
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Managerial Economics from University of California, Davis with a 3.89/4.00 average.

Live Editor Notebooks on the Book Website

LOOK FOR MICHAEL'S NEW BOOK,
QUANTITATIVE ASSET MANAGEMENT, FACTOR INVESTING AND MACHINE LEARNING FOR INSTITUTIONAL INVESTING
TO BE PUBLISHED BY MCGRAW-HILL IN 2022

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MICHAEL ROBBINS

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UNDER CONSTRUCTION

CHAPTER 5: FINANCIAL DATA

- ⊖ CASE STUDY: MANAGING LOW-FREQUENCY AND ARCHIVAL (POINT-IN-TIME) DATA
 - ⊖ LOW-FREQUENCY AND ARCHIVAL 4/5 COLUMN DATA USING KDB* (MATLAB LIVE SCRIPT)
 - ⊖ KDB* 4/5 COLUMN UPLOAD SCRIPT
- ⊖ CASE STUDY: MANAGING MULTI-ASSET TRANSACTION DATA FROM 101 OF THE LARGEST ROBOADVISOR
 - ⊖ PROCESS AND UPLOAD ROBOADVISOR TRANSACTION FILES (MATLAB LIVE SCRIPT)
- ⊖ CASE STUDY: MANAGING 100GB OF HIGH FREQUENCY EQUITY TRANSACTION DATA
 - ⊖ HIGH-FREQUENCY TRANSACTIONS USING DATASTORE, TALL ARRAYS, AND THE KDB* API (MATLAB LIVE SCRIPT)
 - ⊖ KDB* WRDS/TAQ UPLOAD SCRIPT
- ⊖ CASE STUDY: GIBBS SAMPLER
 - ⊖ GIBBS SAMPLER (LIVE MATLAB SCRIPT AND DATA)

QUOTES WEBINARS TRACKS READINGS CODE RESOURCES
ENDNOTES BLOG CONTACT MEET ME BIOGRAPHY COURSE

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- As I complete my book, I will be adding many features to the book's website including computer code.
- Most of the code will be MATLAB live editor notebooks.
- Passwords may be required to protect the intellectual property of third parties, like data providers.

Agenda

Table 10: Comparison of forecast accuracy with alternative deflators

Overview of Columbia Classes & Case Studies from My Book, Michael Robbins
Big data and minority class data generation to enhance extreme market events
Feature engineering and machine learning for selection and sizing
Agent-based simulation for incentives

GTAA and ESG for a Fund with 193 Employees in 7 Offices, Malin Ortenblad
Machine learning using ESG and global macro factors
Risk control overlay
Global Tactical Asset Allocation (GTAA)

Backtesting and Performance Attribution of 101 External Managers, Yao Shang
Agent-based lending and borrowing, cash drag, and forced liquidation effects
Complex path-dependent fees and costs
Multi-period Brinson analysis for detailed performance and risk attribution

Order Book, Transaction Cost Forecasting, and Tax-Loss Harvesting, Richard Wang
Realistic simulation using an order book, taxes, and transaction costs
Tax-Loss Harvesting



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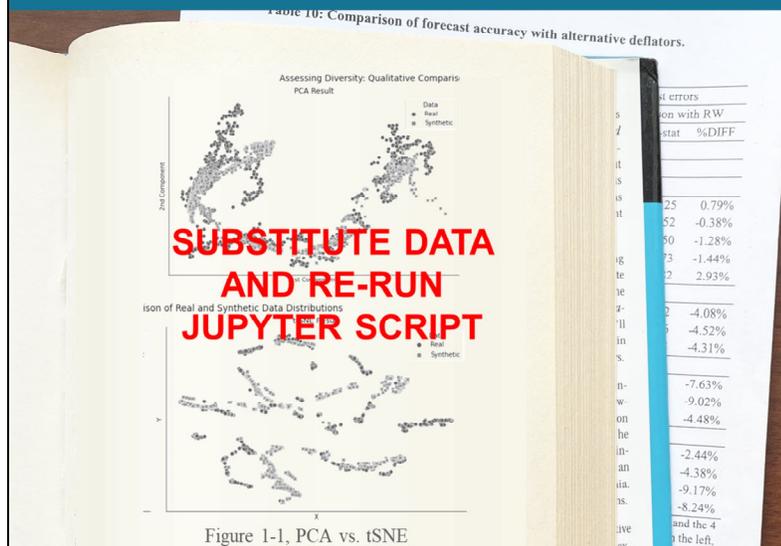
MICHAEL

We will discuss for topics:

- I will give an overview of Columbia Classes & Case Studies from My Book
 - Big data and minority class data generation to enhance extreme market events
 - Feature engineering and machine learning for selection and sizing
 - Agent-based simulation for incentives
- Malin will discuss GTAA and ESG for a fund with 193 Employees in 7 Offices
 - Machine learning using ESG and global macro factors
 - Risk control overlay
 - Global Tactical Asset Allocation (GTAA)
- Yao will discuss backtesting and performance attribution of 101 external managers
 - Agent-based lending and borrowing, cash drag, and forced liquidation effects
 - Complex path-dependent fees and costs
 - Multi-period Brinson analysis for detailed performance and risk attribution
- And, Richard will talk about the order book, transaction cost forecasting, and Tax-Loss Harvesting

- Realistic simulation using an order book, taxes, and transaction costs
- Tax-Loss Harvesting

Big Data and Minority Data Generation



Most financial time series have a great deal of uninteresting data, such as small price changes, and little important data, such as large rallies and routs.

As rare as this minority data is, the rarest and most valuable data are the minority data that look like majority data—the small price movements that warn of large ones to come.



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- Most financial time series have a great deal of uninteresting data, such as small price changes, and little important data, such as large rallies and routs.
- As rare as this minority data is, the rarest and most valuable data are the minority data that look like majority data—the small price movements that warn of large ones to come.
- Both statistical and machine learning methods tend to fit to the majority of data, even if that emphasizes a trivial and useless solution of predicting infinitesimal returns.
- By producing synthetic data that mimics the interesting data we induce our analysis to predict important events.
- More to the point, by producing synthetic data that is difficult to classify we help our analysis distinguish between uninformative events that look like they precede important ones and seemingly innocuous events that actually do predict massive price changes and dislocations.
- Modern methods like Borderline-SMOTE are far more effective than older methods like PCA.

Feature Engineering & Machine Learning for Selection & Sizing

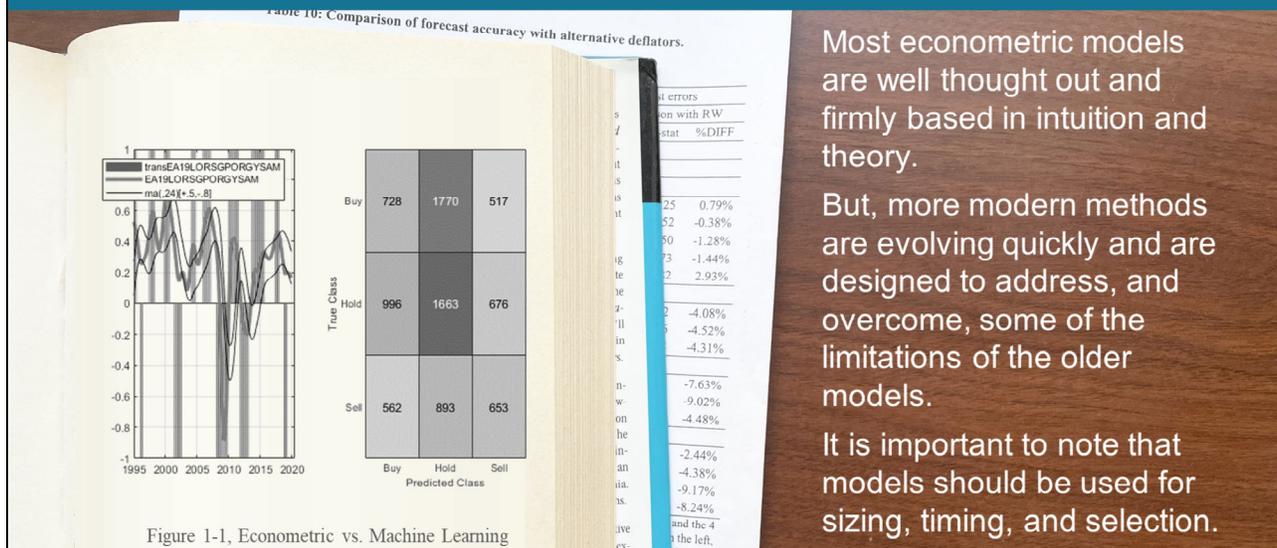


Figure 1-1, Econometric vs. Machine Learning

Most econometric models are well thought out and firmly based in intuition and theory.

But, more modern methods are evolving quickly and are designed to address, and overcome, some of the limitations of the older models.

It is important to note that models should be used for sizing, timing, and selection.



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- Most econometric models are well thought out and firmly based in intuition and theory.
- But, more modern methods are evolving quickly and are designed to address, and overcome, some of the limitations of the older models.
- It is important to note that models should be used for sizing, timing, and selection.
- Most of our time is spent managing data and engineering effective features.
- What most people consider modeling consumes little of our time.
- Even nuanced enhancements to features can greatly improve the accuracy, reliability, and predictive power of our models.
- Conversely, small errors can neuter our models and mislead our strategy.
- Great care is required.

Agent-Based Simulation for Incentives

Table 10: Comparison of forecast accuracy with alternative deflators.

After the performance fee is reset, poor performance incentivizes benchmark hugging to preserve capital.

Near bonus time, small losses incentivize gambling, but only to boost the bonus without risking catastrophic losses.

Figure 2-12, Perverse Incentives

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We were asked some interesting questions by asset allocators, fund managers, and investment advisors.

We used the models we will discuss today to answer those questions.

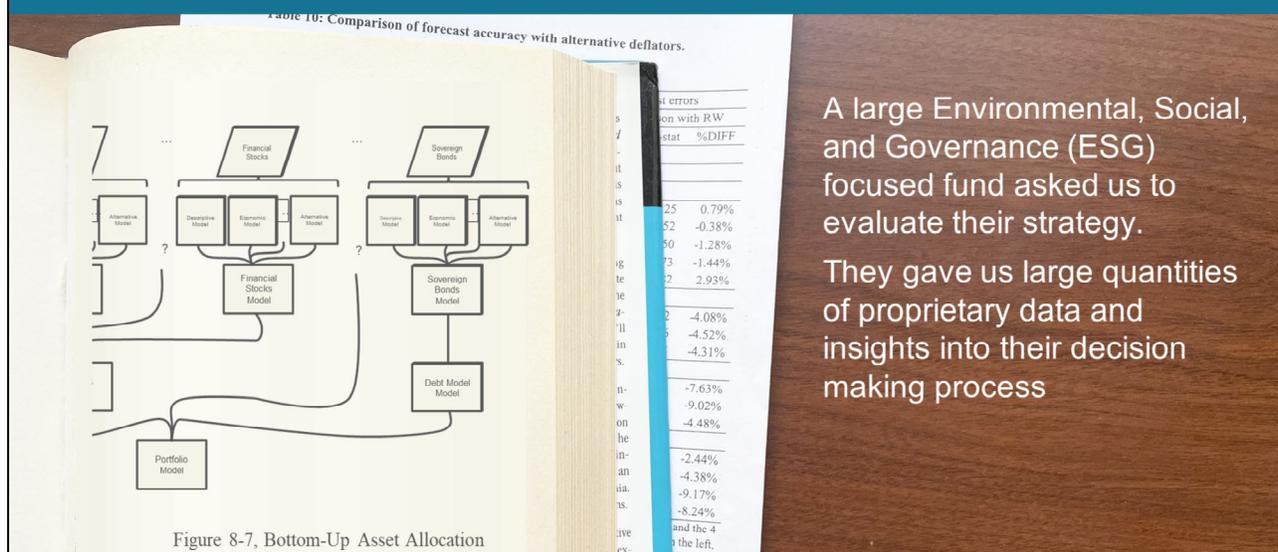
For example, “does our incentive scheme create a conflict of interest with our investment manager?”

MICHAEL

- We were asked some interesting questions by asset allocators, fund managers, and investment advisors.
- We used the models we will discuss today to answer those questions.
- For example, “does our incentive scheme create a conflict of interest with our investment manager?”
- By inserting an agent that maximizes multi-period incentive fees while being adverse to career limiting losses, we can use the backtester to identify which fee structure best aligns the investment manager’s goals with the investor’s needs and risk preferences.
- Historical, simulated, or stochastic models can be used.
- The figure shows a risk-averse manager’s response to the fund’s return.
- The top chart represents the manager’s reaction long before his bonus is given.
- Under this fee structure, a manager may be too cautious.
- He may reduce his exposure as the market moves, preserving capital as it falls and capturing profits as it rallies.
- This is often called tracking or benchmark hugging.
- Proper incentives would entice the manager to take more risk if he is permitted to recover from losses.

- The bottom chart shows the manager's response as his bonus approaches.
- He still realizes small profits when he should let them grow.
- But, now that he has little time to recover from losses he becomes risk-seeking as the market falls.
- He pursues "lottery ticket" gambles in an attempt to get a bonus.
- He reaches maximum risk as his losses become so large that he expects to be fired so he might as well bet it all.

Bottom-Up ESG Security Selection



A large Environmental, Social, and Governance (ESG) focused fund asked us to evaluate their strategy.

They gave us large quantities of proprietary data and insights into their decision making process



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MALIN

- A large Environmental, Social, and Governance (ESG) focused fund asked us to evaluate their strategy.
- They gave us large quantities of proprietary data and insights into their decision making process
- With a bottom-up model, a model's outputs can be used as inputs into the next layer of the boosted model. Layers are added to layers until the whole portfolio is determined.
- We started at the security level, then sector, class, etc.
- This is a common methodology for specialized investors.
- By using the fund's proprietary database of multidimensional ESG factors, combined with other market and fundamental factors, we chose global equities.
- We then bucketed those selections into sectors and then asset classes, according to our asset allocation model.
- Finally, we applied a risk overlay.

Risk Control Overlay

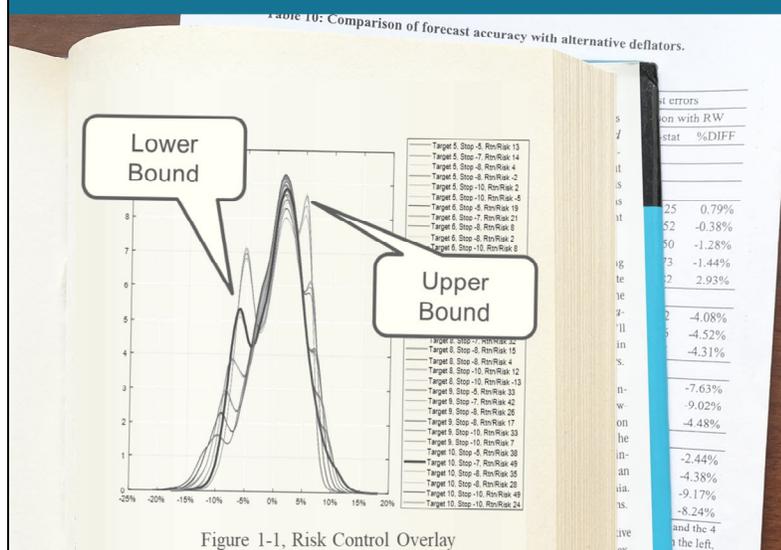


Figure 1-1, Risk Control Overlay

Systematic hedging strategies, like stop-losses and overlays, are designed to enhance risk management.

Risk control is essential to the longevity of most strategies.

Many of these strategies are reactive and fail to prevent the initial loss.

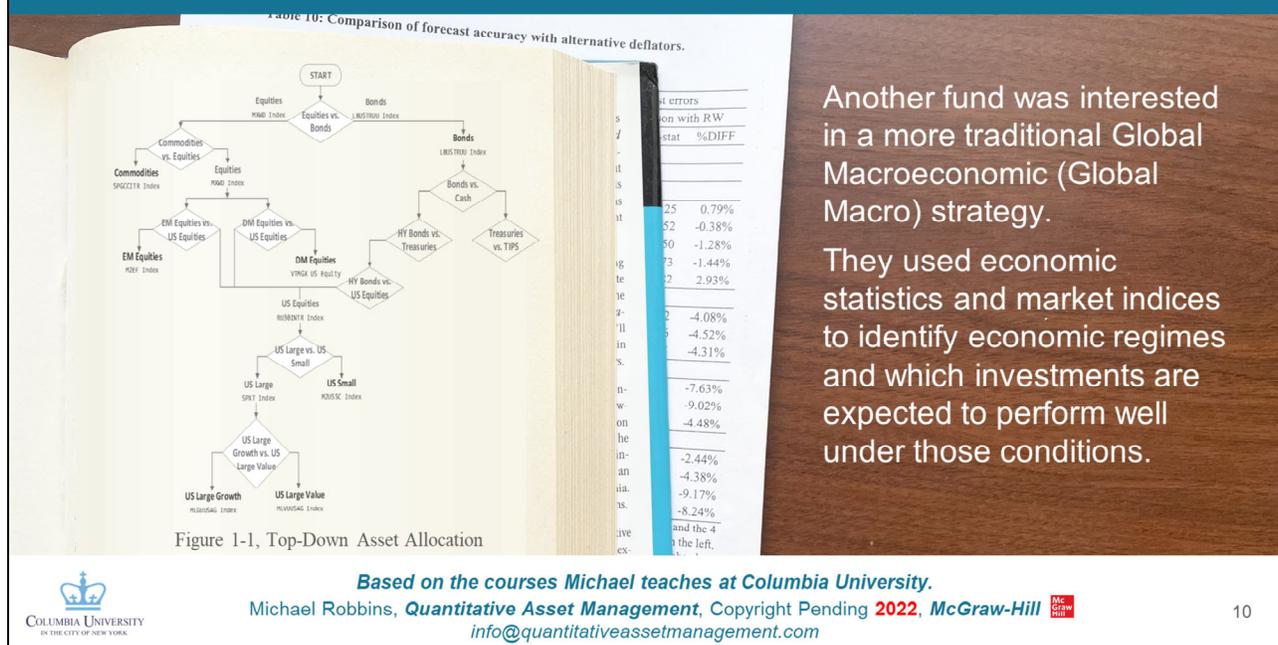
Compounding the error, they can be slow and fail to capture the initial, and often substantial, recovery.

MALIN

- Systematic hedging strategies, like stop-losses and overlays, are designed to enhance risk management.
- Risk control is essential to the longevity of most strategies.
- Many of these strategies are reactive and fail to prevent the initial loss.
- Compounding the error, they can be slow and fail to capture the initial, and often substantial, recovery.
- Most investors are wrong most of the time but benefit from their good decisions much more than they suffer from the bad ones.
- Ongoing management is critical, but systematic hedging is a tailwind. Like many strategies involving mortgages, some are subject to systematic losses in a kind of negative hedge, while others risk large tail losses (“picking up dimes in front of bulldozers”).
- Negative biases may be an unwelcome feature of a strategy, but often protection is available at a cost.
- As a rule, the convenience of insurance costs more than the economic value of the protection.
- It is advisable to purchase protection when the cost of loss is unbearable, even if it is cheaper to self-insure. An overpriced lottery ticket has value if the price is minimal and the payoff is meaningful.
- Dealers are well situated to diversify risks by matching trades and earn nearly riskless income by providing insurance—though it does not mean they will

offer it cheaply.

Top-Down Global Tactical Asset Allocation (GTAA)



Another fund was interested in a more traditional Global Macroeconomic (Global Macro) strategy.

They used economic statistics and market indices to identify economic regimes and which investments are expected to perform well under those conditions.

MALIN

- Another fund was interested in a more traditional Global Macroeconomic (Global Macro) strategy.
- They used economic statistics and market indices to identify economic regimes and which investments are expected to perform well under those conditions.
- Using global macro factors and a risk control overlay we built a top-down Global Tactical Asset Allocation (GTAA) model.
- This mirrors traditional asset management methodologies and aids economic intuition and interpretability, making it easier to gain acceptance and buy-in from investors, management, and co-workers.
- We used a simple decision tree structure for asset allocation that begins with coarse decisions, e.g. stocks vs. FICC—Fixed income, currencies, and commodities.
- In subsequent layers, we predicted the dominance of one asset class, or subclass, over others at each node.
- As we traversed the tree, each branch terminated when a recommendation was indeterminate, unstable, or uncertain.
- The node above the terminus defined the result of that decision.
- Working through many layers of boosted models we arrived at the security selection decision.

Backtesting & Performance Attribution of 101 Managers

Table 10: Comparison of forecast accuracy with alternative deflators.

Figure 1-1, 101 Roboadvisors Provided Transaction Level Data

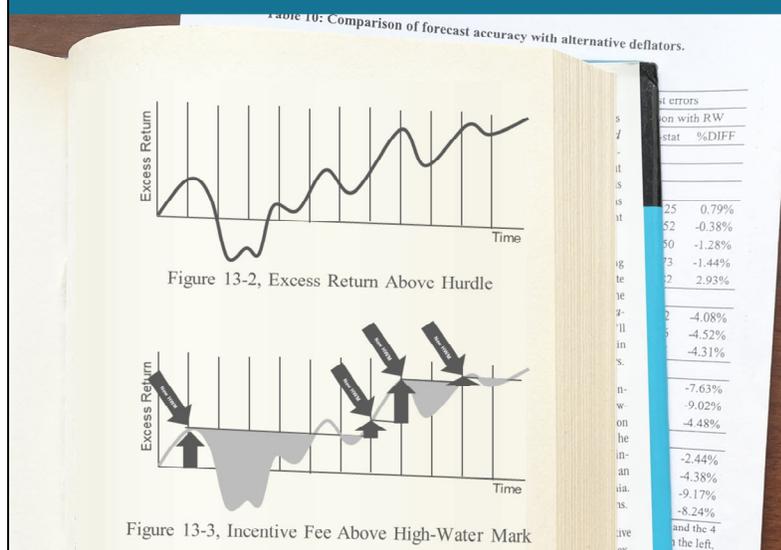
An RIA with an open-source platform invested their clients in 101 of the largest roboadvisors. They invested in traditional qualified (retirement) and non-qualified (taxable) funds as well as thematic funds (like ESG) and special strategies (like TLH). They wanted to know which to use and which to divest from.

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YAO

- An RIA with an open-source platform invested their clients in 101 of the largest roboadvisors.
- They invested in traditional qualified (retirement) and non-qualified (taxable) funds as well as thematic funds (like ESG) and special strategies (like TLH).
- They wanted to know which to use and which to divest from.
- We analyzed the funds' performance attribution vs.:
 - efficient frontier
 - history
 - stress scenarios
 - competitors in a takeover
 - outright and
 - vs. benchmark
 - themes, e.g. ESG
 - on a risk-adjusted basis
 - taxable (nonqualified) vs. nontaxable (qualified)

Path-Dependent Fees & Costs for Sims & Product Development



Fees and costs have a significant effect on a strategy's viability and may dominate performance.

It was critical to accurately model these complex rules.

The interaction between the rules and the path-dependency greatly increased the sophistication of our model.



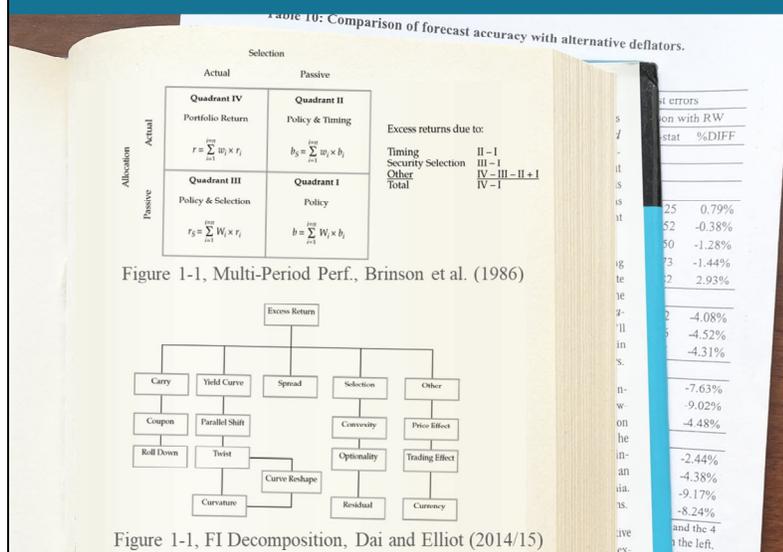
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- Fees and costs have a significant effect on a strategy's viability and may dominate performance.
- It was critical to accurately model these complex rules.
- The interaction between the rules and the path-dependency greatly increased the sophistication of our model.
- We can now produce accurate and realistic simulations of hedge funds, mutual funds, ETFs, structured notes, and many other types of investments.
- We added cost and fee structures including incentive fees, management fees, crystallization dates, hurdle rates, and high-water marks.
- Some of these fees are relative and some are path-dependent.
- The interaction can be complex.

Multi-Period Brinson Performance & Risk Attribution



By distinguishing between luck and skill and by identifying what skills the manager has, we can recommend different managers for different asset classes and purposes

We can also suggest improvements to managers' methods and policies.

For instance one manager may be better than another at choosing technology stocks.

YAO

- By distinguishing between luck and skill and by identifying what skills the manager has, we can recommend different managers for different asset classes and purposes
- We can also suggest improvements to managers' methods and policies.
- For instance one manager may be better than another at choosing technology stocks.
- Or another manager may be particularly skilled at shorting.
- We identify skill (or lack of) by:
 - Policy
 - Timing
 - Allocation
 - Selection
- We also can identify skill by:
 - Shorting
 - Sectors
 - Size
 - Yield Curve
 - And more.

Backtesting using an Order Book

Table 10: Comparison of forecast accuracy with alternative deflators.

Figure 1-1, Order-Book Processing

Similar to our work with costs and fees, accurate execution modeling required us to address complicated orders and transaction costs. Buy and sell orders are rarely executed instantaneously at the closing price of the previous day. So, we implemented an order book to help make our simulations more realistic and predictive.

Year	%DIFF
25	0.79%
52	-0.38%
30	-1.28%
73	-1.44%
2	2.93%
2	-4.08%
5	-4.52%
5	-4.31%
n-	-7.63%
w-	-9.02%
on	-4.48%
he	-2.44%
in-	-4.38%
ia.	-9.17%
is.	-8.24%
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- Similar to our work with costs and fees, accurate execution modeling required us to address complicated orders and transaction costs.
- Buy and sell orders are rarely executed instantaneously at the closing price of the previous day.
- So, we implemented an order book to help make our simulations more realistic and predictive.
- By using realistic orders and an order book, we are able to simulate transactions that:
 - take many days to fulfill (like partial fills and limits)
 - as well as complex strategies involving contingent orders (such as one cancels other and trailing stops).
- This realism provides more confidence in our performance predictions.

Transaction Cost Prediction & Simulation

Table 10: Comparison of forecast accuracy with alternative deflators.

**FINISH AND RUN
MATLAB SCRIPT**

Figure 13-5, Alpha Decay vs/ Market Impact

Figure 13-6, Simulated Market Impact

Stat	%DIFF
25	0.79%
52	-0.38%
30	-1.28%
73	-1.44%
2	2.93%
2	-4.08%
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When making investment decisions we forecast transaction costs, *ex ante*, to determine which investments are prohibitively expensive and the tradeoff between alpha decay and execution time.

We also simulated the *ex post* transaction costs to make our performance attribution more realistic and predictive.

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- When making investment decisions we forecast transaction costs, *ex ante*, to determine which investments are prohibitively expensive and the tradeoff between alpha decay and execution time.
- We also simulated the *ex post* transaction costs to make our performance attribution more realistic and predictive.
- We used several models to predict transaction costs.
- The predictions were used to help select investments and determine the timing and duration of orders.
- When simulating the transaction for performance measurement, we used high-frequency data.
- We determined the weighted average price, or WAP, from the open until the completion of the order.
- The time to completion was determined by estimating how much of that day's volume would have to trade for our order to be filled.
- The volume required was calculated as the order size times the Percent of Volume or POV.

Tax-Loss Harvesting Simulation

Table 10: Comparison of forecast accuracy with alternative deflators.

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MATLAB SCRIPT**

Figure 13-7, Excess Return vs. Time

Figure 13-8, Tax Alpha vs. Turnover

Scenario	%DIFF
25	0.79%
52	-0.38%
30	-1.28%
73	-1.44%
2	2.93%
2	-4.08%
5	-4.52%
5	-4.31%
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- Most tax advantaged research is produced by companies that sell those products.
- Advisors and investors want to know:
 - Does TLH work under all conditions?
 - When doesn't it work?
 - Can we make it more effective?
- Tax-managed strategies experience diminishing returns.
- This is a result of several market forces.
- As low tax-basis investments are harvested and replaced by higher tax-basis trades (top)—a fact often ignored by advisors.
- Intuitively, after-tax alpha is lower than pre-tax alpha and both stop growing as transaction costs outweigh alpha decay (bottom).
- Other assumptions, such as future tax rates and income brackets also greatly affect the strategy's performance

Thank you.

Please write your questions to:
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