Speaker Notes: From Man vs. Machine to Man + Machine

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Slide 1: Title Slide

Good [morning/afternoon], everyone. Thank you for joining me. Today I'm presenting a fascinating study titled *From Man vs. Machine to Man + Machine: The Art and AI of Stock Analyses.* It's a story about forecasting — and whether artificial intelligence can not only match but possibly outperform human analysts in predicting stock returns. Even more importantly, it asks if the best outcomes come from competition… or collaboration.

Slide 2: A Moment in History: Man vs. Machine

Let's begin with a symbolic moment in tech history. In 1997, chess grandmaster Garry Kasparov lost a highly publicized match to IBM's Deep Blue. This event marked a cultural turning point — it wasn't just about chess. It showed the world that machines were starting to outperform humans at intellectual tasks.

Slide 3: From Adversaries to Allies

But Kasparov didn't step away from the board. He did something revolutionary: he partnered with the machine. The result was "centaur chess," where human intuition and machine precision work together. These centaurs began outperforming both traditional grandmasters and even the strongest standalone chess engines. This concept — human + machine — is the spark for the study I'm presenting today.

Slide 4: From Chess to Finance

So the authors asked: could this idea extend to stock forecasting? Can machines outperform human analysts? And more provocatively — could the two work together? To test this, the authors built their own AI analyst and pitted it against thousands of real human analysts from I/B/E/S.

Slide 5: Meet the Analysts

On the left, we have the traditional analyst — intuitive, experienced, sometimes biased. On the right, the AI analyst — objective, data-driven, but context-blind. The study compares their forecasts head to head. But it also explores a third option: what happens when we combine them?

Slide 6: The Prediction Setup

Both analysts — human and AI — are asked to predict 12-month-ahead stock returns. The forecast is based on target prices, which are more reflective of valuation beliefs than earnings. Target prices are used because earnings forecasts can be distorted by managerial manipulation and short-term incentives.

Slide 7: Research Questions

The study is structured around three questions:

1. Can an AI analyst outperform human analysts?
2. In what situations do human analysts outperform AI?
3. Can combining their forecasts improve accuracy and reduce risk?

We'll answer each of these as we go.

Slide 8: Methodology – Overview

The AI analyst is trained using a rolling 3-year window of past data — the same kind of historical context a human might use. It's important to note: the AI doesn't see analyst forecasts. This is a pure, public-data-based model.

Slide 9: Methodology – Modeling Approach

The authors use an ensemble of three machine learning models: LSTM for time-series structure, random forests for interpretability and robustness, and gradient boosting for non-linear patterns. The idea is to combine their strengths to get a well-rounded, accurate prediction.

Slide 10: The Data – Sample Overview

The dataset includes over 1.15 million analyst forecasts from I/B/E/S, covering 2001 to 2018. Inputs include structured financials from Compustat and CRSP, sentiment from RavenPack and Twitter, SEC filings, and patent data for innovation signals.

Slide 11: The Data – AI Analyst Input Overview

The AI analyst uses only public data available at the time of each forecast. Forecasts are made using 3 years of prior history — no lookahead, just like a real analyst.

Slide 12: The Data – Categories of Inputs

These inputs are grouped into six key categories: firm data, industry data, macroeconomic indicators, SEC filings, sentiment, and innovation. This mirrors what a thorough analyst might consider.

Slide 13: The Data – Structured Inputs

Structured data includes accounting ratios, past returns, volatility, liquidity, and macro indicators. These are the classic building blocks of quantitative investing.

Slide 14: The Data – Textual and Alternative Inputs

Beyond the numbers, the model also looks at language. SEC filings are parsed for sentiment and tone. News and Twitter sentiment are captured as well. Finally, patent data gives a sense of firm-level innovation.

Slide 15: Results – Performance: AI vs. Human

Now to the core finding: The AI analyst beats the best human analyst in about 54.5% of forecasts. It's a modest edge, but consistent across time, sectors, and conditions — and it's based purely on public data.

Slide 16: Results – What Drives the AI Analyst

Which input groups matter most? Using a take-one-out method, the authors found that macroeconomic variables, return history, and firm characteristics account for nearly 75% of the AI's predictive power. But unstructured text and sentiment also play a meaningful role.

Slide 17: Results – When Humans Outperform AI

Despite the AI's overall edge, humans still do better in certain settings: firms with high intangibles, in distress, or with low liquidity. These are cases where context and judgment — what humans excel at — still matter.

Slide 18: Results – Man + Machine

So the authors built a hybrid model: Man + Machine. It slightly improves forecast accuracy over AI alone — but more importantly, it significantly reduces extreme errors. That's the power of complementarity.

Slide 19: The Hybrid Model Avoids Extreme Errors

Specifically, the hybrid avoids 90.7% of the worst human errors and 43.6% of the worst AI errors. In finance, where big misses can be costly, this robustness is a major advantage.

Slide 20: Conclusion

To conclude: yes, AI can outperform human analysts. But humans still shine in judgment-heavy cases. And the best results come not from replacing one with the other — but from combining their strengths. From man vs. machine… to man + machine. Thank you.