

From Man vs. Machine to Man + Machine: The Art and AI of Stock Analyses

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Motivation

- Artificial intelligence (AI) makes human reconsider their own roles.
 - Machine replaces man
 - Machine augments man
- Garry Kasparov vs Deep Blue (1997).
 - Story everyone knows: Deep Blue beat Kasparov.
 - Less known part of the story: More chess players and emergence of the “centaur” player.



Objectives of the study

- Inform the debate using stock analyses as a venue:
 - Machine: Can a machine beat most human analysts?
 - Man: What are the human analyst advantages in the age of AI?
 - Man + Machine: How can AI-equipped analysts beat machine?
- Connect and contribute to the growing literature on:
 - Competition and threat to human workers posed by machines, robots, and AI: Aghion, Jones and Jones (2017), Acemoglu and Restrepo (2018), Acemoglu and Restrepo (2019), Brynjolfsson, Mitchell and Rock (2018), Webb (2020), Ray and Mookherjee (2020), Cao, Cong, and Yang (2019), Acemoglu, Autor, Hazell, and Restrepo (2020).
 - Impact of big data and AI in the financial industry: Abis (2020), Abis and Veldkamp (2020), Coleman, Merkle, and Pacelli(2020), Grennan and Michaely (2020), Rossi and Utkus (2021).
 - Development and performance evaluation of machine learning models in performing various tasks especially in finance: Gu, Kelly, and Xiu (2020), Chen, Pelger, and Zhu (2020), Cong, Tang, Wang, and Zhang (2020), Aubry, Kraeusl, Manso, and Spaenjers (2020), van Binsbergen, Han, and Lopez-Lira (2020), Liu (2019), Zheng (2021), Hanley and Hoberg (2019).

Sample of forecasts

- Analyst target price forecasts (Thomson Financial I/B/E/S analyst dataset)
 - Sample periods: 1996 to 2018.
 - Merge I/B/E/S with CRSP and Compustat to obtain price and firm statement information.
 - Final sample: 948,054 analyst target price forecasts (12-month horizon) on 6,190 firms, issued by 11,341 analysts from 820 brokerage firms. from 755 brokerage firms.
- Why price forecasts (instead of earning forecast or analyst's qualitative recommendation, e.g., buy/sell/hold)?
 - 95% of the analysts issue price-based recommendations, suggesting that price forecast constitutes their primary job task.
 - Earnings are subject to insider discretion especially with a motive to beat or meet analyst forecasts, while prices are determined by external forces.
 - There is a clear performance metric for price predictions compared to qualitative recommendations (buy/sell/hold).

Building our own AI analyst

- Different from other studies that build on shocks to technology/Data availability as proxy for strengthened AI advantage (e.g., Grennan and Michaely, 2020), we construct our own AI Analyst.
- Information set for AI (\mathcal{I}_t):
 - Analysts are not expected to have access to private information (Regulation FD).
 - Ideally, \mathcal{I}_t should include all publicly available data and information up to $t-$.
 - Practically, \mathcal{I}_t contains firm and industry information from CRSP and Compustat, textual information from firms' SEC Filings, and macroeconomic data (such as industrial production CPI, oil prices).
- Rolling-window for AI learning:
 - At time t in year u when a human analyst makes a forecast on firm i , use the data over the past three years ($u-3, u-2, u-1$) to train our machine learning models.
 - Additional adjustment if year u is known to be in a recession.
 - Feed data available up to $t-$ into the model to make the prediction at time t .
 - Do not include analysts forecasts, past or current.

Variables as inputs to machine learning

- Firm Characteristics: Stock past price, past returns, past earnings, and firm characteristics known to be related to stock prices.
- Industry Variables:
 - The competition measure from 10K following Li, Lundholm, and Minnis (2013): Counting competition-related words.
 - The product market fluidity measure following Hoberg, Phillips and Prabhala (2014): Changes in rival firms' products relative to the focal firm.
 - Industry affiliation at the Fama-French 48 industries level (48 dummy variables)
 - Industry size, measured by the number of firms in the Fama-French 48 industry, within past 3, 6, 9, 12, 24 and 36 months
 - Equally-weighted industry average earnings per share realized within past 3, 6, 9, 12, 24 and 36 months

Variables as inputs to machine learning

- Macro variables:
 - Industrial Production Index
 - Consumer Price Index
 - Crude Oil Price (WTI)
 - 3-month treasury bill rate
 - 10-Year treasury constant-maturity rate
 - The BAA-AAA yield spread
- Textual sentiment:
 - Percentage of positive and negative sentiment words (Loughran and McDonald, 2011) from the firm-issued SEC filings.
 - Machine-learning-based sentiment variables (Cao, Kim, Wang, and Xiao, 2021): an ML approach capturing the managerial sentiment related to the firm's future performance by isolating it from topics not related to performance.

Machine learning models

- Standalone AI model
 - An ensemble of three different models:
 - Random Forest
 - Gradient Boosting
 - Long Short-Term Memory Neural Networks
 - For comparison, we also examine other models:
 - Lasso
 - Elastic-Net Regression
 - Support Vector Regression
 - Standalone Random Forest
 - Standalone Gradient Boosting
 - Standalone Long Short-Term Memory Neural Networks
- Man + Machine Model
 - The same Ensemble model.
 - Analyst and brokerage characteristics
 - Analyst forecasts up to time t

Potential factors for the relative performance of Man and Machine

- Public information transparency
 - Amihud illiquidity measure
 - Earnings volatility
 - Firm log market capitalization
- Volume of information: Number of 8K reports each year
- Intangible information, proxied as the first PC of four variables:
 - Intangible asset minus goodwill divided by total asset
 - One minus the ratio of PP&E to assets
 - Organization capital (Ewens, Peters, and Wang, 2020) scaled by assets
 - Knowledge capital (Ewens, Peters, and Wang, 2020) scaled by assets
- Analyst information environment, resources, and quality:
 - Star analyst: “all-star” status awarded by the Institutional Investor magazine at the beginning of the year
 - Size of brokerage firm (# analysts in brokerage firm)

Potential factors for the relative performance of Man and Machine (cont'd)

- Shareholder base: Institutional Ownership as percentage of shares outstanding
- Firm distress and macro information environment
 - Book Leverage (Fama and French, 1992): proxies for firms' financial exposure to distress shocks (Babina, 2020).
 - Time trend
- For Man + Machine: AI support within the brokerage house for analysts
 - Brokerage firm ratio of AI-related jobs to the total number of job postings (from Burning Glass) in 2007, and 2010 - 2018
 - Alternative data coverage (2011 - 2016)

[Link to Summary Stats](#)

Assessing the performance of our AI analyst

- A forecast by a human analyst: $F_{i,j,t}^{Man}$ (where i, j, t are indices for the stock, the analyst, and the date; and the superscript *Man* for “Human.”)
- The AI prediction model as:

$$F_{i,t}^{AI} = f(X_{i,t-}) + \epsilon_{it} \quad (1)$$

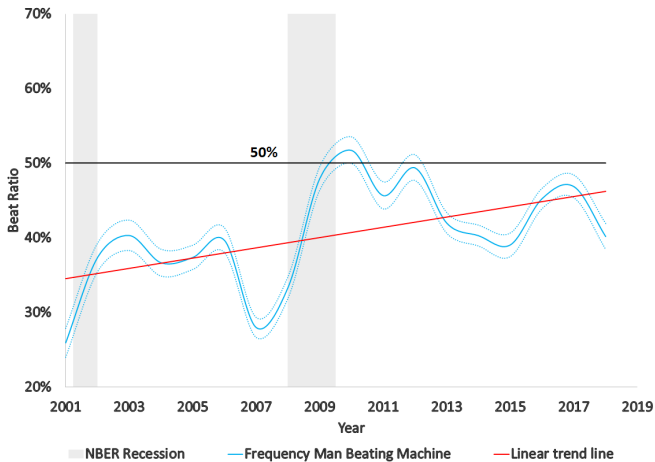
f is the ML model, and $X_{i,t-}$ is the time-adapted set of input variables.

- Human beats AI if $|F_{i,t}^{AI} - \log(P_{i,T(t)})| > |F_{i,j,t}^{Man} - \log(P_{i,T(t)})|$, and vice versa.

$P_{i,T(t)}$ is the stock price, where $T(t)$ is the last trading day of the 12th month in the future of time t .

- The predicted stock price is expressed in natural logarithm in order to mitigate skewness.
- Can human analysts outperform their AI counterparts? What we show is a *higher bound*.

The performance of Man vs. Machine



Performance persistence

- Compare the AI analyst with the more skilled and persistently skilled analysts.
- Test 1:
 - (1) Sort all analysts at median into two groups based on their average prediction error, over the past one, two, three, four and five years.
 - (2) Track the percentage of their future forecasts that are beaten by our AI analyst over the one year horizon going forward.
- Test 2: Same procedure except selecting the analysts that are among top and bottom halves in each of the past one, two, three, four and five years.

Performance persistence

Panel A: Beat ratio by analysts who are among the top or bottom 50% over the past period

	1 year	2 years	3 years	4 years	5 years
Analyst top	47.93%	47.77%	47.68%	47.63%	47.60%
Analyst bottom	41.60%	41.69%	41.74%	41.79%	41.82%

Panel B: Beat ratio by analysts who are among the top or bottom 50% each year during the past period

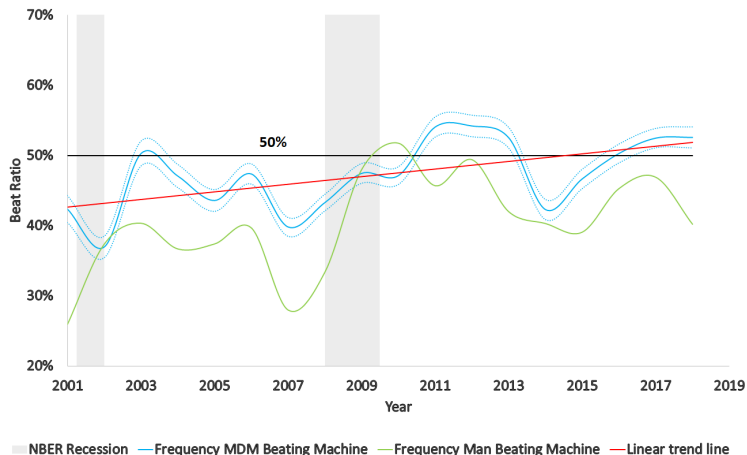
	1 years	2 years	3 years	4 years	5 years
Analyst Persistent top	47.93%	48.66%	49.33%	49.42%	49.88%
Analyst Persistent bottom	41.60%	41.42%	41.09%	40.94%	41.05%

De-biased Analysts and AI

- Analysts exhibit biases in their forecasts (e.g., Abarbanell, 1991; Stikel, 1990). There are a multitude of explanations of such biases, including
 - The incentive to issue more favorable forecasts for corporate clients (Michael and Womack, 1999)
 - The need to obtain access to information from the management (Lim, 2002)
 - Psychological traits of analysts (DeBondt and Thaler, 1990; Hirshleifer, Levi, Lourie, and Teoh, 2019).
- Could human underperformance relative to AI simply be remedied by “de-biasing” analyst forecasts?
- Hence the “de-biased” analyst forecasts or a “Machine-debias man” (henceforth “MDM”):
 - Predict next-period analyst forecast bias (signed) with machine learning, taking into account with analyst and brokerage characteristics.
 - Subtract the predicted bias from analyst forecast to obtain MDM forecasts.

The performance of MDM vs plain Machine

A de-biased man still trails machine.



Performance of portfolio following AI recommendations

- Construct portfolios based on the relative forecast between machine and man (or MDM). Procedure as follows:
 - In each month, gather all predictions made by all human analysts (or MDM analysts) and their correspondent AI forecasts in past 30, 60, 90 and 360 days.
 - For each prediction, if AI predicts a higher/lower price, it is a buy/sell signal.
 - A stock is a long position if there are more buy than sell signals, and vice versa. Form the long-short equal-weight portfolio accordingly.
 - Positions remain till signals reverse.
 - Compute the average return, and alphas estimated using Fama-French three factor, Carhart four factor, Fama-French five factor and Fama-French six factor models.
- Results with a six-month re-balancing portfolio are similar.

Long-short portfolio performance following Machine vs Man recommendations – 30-day rebalancing period

Monthly return in percentage points

		AI vs Analyst			
Retrospect. Info.	Horizon	30 day	60 day	90 day	360 day
Monthly returns	Ret	1.39*** (3.10)	1.51*** (3.54)	1.49*** (3.59)	1.05*** (3.77)
	FF3	1.47*** (3.28)	1.62*** (3.74)	1.58*** (3.77)	1.16*** (4.22)
	FFC4	1.53*** (3.43)	1.66*** (3.84)	1.61*** (3.86)	1.15*** (4.16)
	FF5	0.96** (2.34)	1.14*** (2.89)	1.14*** (2.98)	0.75*** (3.20)
	FF6	1.03*** (2.52)	1.19*** (3.03)	1.18*** (3.11)	0.76*** (3.25)

Long-short portfolio performance following Machine vs MIM recommendations – 30-day rebalancing period

Monthly return in percentage points

		AI vs MDM			
Retrospect. Info. Horizon		30 day	60 day	90 day	360 day
Monthly returns	Ret	0.65** (2.43)	0.73*** (3.81)	0.67*** (3.77)	0.51*** (3.00)
	FF3	0.61** (2.18)	0.70*** (3.51)	0.62*** (3.35)	0.48*** (2.65)
	FFC4	0.67** (2.42)	0.75*** (3.82)	0.67*** (3.65)	0.51*** (2.81)
	FF5	0.52** (1.97)	0.58*** (3.13)	0.54*** (3.13)	0.39** (2.39)
	FF6	0.54** (2.08)	0.60*** (3.28)	0.56*** (3.27)	0.41** (2.49)

Man vs machine: Determinants of the relative advantages

- The dependent variables are Man Beats Machine, a dummy variable, and Absolute Forecast Error Spread (in favor of Man).
- The independent variables include firm, analyst, and brokerage characteristics and information environment.
- Firm (or analyst) and year fixed effects.
- Hypotheses:
 - Humans may be better at interpreting discretionary information.
 - Machines are more powerful in possessing voluminous information.
 - Brokerage resources and analyst expertise matter.
 - Machines tend to be less effective in distress situations.
 - Time Trend.

Man vs. Machine: When Man beats Machine

Variables	Analyst beats AI			
<i>Amihud Illiquidity</i>	0.228** (2.52)	0.189*** (2.66)	0.033 (0.36)	-0.024 (-0.33)
<i>Market Cap</i>	-0.064*** (-9.90)	-0.037*** (-5.87)	-0.086*** (-12.65)	-0.053*** (-8.00)
<i>Standard Deviation of Earnings</i>	-0.050 (-0.44)	-0.064 (-0.53)	0.045 (0.43)	0.049 (0.42)
<i>% Institutional Holdings</i>	0.050 (1.04)	0.072*** (2.68)	0.059* (1.66)	0.075*** (3.62)
<i># 8K Reports</i>	-0.485*** (-4.40)	-0.554*** (-4.88)	-0.400*** (-3.42)	-0.525*** (-4.29)
<i>Intangible Assets</i>	0.031*** (2.99)	0.029*** (2.97)	0.039*** (2.84)	0.037*** (2.79)
<i>Fluidity</i>	0.539*** (3.73)	0.116 (0.74)	0.800*** (4.78)	0.374** (2.02)
<i># Analysts in Brokerage Firm</i>	0.142 (1.06)	0.421*** (3.24)	-0.253 (-0.60)	0.157 (0.37)
<i>Star Analysts</i>	0.455 (0.99)	0.486 (1.07)	-0.494 (-0.89)	-0.478 (-0.87)
<i>Book Leverage</i>	0.064** (2.17)	0.059** (2.54)	0.099*** (5.19)	0.098*** (4.71)
<i>Time Trend</i>	0.013*** (13.64)		0.009*** (7.84)	
Year Fixed Effect	No	Yes	No	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Analyst Fixed Effect	No	No	Yes	Yes
Observations	291,331	291,331	291,331	291,331
Adjusted R-squared	0.109	0.121	0.165	0.174

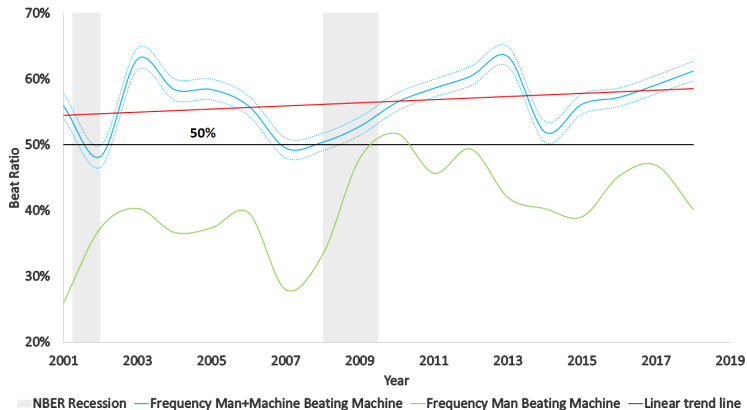
Man vs. Machine: When Man beats Machine

Variables	Forecast Error Difference: Analyst vs. AI			
<i>Amihud Illiquidity</i>	0.532*** (4.41)	0.462*** (5.11)	0.333*** (2.83)	0.231*** (2.63)
<i>Market Cap</i>	-0.104*** (-10.16)	-0.061*** (-6.09)	-0.138*** (-13.11)	-0.087*** (-8.36)
<i>Standard Deviation of Earnings</i>	0.043 (0.28)	0.007 (0.04)	0.148 (0.98)	0.138 (0.76)
<i>% Institutional Holdings</i>	0.051 (0.72)	0.080* (1.96)	0.073 (1.40)	0.090*** (2.89)
<i># 8K Reports</i>	-0.745*** (-4.32)	-0.853*** (-4.85)	-0.593*** (-3.23)	-0.802*** (-4.22)
<i>Intangible Assets</i>	0.048*** (2.95)	0.045*** (2.92)	0.064*** (2.98)	0.061*** (2.92)
<i>Fluidity</i>	0.766*** (3.26)	0.169 (0.65)	1.112*** (4.14)	0.505* (1.69)
<i># Analysts in Brokerage Firm</i>	0.096 (0.47)	0.538*** (2.72)	-0.325 (-0.48)	0.311 (0.46)
<i>Star Analysts</i>	1.159* (1.66)	1.197* (1.73)	0.129 (0.16)	0.156 (0.19)
<i>Book Leverage</i>	0.114*** (2.97)	0.109*** (3.40)	0.124*** (4.15)	0.125*** (4.00)
<i>Time Trend</i>	0.021*** (14.23)		0.015*** (8.13)	
Year Fixed Effect	No	Yes	No	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Analyst Fixed Effect	No	No	Yes	Yes
Observations	291,331	291,331	291,331	291,331
Adjusted R-squared	0.136	0.148	0.199	0.207

Combined wisdom of Man and Machine

- Construct a “Man + Machine” analyst, analogous to the centaur chess player, based on the information of from both analyst and AI predictions, with the same ML model.
- Compare the forecast errors by “Man + Machine” separately with plain Machine and lone Man.
- Machine can help Man in:
 - Augmenting information processing.
 - (Man + Machine) can outperform 57.8% of all human analysts.
 - (Man + Machine) beats 55.8% of AI forecasts with growing advantage over time.
 - Highlight a valuable and growing role for humans in a “centaur” analyst.

The performance of Man + Machine vs plain Machine



Man + Machine: Incremental value of Man and Machine

- Now we compare the performance of Man + Machine with that of Machine alone.
- Dependent variables become:
 - Man + Machine beats Machine.
 - The incremental of machine and that of man: The absolute forecast error spread (in favor of Man + Machine).
- Hypotheses:
 - Some human analysts (e.g., “stars”) enjoy more synergy with machine.
 - Human judgment is useful when the firm is subject to greater information asymmetry, involves more intangible information, has higher exposure to distress risk.

Man + Machine: Incremental value of Man and (synergies with Machine)

Variables	Analyst + AI beats AI			
<i>Amihud Illiquidity</i>	0.139*** (4.04)	0.113*** (3.28)	0.072* (1.84)	0.041 (1.09)
<i>Market Cap</i>	-0.027*** (-6.15)	-0.015*** (-3.44)	-0.036*** (-6.52)	-0.021*** (-3.72)
<i>Standard Deviation of Earnings</i>	0.328*** (4.17)	0.336*** (4.83)	0.322*** (4.15)	0.342*** (5.30)
<i>% Institutional Holdings</i>	0.076*** (3.70)	0.089*** (7.39)	0.078*** (5.11)	0.088*** (9.40)
<i># 8K Reports</i>	-0.176* (-1.66)	-0.192* (-1.73)	-0.168 (-1.39)	-0.187 (-1.48)
<i>Intangible Assets</i>	0.027*** (3.35)	0.026*** (3.32)	0.027*** (3.37)	0.026*** (3.10)
<i>Fluidity</i>	0.319** (2.04)	0.107 (0.66)	0.459** (2.43)	0.239 (1.22)
<i># Analysts in Brokerage Firm</i>	-0.234** (-1.97)	-0.153 (-1.30)	-0.555 (-1.37)	-0.470 (-1.18)
<i>Star Analysts</i>	0.798* (1.70)	0.915** (1.97)	0.986* (1.66)	1.016* (1.72)
<i>Book Leverage</i>	0.006 (0.14)	0.005 (0.10)	-0.023 (-0.48)	-0.025 (-0.50)
<i>Time Trend</i>	0.002** (2.08)		0.002** (2.01)	
Year Fixed Effect	No	Yes	No	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Analyst Fixed Effect	No	No	Yes	Yes
Observations	291,331	291,331	291,331	291,331
Adjusted R-squared	0.042	0.047	0.065	0.069

Man + Machine: Incremental value of Man and (synergies with Machine)

Variables	Forecast Error Difference: Analyst + AI vs. AI			
<i>Amihud Illiquidity</i>	0.193*** (5.70)	0.166*** (4.96)	0.208*** (6.76)	0.191*** (6.24)
<i>Market Cap</i>	-0.020*** (-4.35)	-0.007 (-1.58)	-0.027*** (-5.06)	-0.011** (-2.05)
<i>Standard Deviation of Earnings</i>	0.201 (1.26)	0.204 (1.33)	0.260 (1.29)	0.276 (1.43)
<i>% Institutional Holdings</i>	0.047* (1.80)	0.060*** (3.72)	0.022 (0.94)	0.030** (1.96)
<i># 8K Reports</i>	-0.272** (-2.26)	-0.219* (-1.72)	-0.256* (-1.89)	-0.217 (-1.52)
<i>Intangible Assets</i>	0.021** (2.32)	0.020** (2.24)	0.018* (1.86)	0.016* (1.65)
<i>Fluidity</i>	0.262 (1.61)	0.112 (0.67)	0.392** (2.01)	0.257 (1.25)
<i># Analysts in Brokerage Firm</i>	-0.223* (-1.84)	-0.135 (-1.13)	-0.394 (-0.93)	-0.349 (-0.84)
<i>Star Analysts</i>	0.992** (2.09)	1.117** (2.37)	1.100* (1.86)	1.125* (1.92)
<i>Book Leverage</i>	0.059*** (2.67)	0.060*** (2.61)	0.045** (2.08)	0.045** (2.11)
<i>Time Trend</i>	0.002*** (3.02)		0.003*** (2.82)	
Year Fixed Effect	No	Yes	No	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Analyst Fixed Effect	No	No	Yes	Yes
Observations	291,331	291,331	291,331	291,331
Adjusted R-squared	0.047	0.053	0.072	0.077

Man + Machine event study

- Research question: When human analysts receive AI inputs, can they outperform our AI analyst?
- The event: Firms became covered by satellite data from 2011 to 2016. Katona, Painter, Patatoukas, and Zeng (2020) provide the list of firms and coverage date and if the firm is in industries with retail.
- Design: Compare the performance spread between analysts covering “treated” firms and our AI Analyst with that of the control sample (for which 2014 serves as the placebo event time).
- Further sorting by brokerage AI hiring as proxy for AI investment (Babina, Fedyk, He, and Hodson, 2021) .
- Hypotheses:
 - *Post coverage*, analysts who cover the treated firms have the potential to improve their forecasting accuracy relative to our AI analyst (which does not include such information).
 - Improvement should be stronger among analysts who work for brokerage houses with AI capacity.

Man + Machine event study: Effect of alternative data

Variables	Analyst beats AI			
<i>AI Hiring</i>	0.142*** (2.69)	0.050 (0.80)	0.136*** (2.59)	0.044 (0.69)
<i>Alt data cover</i>				-0.065 (-1.52)
<i>Treat: Alt data cover x Post</i>			-0.012 (-0.22)	0.041 (0.78)
<i>Treat x AI Hiring</i>			1.065*** (2.69)	1.375*** (2.65)
Controls	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	No	Yes	No
Analyst fixed effect	No	Yes	No	Yes
Observations	51,468	51,468	51,468	51,468
Adjusted R-squared	0.123	0.040	0.123	0.040

Conclusion

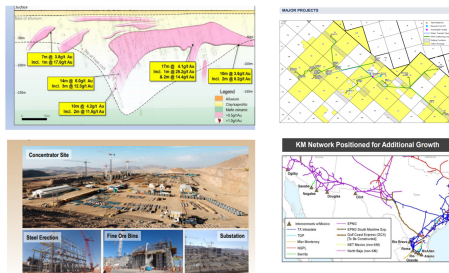
- Build an AI analyst to the extent of beating the majority of human analysts, as a premise to assess the relative advantage between Man and Machine.
 - AI's capability goes beyond overcoming analyst biases
- AI commands advantage when the firm is complex, and when information is high-dimensional, transparent and voluminous.
- Human analysts remain competitive when critical information requires institutional knowledge, and when the situation is unusual.
- The edge of the AI over human analysts declines over time, as analysts gain access to alternative data and to in-house AI resources.
- Combining AI and the art of human expertise produces the highest potential in generating accurate forecasts.

Overview: Interaction between human and AI

- AI implications for manager reporting decisions: Human consuming firm disclosure vs. machine consuming firm disclosure (Cao, Jiang, Yang and Zhang 2021)
- AI implications for investors: An AI stock analyst (Cao, Jiang, Wang and Yang 2021)
 - **replace** human intelligence of analyzing accounting information?
Beating 53% human analysts
 - **augment** human intelligence of analyzing accounting information?
The skills of surviving 47% human analysts + Machine strength
- AI for understanding decision-making: Machine understanding of human vs. human understanding of human (Cao, Xiao, Xu and Yang 2021)

Overview

- AI techniques for trading stocks based on company production/product images (Cao, Chen, Xia and Yang 2021)

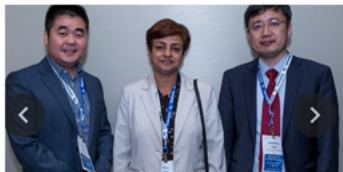


- Search SeanCao google site <https://sites.google.com/view/seancao/home>

Common Challenges in ML studies

- What is the contribution to economic theories in addition to methodology advancement?
- Can we make the technology understandable to a broad audience beyond the CS audience?
- How to justify the use of emerging technologies?

See more at 2020 GSU-RFS Conference summarizing 300 ML papers



2020 GSU-RFS FinTech Conference

with dual submission option to RFS

February 28-29, 2020 | Atlanta, Georgia

*Sponsoring Editors of the RFS: Itay Goldstein (University of Pennsylvania)
and Manju Puri (Duke University)*



The Review of Financial Studies

Summary statistics for factors

Variables	Mean	Median	Std	P25	P75	N
Panel A. Firm-level, industry-level and macroeconomic variables						
<i>Amihud Illiquidity</i>	0.44	0.01	61.55	0.00	0.02	291,331
<i>Intangible Assets</i>	0.02	-0.14	1.14	-0.42	0.14	291,331
<i># Analysts in Brokerage Firm</i>	3.45	3.53	0.91	2.89	4.11	291,331
<i>Star Analyst</i>	0.47	0.50	0.21	0.34	0.60	291,331
<i># 8K Reports</i>	2.77	1.00	15.62	0.00	2.00	291,331
<i>Market Cap</i>	8.00	7.91	1.67	6.81	9.14	291,331
<i>Institutional Ownership</i>	0.66	0.77	2.03	0.53	0.90	291,331
<i>Fluidity</i>	7.16	6.46	3.60	4.52	9.10	291,331
<i>Earnings Volatility</i>	0.19	0.11	0.30	0.06	0.22	291,331
<i>Book Leverage</i>	1.28	1.08	0.58	0.91	1.39	291,331
Panel B. AI and satellite coverage variables						
<i>AI job</i>	0.43	0.00	4.73	0.00	0.00	51,469
<i>Alt data cover</i>	0.03	0.00	0.17	0.00	0.00	51,469
<i>Post</i>	0.45	0.00	0.50	0.00	1.00	51,469