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

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Finance Hub
2023

Motivation

- Trend in Artificial intelligence (AI) development makes human reconsider their roles
  - ▷ Machine replaces Man (Muro, Maxim, and Whiton, 2019)
  - ▷ Machine augments Man
- Garry Kasparov vs Deep Blue (1997)
  - ▷ Story everyone knows: Deep Blue beat Kasparov
  - ▷ Less known part: Emergence of *centaur* player

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Main Objective

Questions

What are the AI advantages over human analysts?

What are the human analyst advantages in the age of AI?

How can analysts ride the AI-advantage?

This paper:

- Seek to respond those questions in a **price forecasting** exercise
- Build an AI analyst equipped with large **Data** and **ML** modelling
- Investigate the **pros** and **cons** of Men vs. AI in **price forecasting**
- Build a Men + AI analyst and study if it can **combine the strength of both**

What they do

- Human analyst: collect the 12-months price forecast from 1996-2018
- AI analyst:
  - Data: **Firm Characteristics**, **Industry** and **Macro Variables**, and **Textual Information**
  - ML Ensemble Modeling: **Random Forest**, **Gradient Boosting**, and **Neural Network**
- Empirical exercises:
  1. Compare the forecasting error of both analysts through time
  2. See the role of **Bias**
  3. Determinants of Relative Performance: **Volume of Information**, **Firm Specificity**, **Asset Distress**...
  4. **Men + Machine analyst** vs. AI and Human analysts
  5. **External Validity:** Study the performance of Men + Machine build using alternative data

What they find

- AI analyst outperforms human analysts in **55.9%** of cases, due to better **information processing** and immunity from **human biases**
  - Even analysts with **superior track record** (top 7.3%) are beaten by AI in **50.2%** of cases
  - AI still beat **Machine-debiased human** analysts (MDM) in 51.8% of cases
  - Human performance improves over **time** with access to more data and AI resources
- AI better when the volume of **public information** is larger
- Human analysts advantage in knowledge in **uncertain scenarios** and **firms specificities**
  - Soft skills allow to excel in analyzing smaller, illiquid firms with intangible assets
- Man + Machine outperforms AI alone in **55.8%** of forecasts
  - Human insights **synergize** with AI, boosting its performance in areas where we excel
  - Significantly reduces **extreme errors** compared to individual human or AI forecasts
- Men + Machine using alternative data improves forecasts, but only in firms with *strong AI capabilities*

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Data and ML Models

Human Analyst Data

- **Target data:** 12-month target price forecasts
  - Merge Thomson Reuters *I/B/E/S* with *CRSP* and *Compustat*
  - Sample periods: 1996 to 2016
  - Final sample: 948,054 analyst target price forecasts on 6,190 firms, issued by 11,341 analysts from 820 brokerage firms

- **Why 12-month?**
  - Other periods forecast are far less common (**1%**)
  - Objective and quantifiable measure that represents an important quality in analyst evaluation (Desai et al., 2000).

- **Why price forecasts instead of earning forecast?**
  - Subject to managerial discretion or even manipulation
  - Endogenous to analyst forecasts due to the risk of feedback loop caused by the incentive to beat analyst consensus (Doyle et al., 2013)

Building our own AI analyst

- **Information set for AI**: $\mathcal{I}_t$
  - Ideally, $\mathcal{I}_t$ should include all publicly available data and information up to $t-$
  - Analysts are not expected to have access to private information (Regulation FD)
  - **Do not include human analysts forecasts**

- **Rolling-window for AI learning**:
  - Use three previous years as training
  - In case of distress, expand the training sample using three years before the distress
  - First prediction is feasible in 2001

Variables as inputs to ML

- **Firm Characteristics**:
  - ▷ Stock past price, past returns, past earnings
  - ▷ *Source:* CRSP and Compustat via WRDS
  - ▷ Anomalies from the 6 broader categories of Hou et al (2020): Momentum, Value versus Growth, Investment, Profitability, Intangibles, and Trading Frictions
- **Industry Variables**:
  - ▷ Competition measure from (Li et al., 2013): Counting competition-related words from 10K
  - ▷ The product market fluidity measure following Hoberg et al. (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 EPS realized within past 3, 6, 9, 12, 24 and 36 months

Variables as inputs to ML

- **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 from the firm-issued SEC filings (Loughran and McDonald, 2011)
  - ML-based sentiment variables: Capture the managerial sentiment related to the firms future performance by isolating it from topics not related to performance (Cao et al, 2020)

Potential factors for the relative performance of Man and Machine

- **Public information transparency**: ▸ Regression
  - Amihud (2002) Illiquidity measure: ratio of stock return to the trading volume
  - Earnings volatility (SD)
  - Firm log market capitalization
- **Volume of information**: Number of 8K reports each year
- **Intangible Assets**: first PC of four proxies:
  - Intangible assets minus goodwill divided by total assets
  - One minus the ratio of PP&E to assets
  - Organization capital scaled by assets (Ewens et al., 2022)
  - Knowledge capital scaled by assets (Ewens et al., 2022)
- **Analyst information environment and resources**:
  - Star Analyst: awarded by the Institutional Investor magazine
  - Number of analysts in Brokerage Firm
  - Total number of institutional owners
  - Book Leverage (Fama and French, 1992; Babina, 2020)

Machine learning models

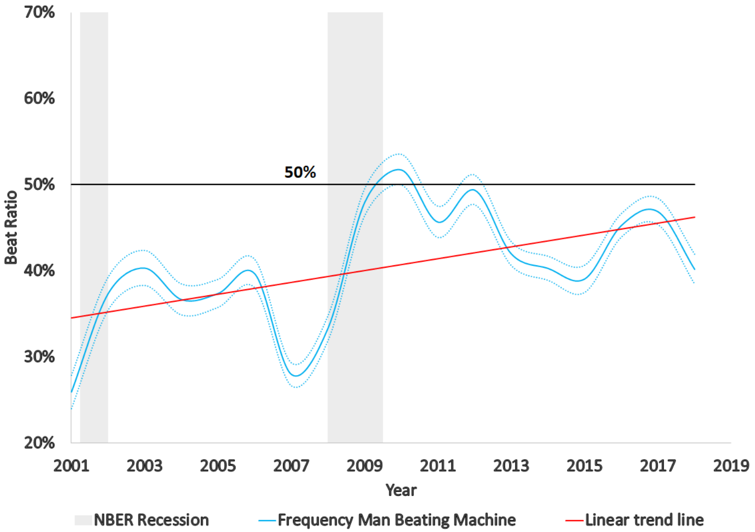
- Database feeds an ML model able to handle large amounts of data
- Select the best models from a ex-ante defined list: ▸ Table IA1
  - Lasso regression
  - Elastic-Net Regression
  - Support Vector Regression
  - Random Forest
  - Gradient Boosting
  - Long Short-Term Memory Neural Networks
- Ensemble three different models:
  - Random Forest
  - Gradient Boosting
  - Long Short-Term Memory Neural Networks

Empirical Results

The Predictive Models

- Let $\{i, j, t\}$ be the indices for the firm, the analyst, and the date
- Human analyst forecast: $F_{i,j,t}^{Man}$
- The AI prediction model: $\log(P_{i,T(t)}) = F_{i,t}^{AI} + \varepsilon_{i,t}$, $F_{i,t}^{AI} = f(X_{i,t-})$ Figure 2
  - f_{t-} is the prediction function for all stocks at time $t-$
  - $P_{i,T(t)}$ is the stock price
  - $T(t)$ is the last trading day of the 12-month forward price from t
- AI beats human if $|F_{i,t}^{AI} - \log(P_{i,T(t)})| < |F_{i,j,t}^{Man} - \log(P_{i,T(t)})|$, and vice versa.
- Did Human analysts outperform the Machine?
  - **No!** Out of 820,099 forecasts made from 2001 to 2018, the AI won **55.9%** of the time.

Figure 1 - Man vs. Machine: The Performance of Analysts vs. AI



Performance persistence

- Compare the AI analyst the analysts with the best track record.
  - ▷ Sort all analysts at median into two groups based on their average prediction error, over the past years.
  - ▷ Track the percentage of their future forecasts that are beaten by the AI analyst over the one year horizon going forward.
  - ▷ **Even analysts with superior track record (top 7.3%) are beaten by AI (50.22% of cases)**

Table 2: Persistence of Performance of AI Analyst

Panel A: Analyst beat ratio sorted by analysts who are above/below median

	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%

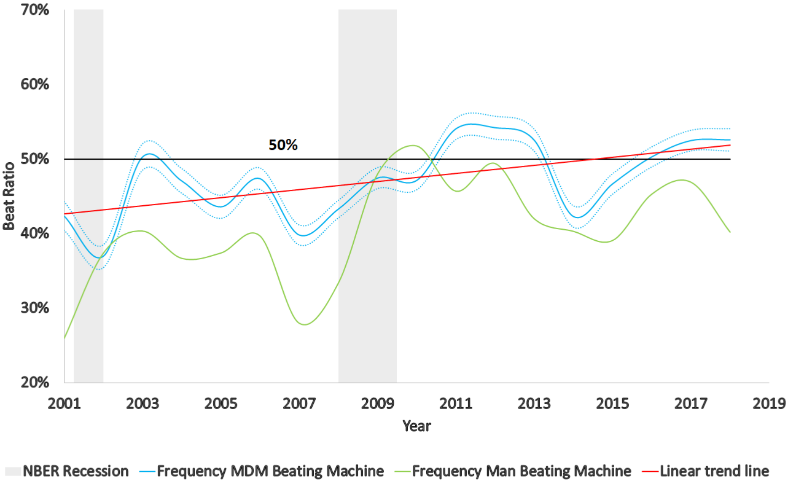
Panel B: Analyst beat ratio sorted by analysts who are above median each of the past years

	1 year	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%

Debiased Analysts vs. AI

- It is a stylize fact the presence of **Bias** in Analysts forecasts
  - Analysts biases stem from incentives for favorable forecasts, and psychological traits
- **Question**: Is the human underperformance driven mainly by human bias?
  - Investigate that by *debiasing* analyst forecasts with ML Models (MDM)
- Steps in constructing MDM:
  - Identifying potential sources of bias (Z): mean and standard error of analysts past prediction biases, analysts past experiences, ...
  - Computing forecast error: $F_{i,j,t}^{Man} - \log(P_i^T(t)) = g(X_{i,t-}, Z_{i,t-}) + \varepsilon_{i,t}$
  - Remove bias: $F_{i,j,t}^{Man} - g(X_{i,t-}, Z_{i,t-})$
- After constructing the *debiased* analysts, AI analysts only beat in **51.8%** of cases
  - **Bias represents around 69% of the Man-Machine gap**

Figure 3 - Man + Machine: The Performance of Machine-Debiased Analyst vs. AI



Performance of portfolio following AI recommendations

- Construct portfolios based on the relative forecast between Machine and Man
  - ▷ In each month, gather all predictions made by all human analysts and their correspondent AI forecasts in past 30, 60, 90 and 360 day
  - ▷ 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
  - ▷ Stocks are held or shorted for one month or until the 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
- AI is able to generate superior returns/alpha, relative to analysts Table 3
  - **Superior returns are significant only on the long side**
  - Results with a six-month re-balancing portfolio, and MDM analysts are similar

Determinants of Relative Performance ▸ Table 6

- Study the pros and cons of Human vs. AI could demystify AI **black box** and guide researchers and investors in the quest for **synergizing** our **strengths**

- For each target price forecast, define two variables that measure the **relative performance** of humans vs AI
  - ▷ Indicator variable Analyst Beats AI
  - ▷ Continuous measure Forecast Error Difference

- Relative Performance$_{i,j,t} = \Theta_{i,j,t}\,\beta + \alpha_i + \alpha_j + \alpha_{year} + \varepsilon_{i,j,t}$
  - ▷ Θ: **Potential factors** for the relative performance of Man and Machine
  - ▷ Include firm, analyst and year fixed effects

- Hypotheses:
  - ▷ Machines are more powerful in possessing **voluminous information**
  - ▷ Humans may be better in **specific firms** or in **uncertain moments**
  - ▷ Brokerage resources
  - ▷ Time trend?

Determinants of Relative Performance

◇ Machines are more powerful in possessing voluminous information

Table 4: Man vs. Machine: The Relative Advantage of Analyst vs AI

Panel B: Forecast Error Difference: Analyst vs. AI

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

Determinants of Relative Performance

- Humans better with soft skills and during firm uncertain moments

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Determinants of Relative Performance

◇ Brokerage resources help Human performance

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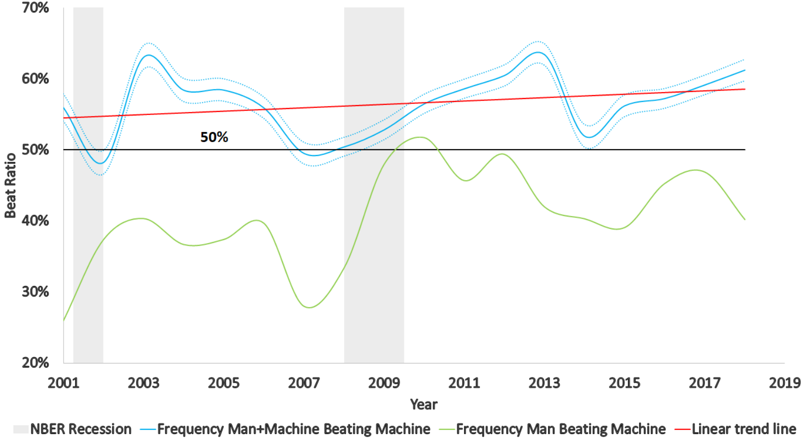
Combined wisdom of Man and Machine

- **Claim:** Analysts forecasts coul contain incremental information to AI predictions
- Build **Man + Machine** analyst based on the information from both Human and AI
  - ▷ Add in Information set forecasts made by analysts during the 90-day window ending on t
  - ▷ Same ML model
- Man + Machine vs. AI alone
  - ▷ Man + Machine outperforms Machine in 16 out of 18 years
  - ▷ The incremental value of human analysts to machines is increasing with time
- Hypotheses:
  - ▷ Man + Machine analysts gain from synergy between Man and Machine
  - ▷ Human judgment is useful when the firm is subject to greater information asymmetry, involved more intangible information, or facing more uncertain scenarios

Combined wisdom of Man and Machine

Figure 4 - Man + Machine: The Performance of AI-assisted Analysts vs. AI



Incremental Value of Analysts Input

Regression

◇ **Synergy**: Man inputs are more valuable in cases related with their **comparative advantage**

Table 6: Man + Machine: The Incremental Value of Analyst

Panel A. Analyst + AI beats AI

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

Can Man + Machine Avoid Extreme Error?

- Extreme forecast errors is terrible for forecasting reputation, specially made by AI (Prahl and Swol, 2017)
- Extreme errors: forecast errors > 90th (70th) percentile of all analyst forecast errors
  - ▷ On the same firm; in the past 3 years

Table 7: Probabilities of Extreme Errors: Man vs. Machine and Man + Machine

Panel A: Probabilities of Extreme Errors (90th percentile)

	Both	Analyst	AI	Neither
Unconditional Probability	2.49%	10.75%	12.44%	79.30%

	M+M Avoids Both/ Both	M+M Avoids Analyst Analyst	M+M Avoids AI/ AI	M+M Creates EE/ Neither
Conditional Probability	15.06%	76.33%	32.18%	1.27%

Panel B: Probabilities of Extreme Errors (75th percentile)

	Both	Analyst	AI	Neither
Unconditional Probability	8.17%	24.86%	22.89%	60.42%

	M+M Avoids Both/ Both	M+M Avoids Analyst Analyst	M+M Avoids AI/ AI	M+M Creates EE/ Neither
Conditional Probability	13.15%	66.51%	24.54%	2.39%

Impact of Man + Machine: An Event Study

- **External Validity**: Case Study with alternative data captures *consumer footprints*
  - ▷ Assumption: analysts who cover firms with access to alternative data are in the Man + Machine situation
- **Question:** When Men analysts receive AI inputs, can they outperform the AI analyst?
- **The event:** Some retail firms became covered by satellite data (Katona et al, 2022)
- **Design:** Difference-in-differences test comparing the performance spread between analysts covering *treated firms* and the AI Analyst with that of the *control* sample
- **Treated firms:**
  - ▷ *Alt Data Covered*: Firms covered by satellite data at any period in the sample
  - ▷ *Post*: Period in which the satellite data was available

Impact of Man + Machine: An Event Study

- Only include data if the brokerage house with which analyst j is affiliated is covered by the *Burning Glass* job posting data any time during $[t-3, t]$

- **Regression:**

$$\begin{aligned}\text{Analyst Beats AI}_{i,j,t} = &\ \beta_1 \text{Treat}_{i,t} \text{ X AI Hiring}_{j,t} + \beta_2 \text{ AI Hiring}_{j,t} \\ &+ \beta_3 \text{ Alt Data Covered}_i + \beta_4 \text{ Treat}_{i,t} \\ &+ \text{Controls}_{i,j,t} + \alpha_i + \alpha_{year} + \varepsilon_{i,j,t}\end{aligned}$$

- AI Hiring: proxy for AI investment (Babina et al, 2021)
  - Reflects the level of AI integration at brokerage firms
  - Improvement should be stronger on analysts from brokerage houses with AI capacity

- Analysts associated with brokerage houses with greater AI capabilities generally perform better against the AI model ($\beta_2 > 0$)
- Analysts covering firms *treated* with alternative data only can effectively leverage this information if AI resources is available in their workplace ($\beta_1 > 0$)

Table 8: Man + Machine Event Study: Alternative Data Coverage

Variables	Analyst beats AI			
AI Hiring	0.142***	0.050	0.136***	0.044
	(2.69)	(0.80)	(2.59)	(0.69)
Alt Data Cover				-0.065
				(-1.52)
Treat: Alt Data Cover x Post			-0.012	0.041
			(-0.22)	(0.78)
Treat x AI Hiring			1.065***	1.375***
			(2.69)	(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

Concluding remark

- The continued progression of AI technology in Finance is expected to be long-lasting
- Build an AI analyst that is able to beat the majority of human analysts
- AI commands advantage when information is high-dimensional, and voluminous
- Human analysts remain competitive when the situation is unusual, and when critical information requires institutional knowledge
- Combining AI and the art of human expertise produces the highest potential in generating the most accurate forecasts

Thank you!

Cao et al. (2022): *From Man vs. Machine to Man + Machine: The Art and AI of Stock Analyses.*

Table IA1: Performance Evaluation of ML Models

Return

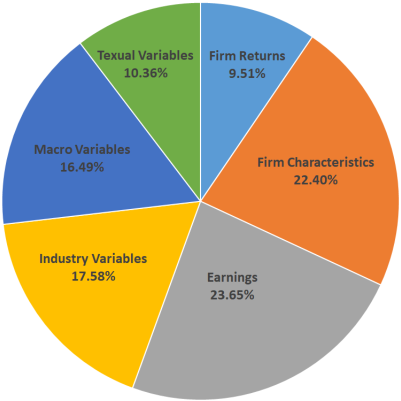
Squared Prediction Errors

Year	Lasso	Elastic Net	SVM	Random Forest	Gradient Boost	LSTM
2001	1.58	1.48	0.69	0.61	0.57	0.48
2002	1.94	1.94	0.90	0.46	0.60	0.62
2003	1.49	1.37	0.44	0.35	0.32	0.33
2004	1.44	1.30	0.46	0.29	0.28	0.28
2005	1.50	1.29	0.38	0.25	0.27	0.25
2006	1.34	1.11	0.40	0.21	0.23	0.25
2007	1.57	1.39	0.46	0.24	0.25	0.25
2008	2.28	2.06	0.88	0.61	0.64	0.63
2009	2.21	1.81	0.64	0.52	0.41	0.44
2010	1.68	1.24	0.68	0.31	0.35	0.65
2011	1.69	1.28	0.75	0.58	0.46	0.52
2012	1.80	1.36	0.48	0.26	0.29	0.25
2013	1.46	1.10	0.47	0.24	0.23	0.20
2014	1.36	1.04	0.38	0.21	0.21	0.22
2015	2.24	1.72	0.63	0.38	0.38	0.39
2016	1.84	1.41	0.65	0.37	0.38	0.41
2017	1.17	0.93	0.45	0.30	0.27	0.23
2018	1.38	1.05	0.42	0.22	0.25	0.22

- **Random Forest**, **Gradient Boost** and **LSTM** present the lowest **Squared Prediction Errors**.

Return

Figure 2 - Contribution of Groups of Variables to the AI Prediction



◂ Return

Table 3: Portfolio Performance following Machine vs. Man: Monthly Rebalancing

Portfolio returns - AI vs. Analyst

	AI vs. Analyst			
Long-Short	30 day inform	60 day inform	90 day inform	360 day inform
Ret	1.39***	1.51***	1.49***	1.05***
	(3.10)	(3.54)	(3.59)	(3.77)
FF3	1.47***	1.62***	1.58***	1.16***
	(3.28)	(3.74)	(3.77)	(4.22)
FFC4	1.53***	1.66***	1.61***	1.15***
	(3.43)	(3.84)	(3.86)	(4.16)
FF5	0.96**	1.14***	1.14***	0.75***
	(2.34)	(2.89)	(2.98)	(3.20)
FF6	1.03**	1.19***	1.18***	0.76***
	(2.52)	(3.03)	(3.11)	(3.25)
Long-Leg	30 day inform	60 day inform	90 day inform	360 day inform
Ret	2.02***	2.13***	2.12***	1.81***
	(4.30)	(4.56)	(4.61)	(5.07)
FF3	1.38***	1.44***	1.40***	1.16***
	(4.71)	(4.92)	(5.00)	(9.90)
FFC4	1.47***	1.51***	1.47***	1.21***
	(5.10)	(5.21)	(5.28)	(10.51)
FF5	1.21***	1.28***	1.27***	1.00***
	(4.39)	(4.68)	(4.83)	(9.85)
FF6	1.27***	1.33***	1.31***	1.03***
	(4.73)	(4.92)	(5.07)	(10.62)
Short-Leg	30 day inform	60 day inform	90 day inform	360 day inform
Ret	0.63	0.62	0.62	0.76
	(1.13)	(1.14)	(1.16)	(1.56)
FF3	-0.09	-0.18	-0.18	0.00
	(-0.30)	(-0.60)	(-0.61)	(-0.01)
FFC4	-0.06	-0.15	-0.14	0.06
	(-0.20)	(-0.50)	(-0.51)	(0.25)
FF5	0.24	0.14	0.12	0.24
	(0.84)	(0.51)	(0.47)	(1.16)
FF6	0.24	0.14	0.13	0.27
	(0.84)	(0.51)	(0.48)	(1.29)

Figure 5 - Man vs. Machine: Disagreement

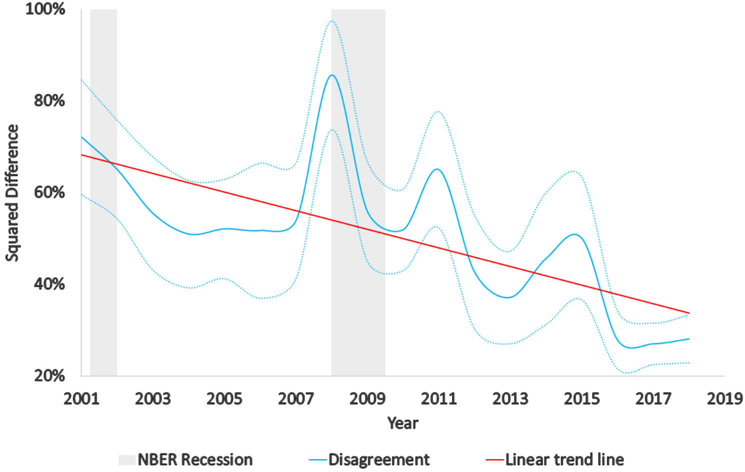


Table 5: Disagreement between Man and Machine

Variables	Disagreement		Disagreement & Machine wins	Disagreement & Man wins	Disagreement & Machine wins	Disagreement & Man wins
# 8K Reports	0.205***	0.214***	0.223***	0.005	0.212***	0.024
	(2.90)	(2.68)	(3.49)	(0.11)	(2.96)	(0.51)
Market Cap	0.001	0.002	0.004**	-0.004***	0.007***	-0.005***
	(0.34)	(0.89)	(2.51)	(-3.53)	(2.91)	(-2.99)
Amihud Illiquidity	-0.013	-0.199***	-0.277***	0.112***	-0.537***	0.030
	(-0.48)	(-6.23)	(-7.09)	(3.57)	(-11.79)	(0.47)
Intangible Assets	0.004*	0.001	-0.418***	0.085*	-0.532***	0.129**
	(1.84)	(0.34)	(-5.71)	(1.68)	(-6.25)	(2.19)
Fluidity	0.177***	0.214***	0.087*	0.115***	0.076	0.174***
	(3.51)	(3.03)	(1.86)	(2.69)	(1.22)	(3.14)
Book Leverage	-0.026	-0.006	-0.005	-0.023	0.001	-0.007
	(-1.55)	(-0.45)	(-0.79)	(-1.57)	(0.14)	(-0.61)
STD Deviation of Earnings	-0.118	-0.130	-0.092	-0.035***	-0.112	-0.022*
	(-0.78)	(-0.48)	(-0.58)	(-4.39)	(-0.40)	(-1.80)
% Institutional Holdings	0.024***	0.060***	-0.056	0.088***	0.684	0.093***
	(3.83)	(16.73)	(-0.13)	(9.26)	(1.17)	(20.45)
# Analysts in Brokerage Firm	-0.956***	-0.458*	-0.671***	-0.386***	-0.249	-0.296*
	(-10.79)	(-1.90)	(-9.21)	(-7.13)	(-1.21)	(-1.83)
Star Analysts	-0.498*	-0.269	-0.450*	-0.078	-0.275	-0.043
	(-1.69)	(-0.74)	(-1.76)	(-0.41)	(-0.88)	(-0.18)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Analyst Fixed Effect	No	Yes	No	No	Yes	Yes
Observations	291,331	291,331	280,716	272,108	280,716	272,108
Adjusted R-squared	0.044	0.095	0.051	0.036	0.112	0.067