Behavioral Machine Learning? Computer Predictions of Corporate Earnings also Overreact

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Plan

Issue 1. Technology and Stock Prices

- Almost nobody alive today trades stocks without the use of some sort of technology
- When technology changes, so too will the stock market
- What can we expect from the recent growth of ML methods?

Issue 2. Behavioral Finance

- Since the late 1980s Behavioral finance has provided an influential challenge to the rational model of market equilibrium
- Is Behavioral on the right track?
- Or, is it just an excuse for introducing convenient free parameters?
    - Behavioral finance does not describe a particular theory. It is a label encompassing what Hirshleifer (2015) calls a "large grab bag of possible behavioral biases to choose from."
    - Behavioral ideas: prospect theory, overconfidence, anchoring, framing, miscalibration, ambiguity aversion, extrapolative expectations, heuristics, diagnostic expectations, etc. Saposnik et al. (2016) review 180 such biases.

Overreaction

“The expectations of professional forecasters, corporate managers, consumers, and investors appear to be systematically biased in the direction of overreaction to news (Bordalo et al., 2020) As a result, beliefs are too optimistic in good times and too pessimistic in bad times, at the individual level and sometimes at the consensus level as well. ” Source: Bordalo, Gennaioli and Shleifer (2022)

Myth, Metaphor, or Deep Human Truth?

... model a type t as representative of a group G when it occurs more frequently in that group than in a reference group -G. For instance, after a positive medical test, the representative patient is t = "sick" because sick people are truly more prevalent among those who tested positive than in the overall population. After such a positive test, the representative sick type quickly comes to mind and the doctor inflates its probability too much, which may still be objectively low if the disease is rare (Casscells, Schoenberger, and Graboys (1978)). There is a kernel of truth in departures from rationality: the doctor overreacts to the objectively useful information from the test.

Source: Bordalo et al. (2019)

Overreaction
One Bias to Rule Them All?

"..., we present the case for the centrality of overreaction in expectations for addressing important challenges in finance and macroeconomics." Source: Bordalo, Gennaioli and Shleifer (2022)

Quite a few recent papers in top economics and finance journals treat overreaction as the central deviation from rationality.

1. It can be measured.
2. It accounts for many puzzles.
3. It relies on good psychological foundations (selective memory, over-weighting recent data)

Stock Analysts Expectations

Analysts forecast fundamentals from observed earnings growth, but overreact to news by exaggerating the probability of states that have become more likely. ... We find that forecasters react about twice as much to information as is objectively warranted.

Source: Bordalo et al. (2019)

Testing for Overreaction

Test applied to predictions of inflation or corporate earnings (Coibion and Gorodnichenko, 2012, 2015; Coibion, Gorodnichenko and Kamdar, 2018; Bordalo et al., 2020, 2021),

$$y_{t+h} - y_{t+h|t} = \beta_0 + \beta_1 x_t + \epsilon_{t,t+h} \tag{1}$$

- At time t let y_{t+h} be the future value of a variable, $y_{t+h|t}$ is the expected value, x_t a variable observable at time t (e.g. forecast revision, $y_{t+h|t} - y_{t+h|t-1}$), $\epsilon_{t,t+h}$ is the error term
- If $\beta_1 > 0$ have under-reaction
- If $\beta_1 = 0$ have rational expectations
- If $\beta_1 < 0$ have over-reaction

From Bordalo et al. (2021)

Table 1: Predictable Forecast Errors

	(1)	(2)	(3)	(4)
		Forecast Error_{t+1}		
Estimation Method:	OLS	GMM	OLS	GMM
Investment_t	-0.618^{***}	-1.459^{***}		
	(0.119)	(0.061)		
Debt_t			-0.562^{***}	-0.887^{***}
			(0.187)	(0.056)
Firm Effects		X		X
Year Effects	X	X	X	X
Years	1999-2018	1999-2018	1999-2018	1999-2018
Firm-Years	4449	4449	4449	4449

Notes: The table reports panel OLS and GMM estimates from the merged Compustat-IBES sample of the coefficients of a regression of forecast errors on the indicated variable. The standard errors are clustered at the firm level. All variables are scaled by the firm's tangible capital stock and measured at the firm-fiscal year level. Forecast errors in $t+1$ are realized earnings in $t+1$ minus firm forecasts in t. Investment in t is capital expenditures. Debt is long-term and short-term liabilities at the end of t. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. The standard deviations of each variable are 0.305 (forecast errors), 0.067 (investment), and 0.056 (debt), where $0.01 = 1\%$ relative to the firm's capital stock.

From Bordalo et al. (2020)

Table 3—Error-on-Revision Regression Results

Variable	Consensus β_1 (1)	Consensus SE (2)	Consensus p-value (3)	Individual β_1^p (4)	Individual SE (5)	Individual p-value (6)	Individual Median (7)
Nominal GDP (SPF)	0.56	0.21	0.01	−0.22	0.07	0.00	−0.20
Real GDP (SPF)	0.44	0.23	0.06	−0.15	0.09	0.09	−0.08
Real GDP (BC)	0.57	0.33	0.08	0.11	0.19	0.58	−0.03
GDP price index inflation (SPF)	1.41	0.21	0.00	0.18	0.13	0.18	−0.11
CPI (SPF)	0.29	0.22	0.17	−0.19	0.12	0.10	−0.25
Real consumption (SPF)	0.24	0.25	0.33	−0.24	0.11	0.02	−0.26
Industrial production (SPF)	0.71	0.30	0.02	−0.16	0.09	0.09	−0.19
Real nonresidential investment (SPF)	1.06	0.36	0.00	0.08	0.15	0.60	0.09
Real residential investment (SPF)	1.22	0.33	0.00	0.01	0.10	0.92	−0.09
Real federal government consumption (SPF)	−0.43	0.23	0.06	−0.59	0.07	0.00	−0.52
Real state and local government consumption (SPF)	0.63	0.34	0.06	−0.43	0.04	0.00	−0.44
Housing start (SPF)	0.40	0.29	0.18	−0.23	0.09	0.01	−0.27
Unemployment (SPF)	0.82	0.2	0.00	0.34	0.12	0.00	0.23
Fed funds rate (BC)	0.61	0.23	0.01	0.20	0.09	0.03	0.22
Three-month Treasury rate (SPF)	0.60	0.25	0.01	0.27	0.10	0.01	0.28
Three-month Treasury rate (BC)	0.64	0.25	0.01	0.21	0.09	0.02	0.17
Five-year Treasury rate (BC)	0.03	0.22	0.88	−0.11	0.10	0.29	−0.17
Ten-year Treasury rate (SPF)	−0.02	0.27	0.95	−0.19	0.10	0.06	−0.24
Ten-year Treasury rate (BC)	−0.08	0.24	0.73	−0.18	0.11	0.11	−0.29
AAA corporate bond rate (SPF)	−0.01	0.23	0.95	−0.22	0.07	0.00	−0.32
AAA corporate bond rate (BC)	0.21	0.20	0.29	−0.14	0.06	0.02	−0.27
BAA corporate bond rate (BC)	−0.18	0.27	0.50	−0.29	0.09	0.00	−0.32

Notes: This table shows coefficients from the CG (forecast error on forecast revision) regression. Columns 1 to 6 show the coefficients of consensus time series regressions and individual-level pooled panel regressions together with standard errors and p-values. Column 7 shows the median coefficients in forecaster-by-forecaster regressions. For consensus time series regressions, standard errors are Newey-West with the automatic bandwidth selection procedure of Newey and West (1994). For individual-level panel regressions, standard errors are clustered by both forecaster and time.

"the average forecaster appears to mostly overreact to information"

A Rationality Disclaimer

- Some papers seem to assume that ML methods produce rational unbiased predictions (Bianchi, Ludvigson and Ma, 2022; van Binsbergen, Han and Lopez-Lira, 2022)
    - There may be conditions such that this is true. For example, the Gauss-Markov theorem gives conditions under which OLS gives minimum variance linear unbiased estimates. But, for real data are the errors independent, constant variance, etc?
- We are not testing rationality. We offer evidence for an alternative perspective. And a model of the likely impact of the growing use of ML methods.

A Current Idea

"A general premise of our approach is that big data algorithms can be productively employed to reveal subjective biases in human judgments. Once we have a method for uncovering those biases, artificial intelligence algorithms can be deployed to "correct" those errors and improve predictive accuracy."

Source: Bianchi, Ludvigson and Ma (2022)

We sharply disagree

Our Approach

1. Use computer algorithms to make predictions. Apply the same overreaction tests that have been used for human predictions.
   - Models: Gradient Boosting, Regressions, Fama-MacBeth
   - Data: many firm and macro factors, used in past studies.

2. Use predictions made by stock analysts. Compare predictions by traditional analysts, to predictions by those with tech education.
   - Analyst earnings forecasts from IBES, 1994-2018.
   - Manually collected data on stock analysts, from LinkedIn and FINRA brokercheck.

3. Provide a model to derive the market impact of increasing number of tech trained stock analysts (in progress)

Our Key Findings

1. Computer predictions of corporate earnings also overreact. Not a reflection of the deep structure of human psychology.
2. Overreaction can be produced by over-fitting, regime switching, missing time trend.
3. A trade-off? Modifying hyperparameters to remove overreaction, reduces overall accuracy.
4. Traditional stock analysts' earnings forecasts overreact more than do those with tech training.
5. Analysts have information not otherwise available in standard data. Automating prediction is not a free lunch.
6. Growing number of tech trained analysts results in less overreaction in equity issuance. Effect on stock market informational efficiency is ambiguous.

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What Computer Algorithms to Use?

- Computer generated predictions are based on data and an algorithm
- For data we use macro-factors and firm attributes that have been widely used in other studies. IBES for analyst forecasts.
- Many prediction algorithms could be used. **Gradient Boosting is our main case.** Fama-MacBeth and OLS regressions are both extremely widely used in finance.

Basic Over-reaction Tests: Humans and Gradient Boosting

	(1) Forecast Error Analysts	(2) Forecast Error Analysts	(3) Forecast Error Machine	(4) Forecast Error Machine
Investment	-0.018*	-0.143***	-0.016**	-0.107***
	(-1.845)	(-10.065)	(-1.978)	(-8.175)
Firm FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Period	1994-2018	1994-2018	1994-2018	1994-2018
N	54536	53324	54536	53324
AdjR2	0.02	0.32	0.03	0.23

OLS Predictions also Overreact

	(1) Forecast Error OLS	(2) Forecast Error OLS	(3) Forecast Error OLS	(4) Forecast Error OLS
Investment	-0.138*** (-8.196)	-0.113*** (-5.336)	-0.128*** (-6.971)	-0.133*** (-7.871)
χ^2	10.696 [0.001]	0.368 [0.544]	3.537 [0.060]	6.649 [0.010]
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Forecasting Variables:				
Lagged Earnings	Yes	Yes	Yes	Yes
Firm Char.	No	Yes	Yes	Yes
Analysts Forecasts	No	No	Yes	Yes
Financial Statement Items	No	No	No	Yes
Period	1994-2018	1994-2018	1994-2018	1994-2018
N	53321	53321	53321	53321
AdjR2	0.22	0.44	0.22	0.23
Forecast MSE	1.881	2.611	1.856	1.850

Firm Shocks or Market Shocks? Approach

- Decompose forecast errors into a market-related variation and a firm-specific variation,

$$e_{i,t} = \beta_i + \beta_{i,m} r_{m,t} + \varepsilon_{i,t}$$

- $e_{i,t}$ is the forecast error of firm i at year t, $r_{m,t}$ is the (equal weighted) market forecast error at year t.
- Define market-related forecast error as $\hat{\beta}_{i,m} r_{m,t}$ and the firm-specific forecast error as $e_{i,t} - \hat{\beta}_{i,m} r_{m,t}$.

Firm Shocks or Market Shocks? Results

	(1) Forecast Error Analysts Market-Related	(2) Forecast Error Analysts Firm-Specific	(3) Forecast Error Machine Market-Related	(4) Forecast Error Machine Firm-Specific
Investment	-0.040***	-0.103***	-0.013**	-0.093***
	(-4.919)	(-9.349)	(-2.023)	(-8.178)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Period	1994-2018	1994-2018	1994-2018	1994-2018
N	53321	53321	53321	53321
AdjR2	1.00	0.99	0.96	0.90

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Getting Rid of Overreaction

- Tried several approaches to getting rid of machine overreaction
- Alternative data sets and/or fixed effects. No luck.
- Alternative hyperparameters for Gradient Boosting. Can work.
  Just ignore everything new, then no overreaction!

Alternative Datasets

	(1) Forecast Error Machine	(2) Forecast Error Machine	(3) Forecast Error Machine	(4) Forecast Error Machine
Investment	-0.109***	-0.114***	-0.107***	-0.109***
	(-5.431)	(-7.692)	(-8.174)	(-8.388)
χ^2	0.0495	1.705	-	2.221
	[0.824]	[0.192]	-	[0.136]
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Forecasting Variables:				
Lagged Earnings	Yes	Yes	Yes	Yes
Firm Char.	No	Yes	Yes	Yes
Analysts Forecasts	No	No	Yes	Yes
Financial Statement Items	No	No	No	Yes
Period	1994-2018	1994-2018	1994-2018	1994-2018
N	53321	53321	53321	53321
AdjR2	0.43	0.23	0.23	0.22
Forecast MSE	1.891	1.500	1.255	1.253

Alternative Hyperparameters

	(1) Forecast Error Machine	(2) Forecast Error Machine	(3) Forecast Error Machine	(4) Forecast Error Machine
Learning rate	0.01	0.03	0.1	0.2
Investment	0.027	-0.075***	-0.107***	-0.110***
	(0.781)	(-4.099)	(-8.174)	(-7.718)
χ^2	39.730	10.464	-	0.576
	[0.000]	[0.001]	-	[0.448]
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Period	1994-2018	1994-2018	1994-2018	1994-2018
N	53321	53321	53321	53321
AdjR2	0.76	0.66	0.23	0.20
Forecast MSE	2.579	1.576	1.255	1.259

'Overreaction' Seems Real. But Why?

- Machine algorithms produce predictions that 'overreact'. Not emotional. Not due to human biases like biased recall.
- Overreaction is stronger for firm-specific than for market-specific shocks.
- Might be due to over-fitting. Might be due to regime switching as in Veronesi (1999).

We can get rid of overreaction, but it comes at the cost of reduced prediction accuracy - a trade-off. In traditional EMH tests, any bias is considered a rejection.

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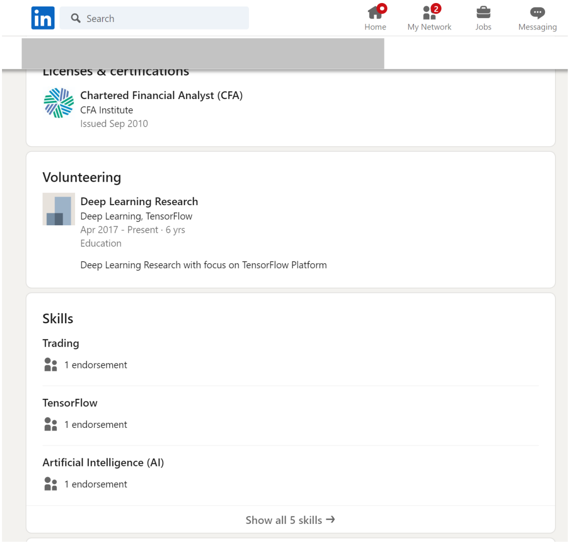
Analyst Education from LinkedIn



Analysts

- 858 analysts LinkedIn profiles, verfified on FINRA brokercheck, 1994-2018
- Self-reported technical skills; use their higher education background to identify whether analysts have technical skills or not. Manually check curriculum for each major
- 173 tech analysts in IBES data
- For each firm in each month, we calculated the median consensus forecast by technical analysts $F_t^T x_{it+1}$ and non-technical analysts $F_t^{NT} x_{it+1}$ separately.
- Tech analysts 14,901 firm-year forecasts. Non-tech analysts 36,155 firm-year forecasts.
- Treat 2013 as a break-year (follows the literature)

Tech versus Non-tech Analysts

	(1) Forecast Error Tech	(2) Forecast Error Non-Tech	(3) Forecast Error Tech	(4) Forecast Error Non-Tech
Investment	-0.181***	-0.127***	-0.109	-0.091**
	(-2.731)	(-6.913)	(-1.424)	(-2.865)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Period	1994-2012	1994-2012	2013-2018	2013-2018
N	7367	21309	6359	12316
AdjR2	0.25	0.28	0.25	0.31

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Conclusion

- Similar to humans, high quality machine predictions overreact
- May be due to overfitting or possible regime switching.
- Trade-off: allowing some overreaction helps forecast accuracy.
- Analysts with ML training overreact less
- More tech analysts means less overreaction
- Traditional analysts provide information beyond standard databases, so increasing number of tech analysts is not free

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