The Prestakes of Stock Market Investing

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How Rational and Efficient is the Stock Market?

- "Prestakes"refer to predictable mistakes in financial markets
- Absence of predictable mistakes a defining feature of rational and efficient stock market
- Plenty of evidence: markets neither perfectly rational nor perfectly efficient
- Quantifying the extent to which this is so has been a fundamental challenge

How Rational and Efficient is the Stock Market?

Extant empirical work:

- Do survey forecast errors deviate from canonical standard of full info & RE (FIRE)?
  - Demands that agents **efficiently** process *all* available information

Yet knowing whether a deviation exists...

- ...is not the same as quantifying its importance for subjective beliefs
- Could be many such deviations, including some **never discovered**
- Quantifying their aggregate importance requires non-distorted and efficient **benchmark**
- i.e., measure of *objective beliefs*, with which to compare to subjective beliefs of investors

Practical Standard of Objective Beliefs

This paper:

- Forms one measure of objective beliefs for equity market & use it to gauge
- *By how much* subjective beliefs deviate from it
- **Objective**: Practical standard of non-distorted & efficient expectation formation, modified for a real-world context
- Refer to any deviation–whether due to nonrational expectations or informational inefficiency–as a *belief distortion*

Predictable Mistakes

A belief distortion is a *predictable* mistake

- Distinct from *ex post* forecast error
- Arises from **demonstrable** misuse of available information
- Sustained pattern of *ex ante* misjudgment

Practical Measure of Objective Beliefs

Four Essential Ingredients:

1. Rooted in FIRE ideal, but with attention to a real-world context
   - **Vast real-world data** environment, but with strict assurance of real-time availability
   - Capture **bounded rationality** arising when investors fail to process all information efficiently
   - But respect the genuine **out-of-sample** nature of the investor outlook
   - E.g., no benchmarking subj beliefs against low-dim models reliant on researcher hindsight
2. Remove human element from decision-making as much as possible
   - Strip out behavioral biases & cognitive limits to info processing
3. Capable of efficiently processing large quantities of information
4. Avoid rigid functional form assumptions difficult or impossible to verify empirically

Machine Learning Algorithm

Accommodate all ingredients with a **ML algorithm**:

- Trained to independently make live stock market projections in data-rich setting
- Adaptive architectures: adapts an ANN to evidence of **changing economic landscape**
- Learns about stock market volatility over initial sample spanning 1970:Q1-2004:Q4
  - Includes several major **boom/bust** episodes
- Algorithm tested repeatedly over **2005:Q1-2023:Q4** (our testing sample)

Machine Learning Algorithm

No look-ahead advantages

1. Machine "beliefs" **independently choose** in real time all aspects of specification ex ante, including which inputs to emphasize, how deep & wide of an architecture to use, etc
2. Input layer uses only historical, time-stamped data
   - We compile ourselves
   - Verify **would have been available to market participants** when making a prediction
   - No commercial LLMs trained on contemporary data, which are known to impart look-ahead bias (Levy (2024), Sarkar and Vafa (2024))

Quantifying Prestakes Period-by-Period

- **Quantify** predictable mistakes in real time
- **Period-by-period check**: could machine have identified a mistake in survey forecast $\mathbb{F}_t$ immediately prior to issuing its own prediction
  - After machine selects it's own prediction $\mathbb{E}_t$, show it $\mathbb{F}_t$
  - If machine judges $\mathbb{F}_t$ to be inferior to $\mathbb{E}_t$ $\rightarrow$ survey is making a predictable mistake
- **Period-specific metric of prestake** quantified as difference between survey and machine forecasts whenever predictable mistakes are found, zero otherwise
- Rather than **merely an average bias**, this metric reveals how prestakes varied in real time

Preview of Findings

1. Do survey respondents make predictable mistakes?
   - Yes. Substantial **forecast accuracy gap** & prestakes largest in **crises**. We investigate why
   - Ask machine to learn about forecasting models that best explain surveys
2. Inefficient selective attention
   - Expectations largely explained by a local mean, a form of **recency bias** (Nagel and Xu (2022))
   - Earnings analysts **excessively attentive** to earnings-related news & overly *in*attentive to broader macro data (Bastianello, Decaire, and Guenzel (2024))
3. Do subj beliefs hold **skewed view** of objective tradeoff between risk and reward?
   - Yes. Subj risk premia are sub-optimally responsive to evidence of changing risk
4. Do market timing strategies that bet on objective beliefs earn abnormal returns?
   - Yes. Defensive strategies with large CAPM & FF 5-factor alphas

Related Literature

(i) ML to quantify distortions builds closely on Bianchi, Ludvigson, and Ma (2022) (BLM)

- BLM focused on $\Delta \ln GDP$ & π beliefs; here stock market
- Here machine trained to adapt network to evidence of economic change
- Higher dimensional specifications more suitable for financial markets
- Use ML to learn about forecasting models best explain surveys

(ii) Evidence departures from FIRE (most from in-sample regressions)

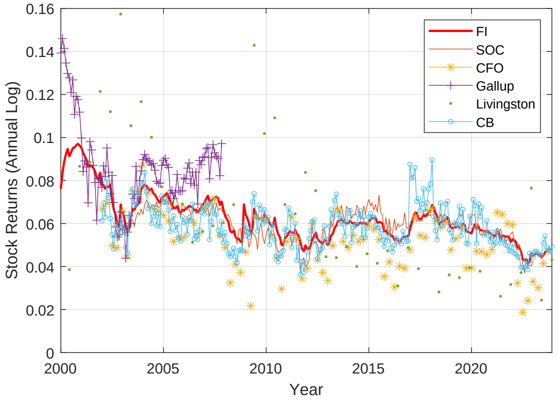
- Overreaction in subj. growth expectations: Barberis, Shleifer, and Vishny (1998), Chen, Da, and Zhao (2013), Bordalo, Gennaioli, and Shleifer (2018), Bordalo, Gennaioli, Ma, and Shleifer (2020), Bordalo, Gennaoili, Laporta, Shleifer (2019, 2022) , Nagel and Xu (2022), De La O and Myers (2021), Hillenbrand and McCarthy (2021)
- *Under*reaction & bounded rationality some contexts: e.g., Mankiw and Reis (2002), Woodford (2002), Sims (2003), Gabaix (2019); Kohlhas and Walther (2021)
- Mental models: Bastianello, Decaire, and Guenzel (2024) build mental model of IBES forecasts using LLM analysis of written reports; different methodologies, key similarities in findings

(iii) ML insights: Bybee, Kelly, Manela, and Xiu (2021), Gu, Kelly, and Xiu (2020), Cong, Tang, Wang, and Zhang (2021), Nagel (2021) showing power of supervised learning for return prediction. We differ in using ML to uncover distortions in subj beliefs

DATA

Subjective Expectations: Returns

- Returns: one-year-ahead expectations from Gallup/UBS, Duke CFO, Livingston, Conference Board, Michigan SOC
  - Price gr surveys adjusted with **div yield** to get subj return expectation
  - Convert mean forecasts into **subj risk premia** by netting out 1Y T-bill
  - Extract common signal: Filtered Investor (FI) state-space model →
- Value Line 4yr return forecasts (Thesmar and Verner (2025))



Filtered Investor Expected Return Series (FI). The FI series based on a Kalman filter that treats multiple survey forecasts as noisy signals and extracts an AR(1) latent factor of expected stock returns (including dividends).

Subjective Expectations: Earnings

IBES median analyst aggregated to S&P 500

- Bottom-up aggregation
- Convert median-analyst EPS expectation to expected earnings level
- Convert these to expected earnings growth over **next 4 quarters (1 yr)**
- "Long term growth"(**LTG**) expectations (Bordalo, Gennaioli, LaPorta, and Shleifer (2019))
- Wording of LTG question does not state precise horizon. Consider 3 possibilities:
  1. Annual five-year forward growth rate (4-5 yr) (Bianchi, Ludvigson, and Ma (2024))
  2. Annualized nine-year growth rate one-year forward (1-10 yr) (Nagel and Xu (2022))
  3. Annual five-year growth (0-5 yr) (Bordalo, Gennaioli, LaPorta, and Shleifer (2022))

Forecast Targets

Realized outcome data

- Stock market returns
  - CRSP value-weighted total return index (includes dividends)
  - Realized **excess returns** computed by subtracting the 1-year Treasury bill yield
- Earnings Growth
  - S&P 500 earnings measured using **IBES "street" earnings**
  - Unlike GAAP earnings, street earnings exclude discontinued operations, extraordinary charges, other non-operating items
  - IBES user guide: analysts submit forecasts excluding transitory components; Hillenbrand and McCarthy (2024): street earnings reflect what IBES analysts target

Machine Inputs

Hundreds of Mixed-frequency time-series inputs

1. Real-time macro dataset (92 indicators) & Monthly panel 147 financial indicators
2. “Up-to-the-forecast”daily financial market indicators
3. Hundreds of others, incl FFF jumps around FOMC news, consensus forecast surprises around data releases, daily text-based factors using natural language processing
4. Three general categories or ”themes”:
   4.1 **Macro fundamentals**: employment, hours, earnings, price level, “Fed-controlled”rates
   4.2 **Non-fundamentals**: longer-dated $>$ 3M financial market bonds, stocks, credit spreads
   4.3 **Media-sentiment**: Real-time LDA factors from 1mill WSJ articles–crude measure of sentiment

MACHINE LEARNING

Notation

- $y_{j,t+h}$ denotes a target: **aggregate earnings growth** or **excess stock market return**
- Subjective belief: $\mathbb{F}_{s,t}[y_{j,t+h}]$ from survey s
- Objective belief: $\mathbb{E}_t[y_{j,t+h}]$ from machine (no reference to current survey)
- $bias_t$: our **period-specific** measure of magnitude of prestakes in survey s

$$\text{bias}_{s,t}[y_{t+h}] \equiv \begin{cases} \mathbb{F}_{s,t}[y_{t+h}] - \mathbb{E}_t[y_{t+h}] & \text{if prestakes found} \\ 0 & \text{otherwise} \end{cases}$$

- Decomposition of survey forecast error:

$$\mathbb{F}_{s,t}[y_{t+h}] - y_{t+h} = \underbrace{\text{bias}_{s,t}[y_{t+h}]}_{\text{prestakes}} + \underbrace{\left(\mathbb{E}_t[y_{t+h}] - y_{t+h}\right)}_{\text{ex post error}}$$

Machine Learning Model

Machine specification:

$$y_{j,t+h} = G\left(\mathcal{X}^t, \boldsymbol{\beta}_{j,h,t}\right) + \epsilon_{jt+h}$$

- $\mathcal{X}^t$: Real-time input layer from time $1, ..., t$
- $G(\cdot)$: LSTM estimator w/ high-dimensional parameter vector $\boldsymbol{\beta}_{j,h,t}$

$$G(\mathcal{X}^t, \boldsymbol{\beta}_{j,h,t}) = W^{(yh^N)} h_t^N(\mathcal{X}^t, \boldsymbol{\beta}_{j,h,t}) + b_y$$

  h_t^N is the top hidden layer with dimension D_{h^N}
- LSTM allows machine to learn whether to draw on **long-term or near-term memory**
- Time subscript on $\boldsymbol{\beta}_{j,h,t}$ denotes sequence of estimates from rolling sub-samples
- $\hat{G}\left(\mathcal{X}^t, \boldsymbol{\beta}_{j,h,t}\right)$ is machine **objective belief** $\mathbb{E}_t\left[y_{j,t+h}\right]$
- 4-step dynamic procedure of training, specification choice, OOS forecast, repeat

RESULTS

Relative Forecast Performance

Does the machine submit better forecasts on average?

Ratio of machine to benchmark mean-squared-forecast-error (MSE)							
(a) Stock Returns							
Horizon h (quarters)	4	4	4	4	4	4	16
Benchmark	CB	SOC	Gallup/UBS	CFO	Livingston	FI	VL
$MSE_{\mathbb{E}}/MSE_{\mathbb{F}}$	0.681	0.663	0.788	0.638	0.745	0.673	0.729
OOS R^2	0.319	0.337	0.212	0.362	0.255	0.327	0.271
Horizon h (quarters)	4	8	12	16			
Benchmark	Mean	Mean	Mean	Mean			
$MSE_{\mathbb{E}}/MSE_{\mathbb{H}}$	0.680	0.697	0.719	0.834			
OOS R^2	0.320	0.303	0.281	0.166			
(b) S&P 500 Earnings Growth							
Horizon h (quarters)	4	LTG 4-5	LTG 1-10	LTG 0-5			
Benchmark	IBES	IBES	IBES	IBES			
$MSE_{\mathbb{E}}/MSE_{\mathbb{F}}$	0.386	0.824	0.164	0.382			
OOS R^2	0.614	0.176	0.836	0.618			

Forecasting Performance: Machine v.s. Benchmarks. $MSE_{\mathbb{E}}$, $MSE_{\mathbb{F}}$, and $MSE_{\mathbb{H}}$ are the mean-squared-forecast-errors of machine, survey, and historical mean forecasts, respectively. OOS R^2 is defined as 1-$MSE_{\mathbb{E}}/MSE_{\mathbb{F}}$. The testing subsample is 2005:Q1 to 2023:Q4 for stock returns when the benchmark is CB, SOC, CFO, FI, and VL, 2005:Q1 to 2008:Q4 when the benchmark is the Gallup/UBS survey, and semi-annual over 2005:Q1 to 2023:Q4 for Q2 and Q4 of each calendar year when the benchmark is the Livingston survey. For earnings growth, the testing subsample is 2005:Q1 to 2023:Q4, with h-quarter forecasts constructed from the middle month of each quarter. LTG 4-5, LTG 1-10, and LTG 0-5 denote Long-Term Growth (LTG) forecasts interpreted as earnings growth for 4-to-5, 1-to-10, and 0-to-5 years, respectively. Value Line (VL) expected returns are the annualized nominal expected total return from Thesmar and Verner (2025). Comparisons with the historical mean ("Mean") are based on a first estimate of the mean CRSP stock market return from 1959:Q1 to 2004:Q4 with recursive updates over 2005:Q1 to 2023:Q4.

Bayesian weights w^*

Relative Forecast Performance

Does the machine submit better forecasts on average?

- Machine MSE-to-Survey MSE ratio < 1 for all surveys over extended testing sample

Ratio of machine to benchmark mean-squared-forecast-error (MSE)

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- Machine MSEs lower than historical mean return (Goyal and Welch (2008))

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Correlations Between Forecasts and Subsequent Realized Returns

- Correlations with realized 4-quarter returns: (A) forecasts and (B) forecast bias (survey minus machine)

Correlations with Realized Returns

(A) Return forecasts & realized returns	
Forecast	**Correlation**
FI	0.049
CFO	-0.242
LIV	0.191
Gallup/UBS	-0.641
SOC	-0.183
CB	0.128
Machine	0.578
(B) Return bias & realized raw returns	
Forecast	**Correlation**
FI bias	-0.543
CFO bias	-0.575
LIV bias	-0.405
Gallup/UBS bias	-0.644
SOC bias	-0.552
CB bias	-0.530

Correlations of stock return forecasts and bias with realized returns. Panel A shows correlations between each forecast of the four-quarter ahead raw CRSP value-weighted market return and the corresponding realized raw return. Panel B shows correlations between the bias in each forecast of the four-quarter ahead CRSP value-weighted market return and the corresponding realized raw return, where bias is the survey forecast minus the machine forecast after rtcheck. The sample covers 2005Q1-2023Q4.

Correlations Between Forecasts and Subsequent Realized Returns

- Correlations with realized 4-quarter returns: (A) forecasts and (B) forecast bias (survey minus machine)
- Machine forecast **positive correlation** with subsequent returns

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- Survey forecasts **negative or weak correlations** with subsequent returns (Greenwood and Shleifer (2014))

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- Machine forecast **positive correlation** with subsequent returns
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- **New**: *prestakes* metric $bias_{s,t}$ **more negatively correlated** with subsequent returns: times of *over*-optimism ($bias_{s,t} = \mathbb{F}_t - \mathbb{E}_t$) drive these inaccuracies

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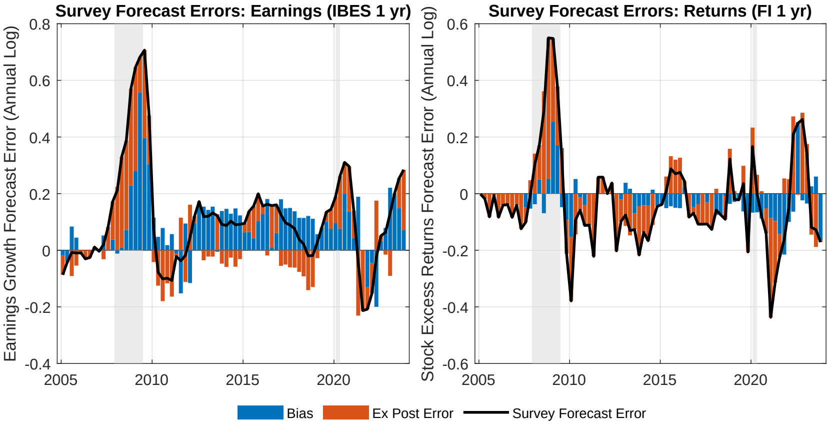
Prestakes over Time

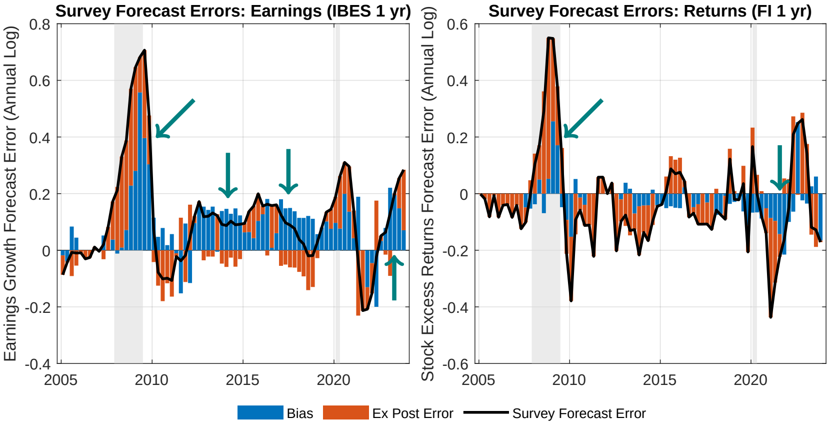
- Decompose survey forecast errors: $\mathbb{F}_{s,t}[y_{t+h}] - y_{t+h} = (\mathbb{F}_{s,t} - \mathbb{E}_t)[y_{t+h}] + (\mathbb{E}_t[y_{t+h}] - y_{t+h})$ if ex-ante bias is detectable, otherwise all ex post error



Sources of Variation in Survey Forecast Errors. The figure plots survey forecast errors and their decomposition for earnings (left panel) and returns (right panel). Survey forecast error is defined as $\mathbb{F}_t[y_{t,t+h}] - y_{t,t+h}$, where $\mathbb{F}_t[y_{t,t+h}]$ is the survey forecast and $y_{t,t+h}$ is the realization at time t. This error is decomposed as $\mathbb{F}_t[y_{t,t+h}] - y_{t,t+h} = (\mathbb{F}_t - \mathbb{E}_t)[y_{t,t+h}] + (\mathbb{E}_t[y_{t,t+h}] - y_{t,t+h})$ when prestakes are detectable, otherwise it is all ex post error. In periods with prestakes, survey bias is $(\mathbb{F}_t - \mathbb{E}_t)[y_{t,t+h}]$. NBER recessions are shaded in gray. The testing sample spans 2005Q1-2021Q4.

Prestakes over Time

- Many periods where survey forecast errors are **almost entirely prestakes**



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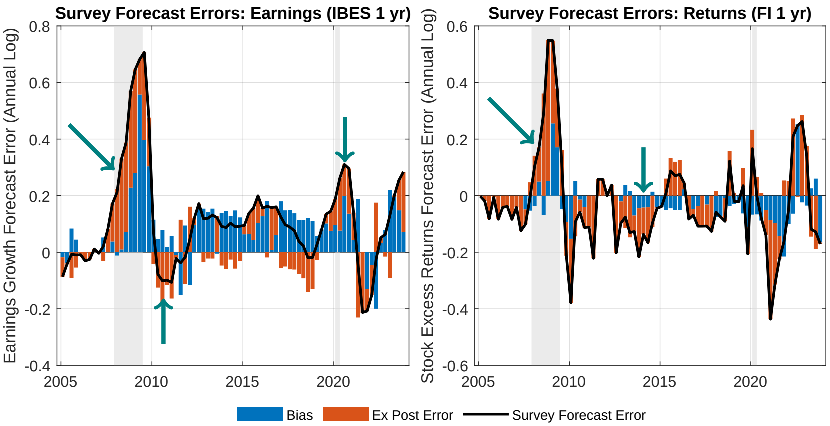
Prestakes over Time

- Other periods show errors largely **ex post mistakes** thus not systamatic error



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Implications of Prestakes for Over-/Underreaction

- $\widehat{\beta} > 0$ on **machine revision**
  - Consistent with **underreaction** to **"objective"news**.
  - Machine forecast revised up, survey moves up too little, so NEG bias (machine minus survey) becomes more positive

NEG bias$_{IBES,t}[y_{t+h}] = \alpha + \beta \cdot (\mathbb{X}_t - \mathbb{X}_{t-1})[y_{t+h}] + u_t$	(1) Machine revision $\mathbb{X}_t = \mathbb{E}_t$	(2) Survey revision $\mathbb{X}_t = \mathbb{F}_{IBES,t}$
(a) 0-to-5 yr LTG		
$\widehat{\beta}$	+0.009	
90% Credible Set	[+0.005, +0.013]	
Adj. R^2 (%)	18.3	
N	72	
(b) 4-to-5 yr LTG		
$\widehat{\beta}$	+0.028	
90% Credible Set	[+0.021, +0.034]	
Adj. R^2 (%)	44.4	
N	72	
(c) 1-yr earnings		
$\widehat{\beta}$	+0.093	
90% Credible Set	[+0.082, +0.105]	
Adj. R^2 (%)	75.8	
N	72	

Predictability of NEG bias by Forecast Revisions. NEG bias is the machine forecast minus the survey forecast, NEG bias$_{IBES,t}[y_{t+h}] \equiv \mathbb{E}_t[y_{t+h}] - \mathbb{F}_{IBES,t}[y_{t+h}]$. Column (1) uses the machine forecast revision. Column (2) uses the survey forecast revision. Row (a) uses the 0-to-5 year cumulative LTG forecast. Row (b) uses the 4-to-5 year forward LTG forecast. Row (c) uses 1-year-ahead earnings growth forecasts. Regressors are standardized. Newey-West standard errors with 1-year lag. 90% Bayesian credible sets from 10000 posterior t-draws under flat priors (Hamilton, 1994). Sample: forecast target dates 2005:Q1–2023:Q4.

Implications of Prestakes for Over-/Underreaction

- $\widehat{\beta} > 0$ on machine revision
  - Consistent with **underreaction** to **“objective”news**.
  - Machine forecast revised up, survey moves up too little, so NEG bias (machine minus survey) becomes more positive
- $\widehat{\beta} < 0$ on **survey revision**
  - Consistent with **overreaction** to **perceived news**.

NEG bias$_{IBES,t}[y_{t+h}] = \alpha + \beta \cdot (\mathbb{X}_t - \mathbb{X}_{t-1})[y_{t+h}] + u_t$		
	(1) Machine revision $\mathbb{X}_t = \mathbb{E}_t$	(2) Survey revision $\mathbb{X}_t = \mathbb{F}_{IBES,t}$
(a) 0-to-5 yr LTG		
$\widehat{\beta}$	+0.009	−0.011
90% Credible Set	[+0.005, +0.013]	[−0.015, −0.007]
Adj. R^2 (%)	18.3	24.1
N	72	76
(b) 4-to-5 yr LTG		
$\widehat{\beta}$	+0.028	−0.012
90% Credible Set	[+0.021, +0.034]	[−0.020, −0.004]
Adj. R^2 (%)	44.4	10.3
N	72	76
(c) 1-yr earnings		
$\widehat{\beta}$	+0.093	−0.066
90% Credible Set	[+0.082, +0.105]	[−0.085, −0.047]
Adj. R^2 (%)	75.8	41.5
N	72	76

Predictability of NEG bias by Forecast Revisions. NEG bias is the machine forecast minus the survey forecast, NEG bias$_{IBES,t}[y_{t+h}] \equiv \mathbb{E}_t[y_{t+h}] - \mathbb{F}_{IBES,t}[y_{t+h}]$. Column (1) uses the machine forecast revision. Column (2) uses the survey forecast revision. Row (a) uses the 0-to-5 year cumulative LTG forecast. Row (b) uses the 4-to-5 year forward LTG forecast. Row (c) uses 1-year-ahead earnings growth forecasts. Regressors are standardized. Newey-West standard errors with 1-year lag. 90% Bayesian credible sets from 10000 posterior t-draws under flat priors (Hamilton, 1994). Sample: forecast target dates 2005:Q1–2023:Q4.

Investigating the Prediction Gap with Forecast Decompositions

LSTM forecast approximated as the sum of 3 terms

$$\mathbb{E}(\cdot) = G(\cdot) \approx \underbrace{b_t}_{\text{Local mean}} + \underbrace{h_t\left(h_{t-1}, \bar{\mathcal{X}}_t; \vec{b}_t, \widehat{\boldsymbol{\beta}}_t\right)}_{\text{Nonlinear history}} + \underbrace{\nabla G(\cdot)' \mathcal{X}_t}_{\text{Current information}}$$

- Arbitrarily accurate w/ vanishingly small step sizes
- Local mean b_t: Outer bias, evolves slowly & akin to a local mean in predicted variable
- Nonlinear history $h_t(\cdot)$: Nonlinear func of history $\mathcal{X}^{t-1}$ & fix $\mathcal{X}_t$ at training sample mean
- Current info $\nabla G(\cdot)' \mathcal{X}_t$: Nonlinearities in $\mathcal{X}_t$ given by gradients magnitudes
- Current info term: Read off contribution of $\mathcal{X}_t$ elements to forecasts

Survey Forecast Decomposition

Use machine to learn about forecasting models that best explain survey responses

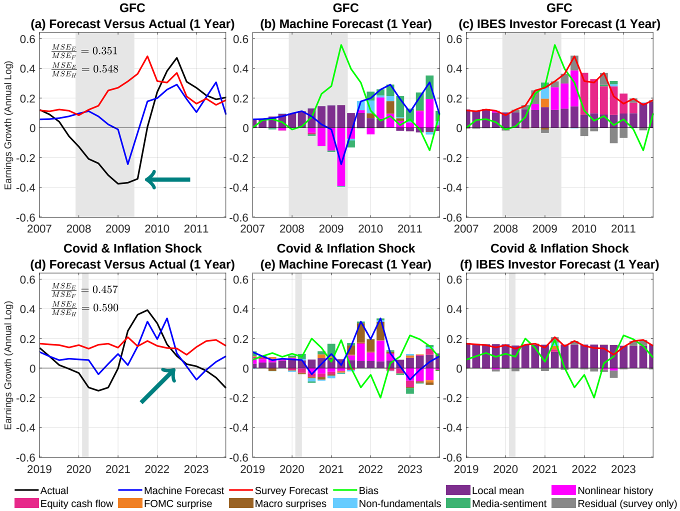
- Use LSTM estimator to **predict** $\mathbb{F}_t[y_{t+h}]$ OOS
- Minimize dist between survey response and LSTM est using data up to t
- Decompose survey into same 3 components plus residual

$$\mathbb{F}_t = \underbrace{b_{\mathbb{F},t}}_{\text{local mean}} + \underbrace{h_{\mathbb{F},t}\left(h_{t-1}, \bar{\mathcal{X}}_t; \vec{b}_{\mathbb{F},t}, \widehat{\boldsymbol{\beta}}_{\mathbb{F},t}\right)}_{\text{nonlinear history}} + \underbrace{\nabla G_{\mathbb{F}}(\cdot)' \mathcal{X}_t}_{\text{current information}} + \underbrace{u_t}_{\text{residual}}$$

- Residual u_t captures features intangible to machine (private info, forecaster judgment)

Crisis Episodes: Earnings Growth

GFC and 2022 bear market



Analysis of Street Earnings Growth Expectations: Crisis Episodes. Figure plots the machine and survey forecast and their decomposition into common economic themes, with Fundamentals split into Equity cash flow, FOMC surprise, and Macro surprises (alongside Local mean, Nonlinear history, Non-fundamentals, and Media-sentiment). For the investor forecast, an additional residual term captures the portion of the forecast not explained by the LSTM model out of sample. NBER recessions are shaded in gray. The sample spans: 2007:Q1-2011:Q4 (GFC) and 2019:Q1-2023:Q4 (Covid-19 & Inflation Shock). The x-axis represents the date at which the forecast target is realized. Forecasts (machine and survey) are aligned with the realized values over the

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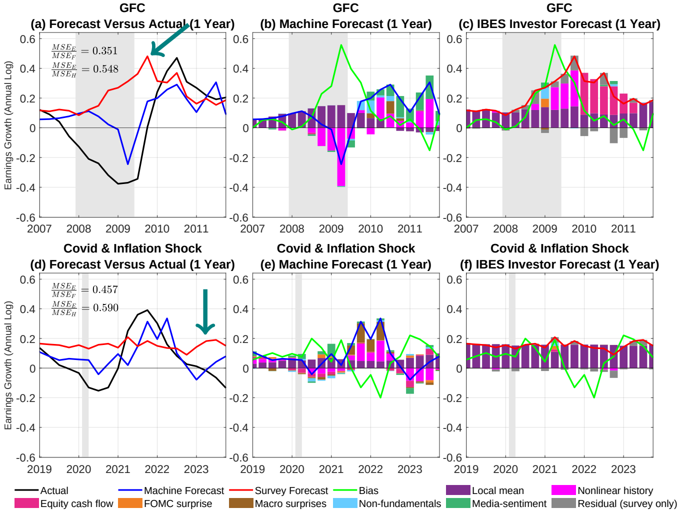

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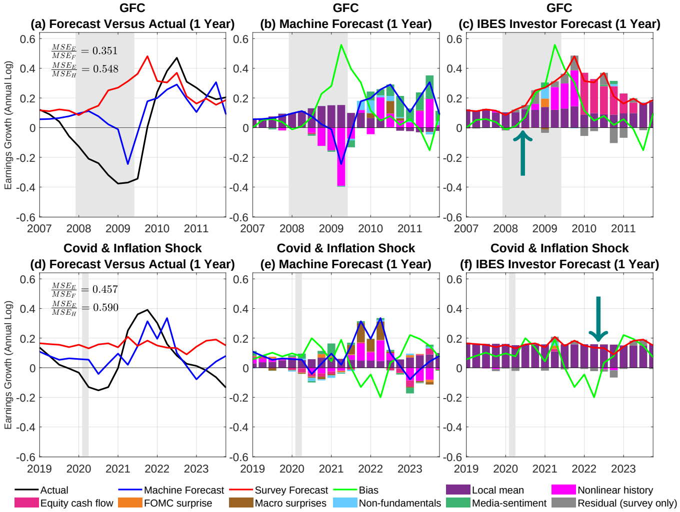

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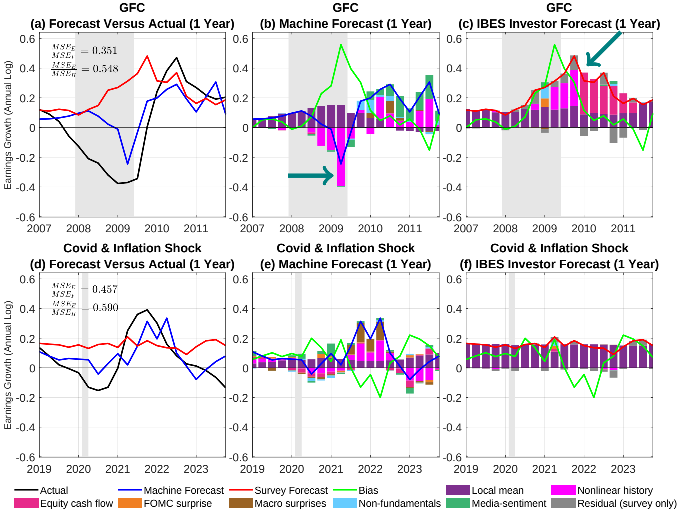

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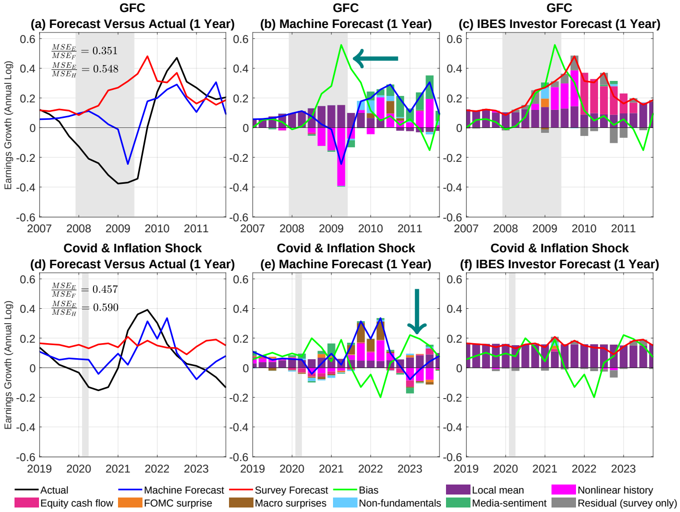
- Surveys follow **local mean** a form of recency bias (Nagel and Xu (2022))
- GFC machine **pessimistic** while survey **optimistic**
- Prestakes **large and positive** → non-GFC, little adaptation to new information (Bastianello, Decaire, and Guenzel (2024))



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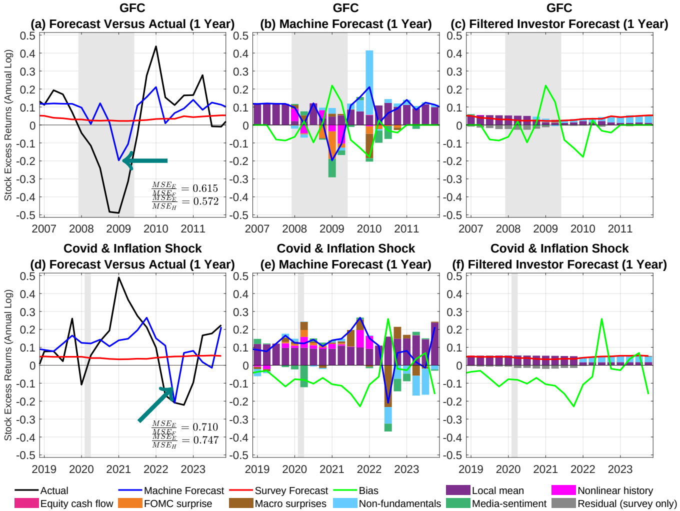
Crisis Episodes: Returns

GFC and 2022 bear market

- Machine predicts part of GFC and 2022 bear markets



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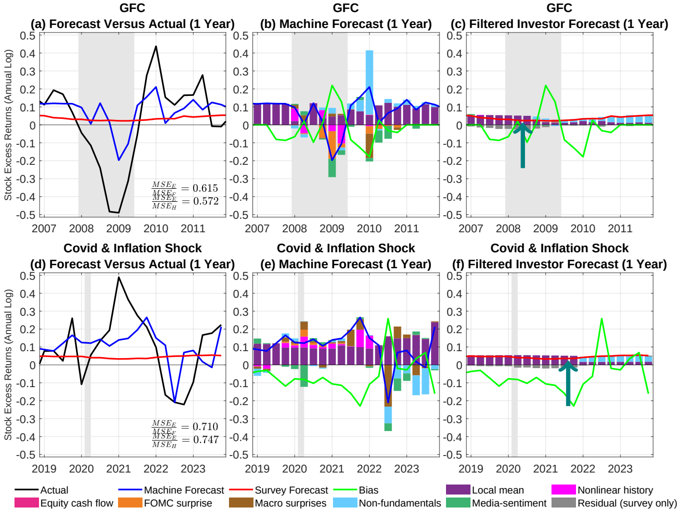
Crisis Episodes: Returns

GFC and 2022 bear market

- Machine predicts part of GFC and 2022 bear markets
- During the GFC and 2022 bear mkt, surveys follow **local mean**



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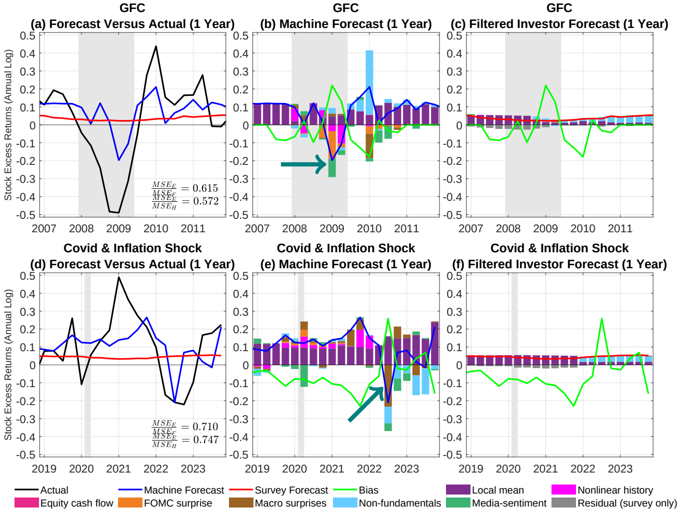
Crisis Episodes: Returns

GFC and 2022 bear market

- Machine predicts part of GFC and 2022 bear markets
- During the GFC and 2022 bear mkt, surveys follow **local mean**
- Objective beliefs course-correct & use macro, non-fund and sentiment information



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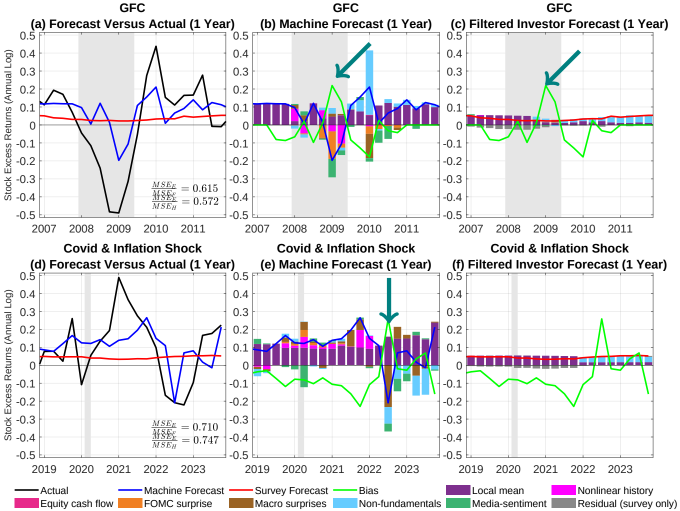
GFC and 2022 bear market

- Machine predicts part of GFC and 2022 bear markets
- During the GFC and 2022 bear mkt, surveys follow **local mean**
- Objective beliefs course-correct & use macro, non-fund and sentiment information
- Prestakes largest in turbulent times; divergence between $\mathbb{F}_t$ and $\mathbb{E}_t$ greatest



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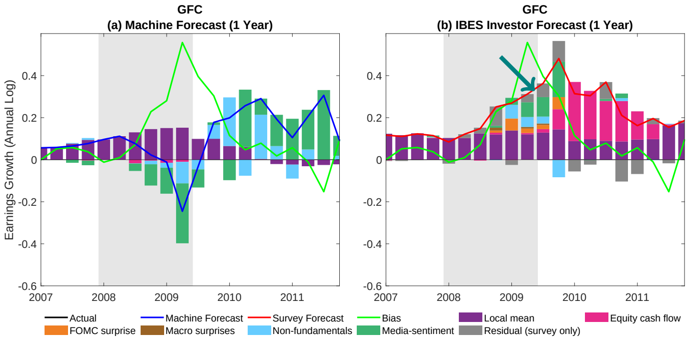
GFC: Most Important Instance of IBES Prestakes in our Sample

- IBES expectations fail to predict **any part of plunge** in earnings



Forecast Decompositions, GFC. The figure plots the GFC-window decomposition of the machine and IBES investor forecasts. The x-axis represents the date at which the forecast target is realized. Forecasts (machine and survey) are aligned with the realized values over the corresponding period being forecast, so that a vertical slice shows the forecast error.

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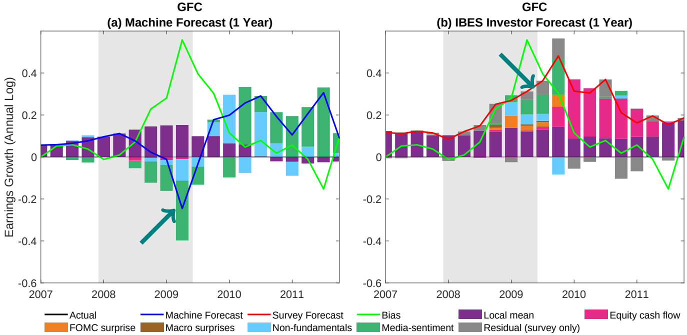
- **Nonlinear history sentiment and non-fundamental components** play large roles in both IBES & machine beliefs



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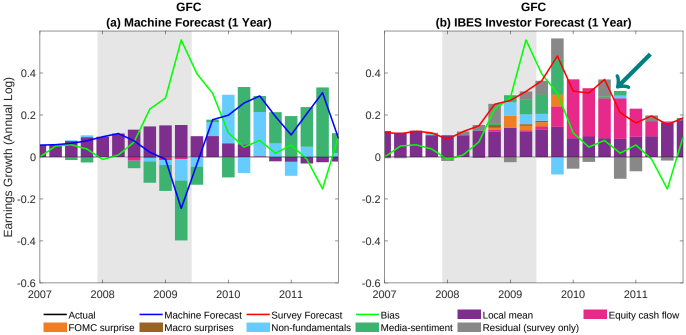
- **Nonlinear history sentiment and non-fundamental components** play large roles in both IBES & machine beliefs
- Later, **cash flows** account for optimism in IBES survey



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Additional Results (Appendix)

- Relative Forecast Accuracy: Rolling MSE Ratio ▸ Link
- Decomposition of Relative Forecast Accuracy ▸ Link
- Prestakes over Time: All benchmarks ▸ Link
- Earnings Growth Bias and LTG Forecast Error IV ▸ Link
- Prestakes and over-/underreaction ▸ Link
- Machine Forecast Errors and Forecast Revisions: Out-of-Sample ▸ Link

Subjective vs. Objective Risk–Return Trade-off

- So far: meaningful predictable mistakes in subjective beliefs
- Possibility: investors have skewed view of objective tradeoff between risk and reward

Subjective vs. Objective Risk–Return Trade-off

- So far: meaningful predictable mistakes in subjective beliefs
- Possibility: investors have skewed view of objective tradeoff between risk and reward
- Compare risk-return tradeoff in subjective beliefs with that for objective beliefs
- **Subjective risk premia**: FI & Nagel and Xu (2022) ind investor series (NX)
- **Subj risk**: perceived variance (CFO survey); perceived crash risk (Crash Conf Index)
- **Objective risk premium**: (machine)
- **Obj risk**: financial uncertainty (Ludvigson, Ma, and Ng (2021))

Subjective vs. Objective Risk–Return Trade-off

- Table shows ratio of slope coefficients $\widetilde{\beta}_{\mathbb{F}} / \beta_{\mathbb{E}}$: survey expectations on **perceived risk** vs. machine expectations on **objective risk**

Survey: $\mathbb{F}_t^s[r^e_{t,t+h}] = \beta_{\mathbb{F},0} + \widetilde{\beta}_{\mathbb{F},1} \widetilde{\mathbb{V}}_t[r_{t,t+h}] + \epsilon_{\mathbb{F},t}$		
Machine: $\mathbb{E}_t[r^e_{t,t+h}] = \beta_{\mathbb{E},0} + \beta_{\mathbb{E},1} \mathbb{V}_t[r_{t,t+h}] + \epsilon_{\mathbb{E},t}$		
Survey s	Filtered Investor (FI)	Nagel and Xu (NX)
Horizon h (quarters)	4	4
(A) Perceived Risk $\widetilde{\mathbb{V}}_t[r_{t,t+h}]$: Crash Confidence Index (Individuals)		
Objective Risk $\mathbb{V}_t[r_{t,t+h}]$: Financial Uncertainty Index		
$\widetilde{\beta}_{\mathbb{F},1} / \beta_{\mathbb{E},1}$	0.338	0.317
90% Credible Set	$[-1.33, 1.78]$	$[-1.29, 1.79]$
$P(\widetilde{\beta}_{\mathbb{F},1} / \beta_{\mathbb{E},1} < 1)$	0.901	0.898
(B) Perceived Risk $\widetilde{\mathbb{V}}_t[r_{t,t+h}]$: Perceived Variance (CFO)		
Objective Risk $\mathbb{V}_t[r_{t,t+h}]$: Financial Uncertainty Index		
$\widetilde{\beta}_{\mathbb{F},1} / \beta_{\mathbb{E},1}$	0.160	0.124
90% Credible Set	$[-0.66, 1.10]$	$[-0.74, 1.05]$
$P(\widetilde{\beta}_{\mathbb{F},1} / \beta_{\mathbb{E},1} < 1)$	0.944	0.947
(C) Perceived Risk $\widetilde{\mathbb{V}}_t[r_{t,t+h}]$: Crash Confidence Index (Institutions)		
Objective Risk $\mathbb{V}_t[r_{t,t+h}]$: Financial Uncertainty Index		
$\widetilde{\beta}_{\mathbb{F},1} / \beta_{\mathbb{E},1}$	0.656	0.485
90% Credible Set	$[-2.48, 3.28]$	$[-1.83, 2.42]$
$P(\widetilde{\beta}_{\mathbb{F},1} / \beta_{\mathbb{E},1} < 1)$	0.788	0.844
(D) Objective Risk $\mathbb{V}_t[r_{t,t+h}]$: Financial Uncertainty Index		
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$\beta_{\mathbb{F},1} / \beta_{\mathbb{E},1}$	0.205	0.009
90% Credible Set	$[-0.84, 1.21]$	$[-0.82, 0.73]$
$P(\beta_{\mathbb{F},1} / \beta_{\mathbb{E},1} < 1)$	0.939	0.965

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- Ratio $\beta_{\mathbb{F},1} / \beta_{\mathbb{E},1} \approx 0 => $ subjective risk premia bear virtually no relationship with objective measures of risk

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Horizon h (quarters)	4	4
(A) Perceived Risk $\widetilde{\mathbb{V}}_t[r_{t,t+h}]$: Crash Confidence Index (Individuals); Objective Risk $\mathbb{V}_t[r_{t,t+h}]$: Financial Uncertainty Index		
$\widetilde{\beta}_{\mathbb{F},1} / \beta_{\mathbb{E},1}$	0.338	0.317
90% Credible Set	$[-1.33, 1.78]$	$[-1.29, 1.79]$
$P(\widetilde{\beta}_{\mathbb{F},1} / \beta_{\mathbb{E},1} < 1)$	0.901	0.898
(B) Perceived Risk $\widetilde{\mathbb{V}}_t[r_{t,t+h}]$: Perceived Variance (CFO); Objective Risk $\mathbb{V}_t[r_{t,t+h}]$: Financial Uncertainty Index		
$\widetilde{\beta}_{\mathbb{F},1} / \beta_{\mathbb{E},1}$	0.160	0.124
90% Credible Set	$[-0.66, 1.10]$	$[-0.74, 1.05]$
$P(\widetilde{\beta}_{\mathbb{F},1} / \beta_{\mathbb{E},1} < 1)$	0.944	0.947
(C) Perceived Risk $\widetilde{\mathbb{V}}_t[r_{t,t+h}]$: Crash Confidence Index (Institutions); Objective Risk $\mathbb{V}_t[r_{t,t+h}]$: Financial Uncertainty Index		
$\widetilde{\beta}_{\mathbb{F},1} / \beta_{\mathbb{E},1}$	0.656	0.485
90% Credible Set	$[-2.48, 3.28]$	$[-1.83, 2.42]$
$P(\widetilde{\beta}_{\mathbb{F},1} / \beta_{\mathbb{E},1} < 1)$	0.788	0.844
(D) Objective Risk $\mathbb{V}_t[r_{t,t+h}]$: Financial Uncertainty Index; Survey: $\mathbb{F}_t^s[r_{t,t+h}] = \beta_{\mathbb{F},0} + \beta_{\mathbb{F},1} \mathbb{V}_t[r_{t,t+h}] + \epsilon_{\mathbb{F},t}$; Machine: $\mathbb{E}_t[r_{t,t+h}] = \beta_{\mathbb{E},0} + \beta_{\mathbb{E},1} \mathbb{V}_t[r_{t,t+h}] + \epsilon_{\mathbb{E},t}$		
$\beta_{\mathbb{F},1} / \beta_{\mathbb{E},1}$	0.205	0.009
90% Credible Set	$[-0.84, 1.21]$	$[-0.82, 0.73]$
$P(\beta_{\mathbb{F},1} / \beta_{\mathbb{E},1} < 1)$	0.939	0.965

Subjective vs. Objective Risk-Return Trade-off. Table reports the ratio of slope coefficients from two regressions: (1) subjective expectations of stock returns in excess of the prevailing 1-year T-bill rate on perceived risk measures, and (2) machine expectations of the same on objective risk measures.

Betting on Objective Beliefs

- Could obj beliefs be exploited to earn "alpha"?
- Since episodes in which $\mathbb{E}[\cdot]$ diverges strongly from $\mathbb{F}[\cdot]$ occur only when **prestakes are large**, betting on objective beliefs tantamount to betting *against* prestakes

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- Two market timing strategies:
  1. **Long-only**: Invest in CRSP-VW return when $\mathbb{E}_t[r_{t,t+h} - r_{f,t}] > 0$ otherwise hold T-bill
  2. **Long-short**: Invest in CRSP-VW when $\mathbb{E}_t[r_{t,t+h} - r_{f,t}] > 0$ otherwise hold T-bill but short market when $\mathbb{E}_t[r_{t,t+h}] < 0$

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- Machine makes true OOS predictions from 2005:Q1-2023:Q4
- Starting in 2005, use forecasts to decide which one-year investment to make
- Roll forward, repeat for next 4Q period until 2023:Q4, rebalance every 4Q
- Infeasible benchmark: perfect foresight strategy where CRSP return predicted w/o error

Betting on Objective Beliefs: Long-Only

Table: FF 5-Factor Alphas from Long-Only Strategy

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	α	β_m	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}
Machine	0.025	0.790	-0.375	0.320	1.034	0.398
90% Credible Set	[0.01,0.04]	[0.71,0.86]	[-1.29,0.53]	[-0.64,1.28]	[-0.13,2.18]	[-1.05,1.85]
FI	-0.000	1.000	-0.000	0.000	0.000	0.000
90% Credible Set	[-0.00,0.00]	[1.00,1.00]	[-0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]
CFO	-0.000	1.000	-0.000	0.000	0.000	0.000
90% Credible Set	[-0.00,0.00]	[1.00,1.00]	[-0.00,0.00]	[0.00,0.00]	[0.00,0.00]	[0.00,0.00]
Livingston	-0.004	0.512	0.646	1.117	0.564	0.570
90% Credible Set	[-0.03,0.02]	[0.40,0.62]	[-0.65,1.96]	[-0.32,2.54]	[-1.13,2.27]	[-1.54,2.71]
Perfect Foresight	0.073	0.526	-1.057	-0.265	0.585	0.988
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Betting on Objective Beliefs: Long-Only

- **Large machine alphas** are product of defensive strategies & "earned"in downturns when strategies were relatively successful at mitigating losses

Table: FF 5-Factor Alphas from Long-Only Strategy

$$r_{s,t,t+4} - r_{f,t} = \alpha + \beta_m(r_{m,t} - r_{f,t}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{RMW}RMW_t + \beta_{CMA}CMA_t + \varepsilon_t$$

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CFO	-0.000	1.000	-0.000	0.000	0.000	0.000
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Betting on Objective Beliefs: Long-Only

- Trades based on surveys ≈ 0 alphas b/c surveys rarely anticipate negative excess returns

Table: FF 5-Factor Alphas from Long-Only Strategy

$$r_{s,t,t+4} - r_{f,t} = \alpha + \beta_m(r_{m,t} - r_{f,t}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{RMW}RMW_t + \beta_{CMA}CMA_t + \varepsilon_t$$

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Betting on Objective Beliefs: Long-Short

Table: FF 5-Factor Alphas from Long-Short Strategy Using Forecasts

$$r_{s,t,t+4} - r_{f,t} = \alpha + \beta_m (r_{m,t} - r_{f,t}) + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \varepsilon_t$$

	α	β_m	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}
Machine	0.052	0.591	-0.598	0.576	1.758	0.366
90% Credible Set	[0.02,0.08]	[0.45,0.73]	[-2.32,1.14]	[-1.26,2.41]	[-0.47,3.88]	[-2.40,3.07]
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90% Credible Set	[-0.00,0.00]	[1.00,1.00]	[-0.00,0.00]	[-0.00,0.00]	[0.00,0.00]	[-0.00,0.00]
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90% Credible Set	[-0.00,0.00]	[1.00,1.00]	[-0.00,0.00]	[-0.00,0.00]	[0.00,0.00]	[-0.00,0.00]
Perfect Foresight	0.138	0.091	-2.004	-0.524	1.225	1.960
90% Credible Set	[0.11,0.16]	[-0.03,0.21]	[-3.45,-0.61]	[-2.02,1.00]	[-0.65,3.08]	[-0.38,4.34]

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Betting on Objective Beliefs: Long-Short

- Surveys have ≈ 0 alphas b/c they rarely anticipate neg excess returns, let alone losses

Table: FF 5-Factor Alphas from Long-Short Strategy Using Forecasts

$$r_{s,t,t+4} - r_{f,t} = \alpha + \beta_m (r_{m,t} - r_{f,t}) + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \varepsilon_t$$

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Betting on Objective Beliefs: Long-Short

- Large machine alphas; point of comparison: infeasible perfect foresight alphas

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Conclusion

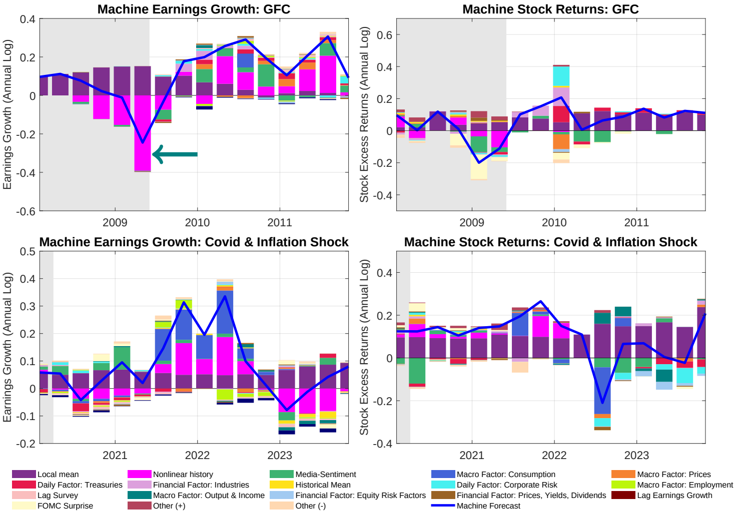
We started with the question: how important are predictable mistakes in the stock market?

- ML to establish a practical measure of rational and efficient expectation formation
- Quantifies magnitude of predictable mistakes in subjective beliefs
- Magnitude varies over time, sizable on avg., largest in times of market turbulence
  - Survey expectations dominated by local mean in predicted variable–form of recency bias
  - IBES analysts too attentive to earnings-related news; sub-optimally inattentive to macro data
- Subjective risk premia are sub-optimally responsive to evidence of changing risk
- Betting on objective beliefs would have earned sizable alphas from 2005-2023
  - Suggestive of connection between prestakes and market dynamics
  - Betting on objective beliefs is profitable only in episodes where prestakes are largest

APPENDIX

Detailed Machine Forecast Decompositions

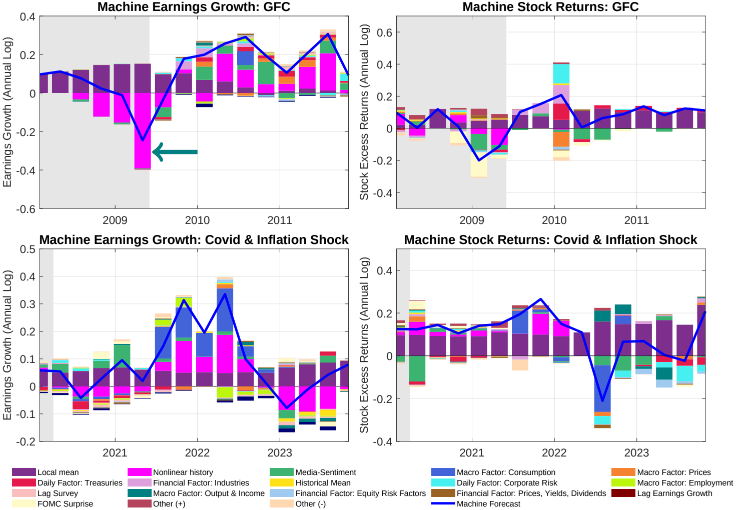
- During the GFC **non-linear history** important for earnings predictions



Detailed Machine Forecast Decompositions. The figure plots the machine forecast and its decomposition. The x-axis denotes the target period of forecast.

Detailed Machine Forecast Decompositions

- During the GFC **non-linear history** important for earnings predictions
- During GFC and 2022 bear market machine switches to deeper, wider networks => more nonlinearity
- Allows the machine to **predict part of sharp downturns** in episodes



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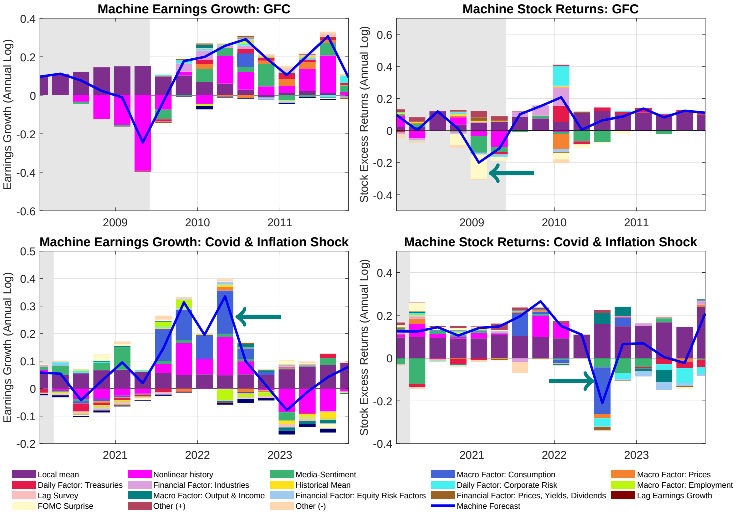
- During GFC and 2022 bear market machine switches to deeper, wider networks => more nonlinearity
- Allows the machine to **predict part of sharp downturns** in episodes
- High-Freq FFF surprises, media, consumption data



Detailed Machine Forecast Decompositions. The figure plots the machine forecast and its decomposition. The x-axis denotes the target period of forecast.

Characterizing Uncertainty in Relative Forecast Performance

- Standard equal-accuracy tests inappropriate for point-forecasting & don't quantify magnitude of out-performance; use **Bayesian method** on optimal forecast combination
- Key idea: optimal forecast typically includes several models with positive weights; being better on avg $\neq$ always better
- Hybrid forecast: $\mathbb{EF}_t[y_{j,t+h}] \equiv w \cdot \mathbb{E}_t[y_{j,t+h}] + (1-w) \cdot \mathbb{F}_t[y_{j,t+h}], w \in [0,1]$
- w^* minimizes hybrid MSE over testing sample
- $w^* = 1$: machine always better; $w^* = 0.5$: equally good

Optimal hybrid weights on machine forecast (w^*)							
(a) Stock Returns							
Horizon h (quarters)	4	4	4	4	4	4	16
Survey/benchmark	CB	SOC	Gallup/UBS	CFO	Livingston	FI	VL
w^*	1.000	1.000	1.000	1.000	0.999	1.000	0.653
Horizon h (quarters)	4	8	12	16			
Survey/benchmark	Mean	Mean	Mean	Mean			
w^*	1.000	1.000	0.927	0.664			
(b) S&P 500 Earnings Growth							
Horizon h (quarters)	4	LTG 4-5	LTG 1-10	LTG 0-5			
Survey/benchmark	IBES	IBES	IBES	IBES			
w^*	1.000	1.000	1.000	0.999			

Optimal hybrid weights on the machine forecast. w^* is the weight on the machine forecast $\mathbb{E}$ that minimizes the mean squared forecast error of the hybrid forecast $\mathbb{EF}_t[y_{j,t+h}] \equiv w \cdot \mathbb{E}_t[y_{j,t+h}] + (1-w) \cdot \mathbb{F}_t[y_{j,t+h}]$ over the evaluation sample. $w^* = 1$ obtains when the machine is always better than the survey.

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Decomposition of Relative Forecast Accuracy

- Decompose the ratio of machine to survey MSE as:

$$\frac{\mathrm{MSE}(\mathbb{E})}{\mathrm{MSE}(\mathbb{F})} = \frac{\mathrm{MSE}(\mathbb{E})}{\mathrm{MSE}(\mathbb{E}_1)} \times \frac{\mathrm{MSE}(\mathbb{E}_1)}{\mathrm{MSE}(\mathbb{F})}$$

- Taking logs:

$$\ln\left[\frac{\mathrm{MSE}(\mathbb{E})}{\mathrm{MSE}(\mathbb{F})}\right] = \ln\left[\frac{\mathrm{MSE}(\mathbb{E})}{\mathrm{MSE}(\mathbb{E}_1)}\right] + \ln\left[\frac{\mathrm{MSE}(\mathbb{E}_1)}{\mathrm{MSE}(\mathbb{F})}\right]$$

- Integrated gradients identify the equity cash-flow theme as the top driver of the IBES survey forecast
- $\mathbb{E}_1$ denotes a simpler machine forecast that uses only the equity cash-flow theme as input
- **Distance from 1 in** $\frac{\mathrm{MSE}(\mathbb{E})}{\mathrm{MSE}(\mathbb{F})}$ (0 in log points) decomposed into two components:
  - Information advantage ($\ln[\mathrm{MSE}(\mathbb{E})/\mathrm{MSE}(\mathbb{E}_1)]$): $\mathbb{E}$ uses a broad input set, $\mathbb{E}_1$ uses only the equity cash-flow theme
  - Specification advantage ($\ln[\mathrm{MSE}(\mathbb{E}_1)/\mathrm{MSE}(\mathbb{F})]$): $\mathbb{E}_1$ uses an LSTM, $\mathbb{F}$ uses a subjective model

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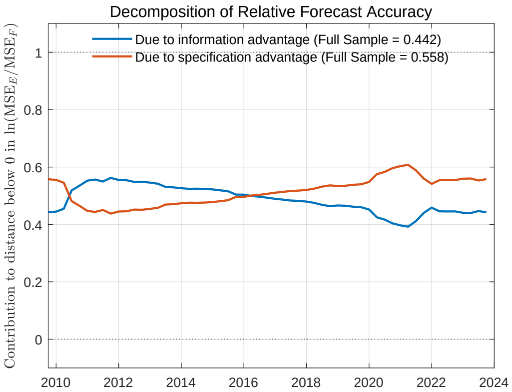
Decomposition of Relative Forecast Accuracy

- Shares of contribution to distance below 0 in $\ln[\text{MSE}(\mathbb{E})/\text{MSE}(\mathbb{F})]$:
  - Information advantage share
  - Specification advantage share
- Machine's relative forecast accuracy over survey increasingly over the sample reflects superior specification over broader information



Decomposition of relative forecast accuracy. Contributions to the distance below 0 in $m^* \equiv \ln[\text{MSE}(\mathbb{E})/\text{MSE}(\mathbb{F})]$, decomposed as $1 = \ln[\text{MSE}(\mathbb{E})/\text{MSE}(\mathbb{E}_1)]/m^*$ (information advantage) $+ \ln[\text{MSE}(\mathbb{E}_1)/\text{MSE}(\mathbb{F})]/m^*$ (specification advantage). MSE ratios are for 1yr earnings growth forecasts over expanding windows starting in 2005:Q1 with a five-year minimum.

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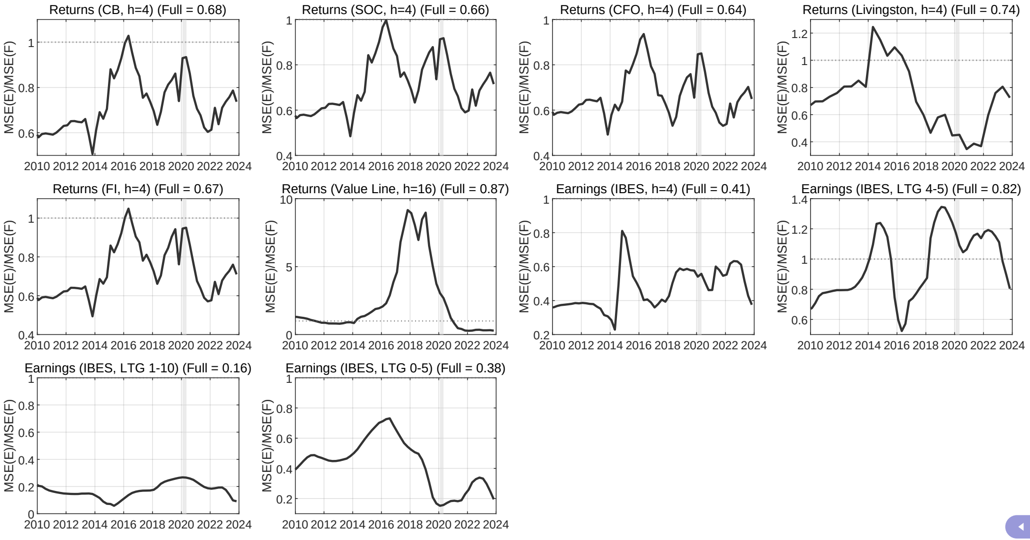
Relative Forecast Accuracy: Rolling MSE Ratio



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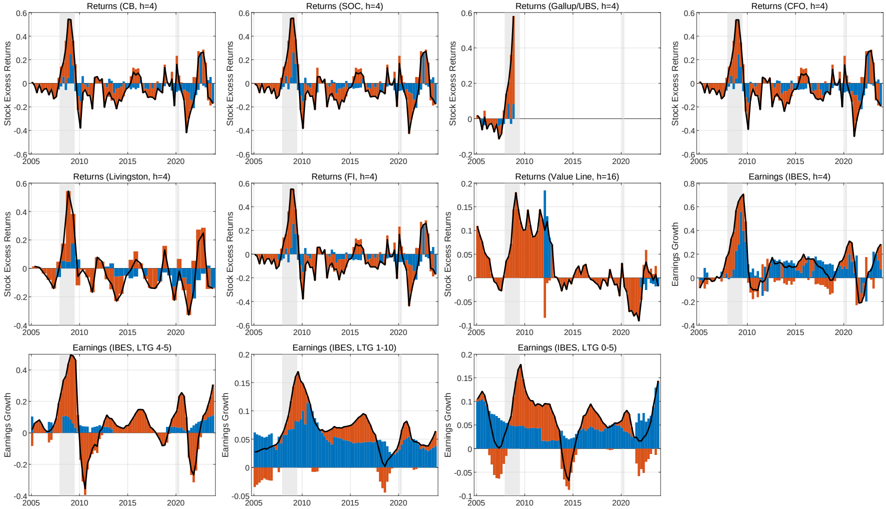
Prestakes over Time: All benchmarks



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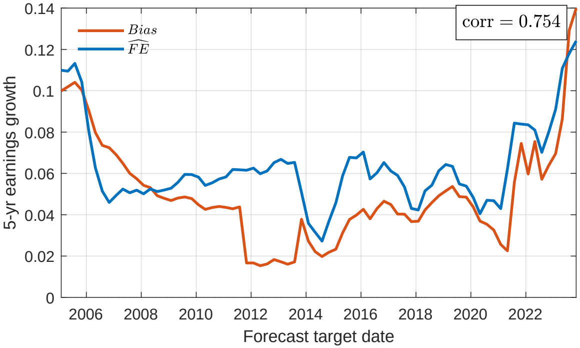
Earnings Growth Bias and LTG Forecast Error IV

- **Bias**: IBES LTG minus machine forecast in 0-to-5 year earnings growth (Bordalo, Gennaioli, LaPorta, and Shleifer (2022))
- $\widehat{FE}$: Fitted forecast error from regressing the LTG forecast error on ΔLTG and lagged LTG
- Correlation between the two series: 0.685



Notes. The figure plots our Bias (IBES LTG minus machine forecast) and $\widehat{FE}$, the fitted forecast error from a regression of the IBES LTG forecast error on the change in LTG and lagged LTG. The correlation between the two series is 0.685. Sample: 2005:Q1–2023:Q4.

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Implications of Prestakes for Over-/Underreaction

- $\widehat{\beta} > 0$ on **machine revision**
  - Consistent with **underreaction** to **"objective"news**.
  - Machine forecast revised up, survey moves up too little, so NEG bias (machine minus survey) becomes more positive

$\text{NEG bias}_{IBES,t}[y_{t+h}] = \alpha + \beta \cdot (\mathbb{X}_t - \mathbb{X}_{t-1})[y_{t+h}] + u_t$	(1) Machine revision $\mathbb{X}_t = \mathbb{E}_t$	(2) Survey revision $\mathbb{X}_t = \mathbb{F}_{IBES,t}$
(a) 0-to-5 yr LTG		
$\widehat{\beta}$	+0.009	
90% Credible Set	[+0.005, +0.013]	
Adj. R^2 (%)	18.3	
N	72	
(b) 4-to-5 yr LTG		
$\widehat{\beta}$	+0.028	
90% Credible Set	[+0.021, +0.034]	
Adj. R^2 (%)	44.4	
N	72	
(c) 1-yr earnings		
$\widehat{\beta}$	+0.093	
90% Credible Set	[+0.082, +0.105]	
Adj. R^2 (%)	75.8	
N	72	

Predictability of NEG bias by Forecast Revisions. NEG bias is the machine forecast minus the survey forecast, $\text{NEG bias}_{IBES,t}[y_{t+h}] \equiv \mathbb{E}_t[y_{t+h}] - \mathbb{F}_{IBES,t}[y_{t+h}]$. Column (1) uses the machine forecast revision. Column (2) uses the survey forecast revision. Row (a) uses the 0-to-5 year cumulative LTG forecast. Row (b) uses the 4-to-5 year forward LTG forecast. Row (c) uses 1-year-ahead earnings growth forecasts. Regressors are standardized. Newey-West standard errors with 1-year lag. 90% Bayesian credible sets from 10000 posterior t-draws under flat priors (Hamilton, 1994). Sample: forecast target dates 2005:Q1–2023:Q4.

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Implications of Prestakes for Over-/Underreaction

- $\widehat{\beta} > 0$ on machine revision
  - Consistent with **underreaction** to **"objective"news**.
  - Machine forecast revised up, survey moves up too little, so NEG bias (machine minus survey) becomes more positive
- $\widehat{\beta} < 0$ on **survey revision**
  - Consistent with **overreaction** to **perceived news**.

$\text{NEG bias}_{IBES,t}[y_{t+h}] = \alpha + \beta \cdot (\mathbb{X}_t - \mathbb{X}_{t-1})[y_{t+h}] + u_t$	(1) Machine revision $\mathbb{X}_t = \mathbb{E}_t$	(2) Survey revision $\mathbb{X}_t = \mathbb{F}_{IBES,t}$
(a) 0-to-5 yr LTG		
$\widehat{\beta}$	$+0.009$	-0.011
90% Credible Set	$[+0.005, +0.013]$	$[-0.015, -0.007]$
Adj. R^2 (%)	18.3	24.1
N	72	76
(b) 4-to-5 yr LTG		
$\widehat{\beta}$	$+0.028$	-0.012
90% Credible Set	$[+0.021, +0.034]$	$[-0.020, -0.004]$
Adj. R^2 (%)	44.4	10.3
N	72	76
(c) 1-yr earnings		
$\widehat{\beta}$	$+0.093$	-0.066
90% Credible Set	$[+0.082, +0.105]$	$[-0.085, -0.047]$
Adj. R^2 (%)	75.8	41.5
N	72	76

Predictability of NEG bias by Forecast Revisions. NEG bias is the machine forecast minus the survey forecast, $\text{NEG bias}_{IBES,t}[y_{t+h}] \equiv \mathbb{E}_t[y_{t+h}] - \mathbb{F}_{IBES,t}[y_{t+h}]$. Column (1) uses the machine forecast revision. Column (2) uses the survey forecast revision. Row (a) uses the 0-to-5 year cumulative LTG forecast. Row (b) uses the 4-to-5 year forward LTG forecast. Row (c) uses 1-year-ahead earnings growth forecasts. Regressors are standardized. Newey-West standard errors with 1-year lag. 90% Bayesian credible sets from 10000 posterior t-draws under flat priors (Hamilton, 1994). Sample: forecast target dates 2005:Q1–2023:Q4.

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Machine Forecast Errors and Forecast Revisions: Out-of-Sample

- Two forecasting models:
  - Intercept only benchmark
  - Intercept and machine forecast revision
- For each model, construct out-of-sample forecasts estimated over rolling or recursive estimation windows.
- MSE(intercept + revision) / MSE(intercept only) $> 1 =>$ Intercept-only is more accurate, adding the revision worsens OOS MSE.

$$y_{t+h} - \mathbb{E}_t[y_{t+h}] = \alpha + \beta \cdot (\mathbb{E}_t - \mathbb{E}_{t-1})\,[y_{t+h}] + u_{t+h}$$

Window	Intercept only	Intercept + revision	MSE ratio
(a) Panel A: Earnings growth			
Rolling 5y	0.0172	0.0211	1.225
Rolling 10y	0.0183	0.0211	1.155
Recursive 5y	0.0119	0.0137	1.148
(b) Panel B: Stock returns			
Rolling 5y	0.0214	0.0215	1.003
Rolling 10y	0.0215	0.0219	1.022
Recursive 5y	0.0179	0.0198	1.105

OOS MSE for Predicting Machine Forecast Errors with Machine Forecast Revision. The dependent variable is the machine forecast error $y_{t+h} - \mathbb{E}_t[y_{t+h}]$. Two forecasting models are compared: an intercept-only benchmark and a model that adds the four-quarter machine forecast revision $\mathbb{E}_t[y_{t+h}] - \mathbb{E}_{t-1}[y_{t+h}]$. Panel A reports results for one-year earnings growth and Panel B for one-year stock returns. Rolling windows use the previous 5 or 10 years of usable post-2005 data. The recursive scheme begins after an initial 5-year usable estimation sample, then expands by one quarter at a time. Reported quantities are the OOS MSE for each model and the MSE ratio $\equiv$ MSE(intercept + revision) / MSE(intercept only), so values above one indicate the revision worsens OOS accuracy. Sample begins 2016:Q1.

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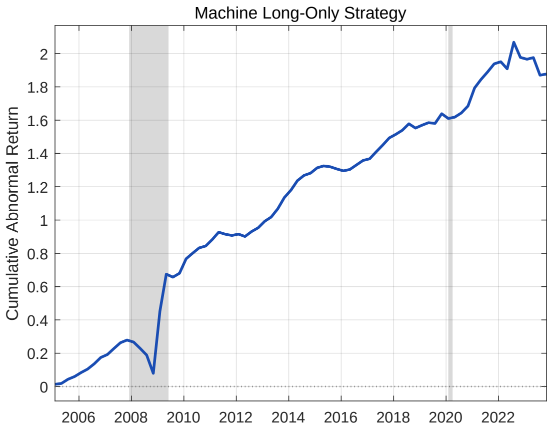
Machine Forecast Errors and Past Forecast Revisions

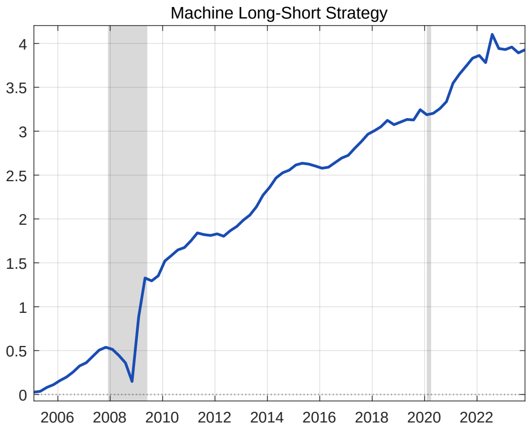
- Coibion-Gorodnichenko regression of machine forecast errors on past forecast revisions
- Machine forecast revisions do not predict future earnings growth or returns

	(1) Earnings Machine	(2) Returns Machine
Forecast revision	0.078	0.401
	(0.155)	(0.246)
90% Credible Set, revision	$[-0.181, 0.338]$	$[-0.007, 0.811]$
R^2	0.006	0.130

Notes: Each column reports the Coibion-Gorodnichenko regression in which the forecast error is regressed on the four-quarter forecast revision and the lagged realized outcome. Forecast error is realized outcome minus forecast, and the forecast revision is the current forecast minus the forecast made four quarters earlier. Newey-West standard errors with four lags are reported in parentheses. The bracketed entry reports the 90% Bayesian credible set for the forecast-revision coefficient. The sample spans 2005Q1 to 2023Q4. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Cumulative Abnormal Returns: Betting on Objective Beliefs





Cumulative abnormal returns of machine market-timing strategies. Each panel plots $CAR_t = \sum_{\tau \le t} \left[r_{s,\tau,\tau+4} - r_{f,\tau} - \hat{\beta}m(r_{m,\tau} - r_{f,\tau}) - \hat{\beta}_{SMB} SMB_\tau - \hat{\beta}_{HML} HML_\tau - \hat{\beta}_{RMW} RMW_\tau - \hat{\beta}_{CMA} CMA_\tau \right]$, where $r_{s,t,t+4}$ is the quarterly machine trading strategy return of long-only and long-short strategies. The betas are estimated by OLS over the testing sample from $r_{s,t,t+4} - r_{f,t} = \alpha + \beta m(r_{m,t} - r_{f,t}) + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \varepsilon_t$. Shaded bars denote NBER recessions. Sample: 2005:Q1–2023:Q4.

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Betting on Objective Beliefs: Long-Only at 4-Year Horizon

Table: Alphas from Long-Only Strategy at 4-Year Horizon

$$r_{s,t,t+16} - r_{f,t,t+16} = \alpha + \beta_m(r_{m,t} - r_{f,t,t+16}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{RMW}RMW_t + \beta_{CMA}CMA_t + \varepsilon_t$$

	α	β_m	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}
Machine	0.012	0.884	-0.188	-0.148	-0.153	0.134
90% Credible Set	[0.01,0.02]	[0.85,0.92]	[-0.36,-0.02]	[-0.31,0.01]	[-0.34,0.03]	[-0.12,0.39]
Value Line	0.000	1.000	-0.000	-0.000	-0.000	0.000
90% Credible Set	[0.00,0.00]	[1.00,1.00]	[-0.00,-0.00]	[-0.00,0.00]	[-0.00,0.00]	[0.00,0.00]
Perfect Foresight	0.031	0.712	-0.052	-0.294	-0.291	0.006
90% Credible Set	[0.03,0.03]	[0.67,0.75]	[-0.23,0.12]	[-0.47,-0.12]	[-0.48,-0.10]	[-0.27,0.28]

This table reports regression-based alphas from regressions of trading strategy returns in excess of the 4-year Treasury yield on excess factor returns over the period 2005:Q1-2020:Q4. The trading strategy invests in the CRSP value-weighted market index when the 4-year-ahead annualized excess return forecast (relative to the 4-year Treasury) is positive, and otherwise invests in the 4-year Treasury: $r_{s,t,t+16} = r_{t,t+16} \times \mathbf{1}_{\{\mathbb{P}_{s,t}[r_{t,t+16}]-r_{f,t,t+16}>0\}} + r_{f,t,t+16} \times \mathbf{1}_{\{\mathbb{P}_{s,t}[r_{t,t+16}]-r_{f,t,t+16}\leq 0\}}$. The Value Line forecast is the annualized nominal expected total return from Thesmar and Verner (2025), in excess of the 4-year Treasury yield. The Machine forecast is the LSTM 4-year annualized return forecast. Alphas represent the additional annualized log return of the trading strategy after controlling for the specified risk factors. 90% credible sets are based on 10,000 posterior draws from the marginal t-distribution under flat priors (Hamilton, 1994), given by the 5th and 95th percentiles of the posterior distribution.

Betting on Objective Beliefs: Long-Only at 4-Year Horizon

- **Large machine alphas** are product of defensive strategies & "earned"in downturns when strategies were relatively successful at mitigating losses

Table: Alphas from Long-Only Strategy at 4-Year Horizon

$r_{s,t,t+16} - r_{f,t,t+16} = \alpha + \beta_m (r_{m,t} - r_{f,t,t+16}) + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \varepsilon_t$						
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Betting on Objective Beliefs: Long-Only at 4-Year Horizon

- Trades based on surveys ≈ 0 alphas b/c surveys rarely anticipate losses

Table: Alphas from Long-Only Strategy at 4-Year Horizon

$$r_{s,t,t+16} - r_{f,t,t+16} = \alpha + \beta_m (r_{m,t} - r_{f,t,t+16}) + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \varepsilon_t$$

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Construction of Bayesian Credible Sets

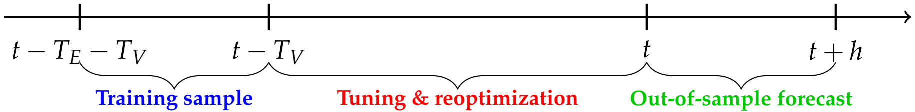
Linear regression model:

$$y_t = X_t'\beta + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \sigma^2)$$

- **Prior specification**: Flat (non-informative) priors for both:
  - Regression coefficients β
  - Residual variance σ^2
- **Posterior distribution** (Hamilton 1994, Proposition 12.3, result (b)):
  - Under flat priors, marginal posterior of coefficients is multivariate t-distribution
  - $\beta \mid y, X \sim \mathcal{T}_T\left(\hat{\beta}, \hat{\sigma}^2 (X'X)^{-1}\right)$
  - Degrees of freedom: T (sample size)
- **Simulation**: Draw $M = 100{,}000$ realizations from posterior of β
- **Credible set**: 90% interval given by 5th and 95th percentiles of posterior draws

Dynamic Machine Learning Algorithm Summary

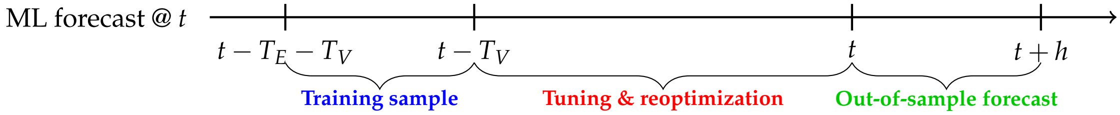
ML forecast @ t



Five-Step procedure of BLM

1. Sample partitioning: Time t, prior sample of size $\dot{T}$ partitioned into **training** subsample with T_E obs. and a **hold-out validation** subsample with T_V obs.

Dynamic Machine Learning Algorithm Summary



Five-Step procedure of BLM

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2. Training: Estimate $\beta_{j,h,t}$ over multiple hyperparameters, architecures, T_E & T_V

Dynamic Machine Learning Algorithm Summary

ML forecast @ t

$t - T_E - T_V$ $\qquad$ $t - T_V$ $\qquad$ t $\qquad$ $t + h$

Training sample $\qquad$ Tuning & reoptimization $\qquad$ Out-of-sample forecast

Five-Step procedure of BLM

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2. Training: Estimate $\beta_{j,h,t}$ over multiple hyperparameters, architecures, T_E & T_V
3. Tuning & reoptimization: choose hyperparams, architecture & windows to optimize *pseudo* OOS forecasts, & check for predictable mistakes in survey response $=> \hat{\beta}_{j,h,t}$

Dynamic Machine Learning Algorithm Summary

ML forecast @ t

$t - T_E - T_V$ | $t - T_V$ | t | $t + h$

Training sample | **Tuning & reoptimization** | **Out-of-sample forecast**

Five-Step procedure of BLM

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4. Out-of-sample prediction: Use $\hat{\beta}_{j,h,t}$ to get a *true* out-of-sample prediction of $y_{j,t+h}$ & save each iteration as part of testing sample

Dynamic Machine Learning Algorithm Summary

ML forecast @ t

$$\underbrace{t - T_E - T_V \quad\quad t - T_V}_{\text{Training sample}} \quad \underbrace{t - T_V \quad\quad t}_{\text{Tuning \& reoptimization}} \quad \underbrace{t \quad\quad t+h}_{\text{Out-of-sample forecast}}$$

Five-Step procedure of BLM

1. Sample partitioning: Time t, prior sample of size $\dot{T}$ partitioned into **training** subsample with T_E obs. and a **hold-out validation** subsample with T_V obs.
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3. Tuning & reoptimization: choose hyperparams, architecture & windows to optimize *pseudo* OOS forecasts, & check for predictable mistakes in survey response $=>$ $\hat{\beta}_{j,h,t}$
4. Out-of-sample prediction: Use $\hat{\beta}_{j,h,t}$ to get a *true* out-of-sample prediction of $y_{j,t+h}$ & save each iteration as part of testing sample
5. Roll forward and repeat: Roll forward t to $t+1$ and repeat steps 1-4 until T.

Algorithm Details

1. Predictable mistakes: machine matched with **each survey**

    - $\mathbb{E}_t[\cdot]$ differs from $\mathbb{F}_t[\cdot]$ only if demonstrate a better way to use data
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   - Must learn about changing economic landscape/structural shifts
3. Adaptive architecture selection to optimize validation objective
   - 1, 3, or 5 hidden layers & 16, 32, or 64 neurons

Illustrative Example: Earnings Relative to Trend

- Real stock market payout $E_t \equiv \exp(e_t)$ be a **share** K_t of real **output** Y_t, i.e., $E_t = K_t Y_t$
- Log growth Δe_t follows (approximate) **objective** law of motion (LOM):

$$\begin{aligned} \Delta e_t &= \Delta y_t + k_t - k_{t-1} && (1) \\ k_t &= (1-\rho_k)k + \rho_k k_{t-1} + \varepsilon_{k,t} && (2) \\ \Delta y_t &= (1-\rho_{\Delta y})\Delta y + \rho_{\Delta y}\Delta y_{t-1} + \varepsilon_{\Delta y,t}, && (3) \end{aligned}$$

- Let **deviations from steady-state** denoted using "hats"
- Assume $0 \leq \rho_k, \rho_{\Delta y} < 1$. Eq (1), (2), (3) =>

$$\mathbb{E}_t[\hat{\Delta e}_{t+1}] = (\rho_k - 1)\hat{k}_t + \rho_{\Delta y}\hat{\Delta y}_t \tag{4}$$

- A *negative* impulse to $\varepsilon_{k,t}$ => $\mathbb{E}_t[\hat{\Delta e}_{t+1}] > 0$, i.e., *positive* **catch-up growth** next period

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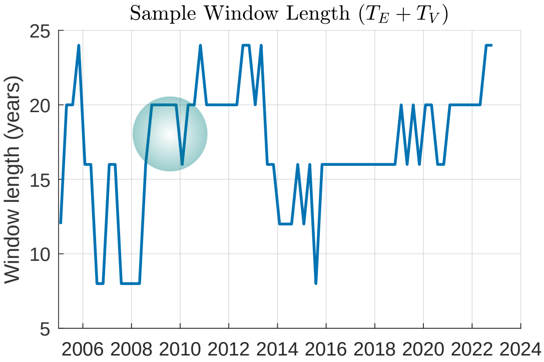
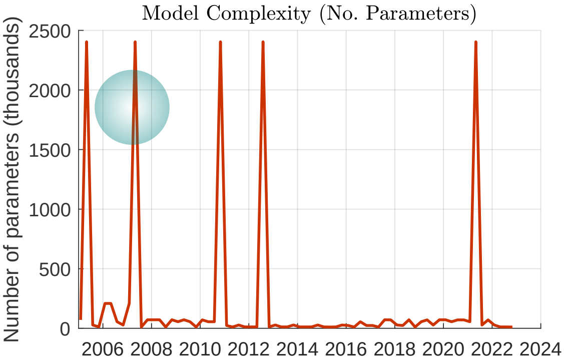
Machine Forecast: Training Window and Model Complexity

Machine forecast during the GFC

- Extends sample window to train using longer historical data (left)
- Selects a more complex architecture to better learn from this long-term history (right)





Sample Window Length and Model Complexity. Left panel plots $T_E + T_V$, the total window chosen by the machine each period for the earnings growth forecast. Right panel plots the implied number of LSTM parameters under the pyramid rule.

Lasso Procedure for Drivers of Nonlinear History

- Regress the nonlinear history on the full set of LSTM input predictors, using Lasso along a grid of ℓ_1 penalties λ
- For each k, identify the smallest λ at which exactly k predictors are selected; among these candidates, choose λ minimizing BIC

Variable	Description	Coef.
Panel A: Machine Nonlinear History		
FOMC Surprise (2M FFF) (L1)	2-month-ahead fed funds surprise	0.086
Panel B: IBES Survey Nonlinear History		
Lagged earnings growth (L1)	Lagged realized 4-quarter earnings growth	-0.169
Employment (L1)	Total nonfarm employment	-0.158
Import prices (L1)	Import price index	0.107
EGDP (L1)	Earnings-to-GDP ratio	-0.080
Momentum (UMD) (L1)	Up-minus-down (momentum) factor	-0.068
Media topic 11 (L1)	LDA news-text factor 11	0.063
`CSYCS00` (L1)	(real-time series; description to verify)	-0.041
Personal taxes (L1)	Personal current taxes	-0.016
Real business investment (L1)	Real business fixed investment	-0.014

Notes: Selected variables and coefficients from a Lasso regression of the nonlinear-history component on lag-1 inputs, with the penalty λ chosen to minimize BIC. Inputs are standardized to mean 0, standard deviation 1; coefficients are Lasso estimates in standardized units. The survey nonlinear history is the EN-switch-corrected series (zero whenever the survey falls back to the elastic net). Both panels are estimated over the common testing sample ($T = 76$ quarters, 2005:Q1–2023:Q4); BIC retains a single variable for the machine nonlinear history.

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