Machine Traders, Human Behavior, and Model (Mis)Specification

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Machine traders

Already prevalent, and improve our ability to make sense of data

- Machine-driven funds account for $1/3$ of all institutional trading ($>$ pension + mutual funds combined), and 30% of hedge fund AuM
- As Data becomes Bigger, we are likely to rely even more heavily on machines as part of the investment process

Machines *can* be beneficial to human investors...

- Detect asset return predictability (Gu, Kelly, and Xiu 2020, ...)
- Improve upon human forecasts (Bianchi, Ludvigson, and Ma 2022; Van Binsbergen, Han, and Lopez-Lira 2023; Silva and Thesmar 2021; Cao, Jiang, Wang, and Yang 2021)

... but *are* they beneficial in practice?

- Machines are designed by humans
- We humans suffer from cognitive biases (Tversky and Kahneman 1974)
- Do machines encode our biases and hold us back from our goals?

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This paper

- I examine how investors specify machine-driven trading strategies
- I quantify extent to which they benefit from data as a result
- Highly controlled (yet realistic) setting: the Quantiacs platform, which runs contests for trading futures contracts
  - Investors face a prediction problem, using (only) historical data
  - I know exactly what predictive variables investors can use
  - Investors' objectives are fixed (risk preferences, horizon, ...)
  - Sizable financial incentives offered to top performers

Findings

- Investors in this setting use systematic machine-driven trading strategies to solve their prediction problem
- Yet their human behavioral biases play play an important role in how they use data in specifying their trading strategies
  - They are overly reliant on familiar variables...
  - ... even for "hard" information that they are endowed with
  - Big(ger) Data is not necessarily helpful
- Investors who *do* overcome their biases (with experience) can benefit substantially from data availability
  - Economically significant: up to 2 units of OOS SR
  - Experienced investors more optimally weight predictors...
  - ... and ignore fewer variables altogether

Related literature

Models

- Disagreement: Cookson and Niessner (2020)
- Mis-specification: Arthur et al. (1996), Barberis, Shleifer, and Vishny (1998), Hong, Stein, and Yu (2007), and Branch and Evans (2010)

(Big) Data and asset pricing

- Martin and Nagel (2022); Farboodi and Veldkamp (2020); Dugast and Foucault (2021)

Inexperience and behavioral biases

- List (2003), Feng and Seasholes (2005), Dhar and Zhu (2006), Greenwood and Nagel (2009), Abreu, Mendes, and Santos (2011), Da Costa Jr et al. (2013), and Campbell, Ramadorai, and Ranish (2014)

Principle of sparsity

- Gabaix (2014); Hanna, Mullainathan, and Schwartzstein (2014); Molavi, Tahbaz-Salehi, and Vedolin (2021)

Quantiacs FinTech platform

Business model

- Run futures paper trading contests for investors, incentivizing out-of-sample Sharpe Ratio maximization ⇒ common goal
- Offer profit-sharing contracts to top 3 ⇒ monetary payoffs[1]
- Seek successful systematic investors

Investors follow systematic portfolio rules

- Total of 874 participants over 12 contests (live: 2014-2019)

Controlled information environment

- Investors have access to the same predictive variables
  - Not possible to upload external variables
- Added 54 macro variables between contests 7 and 8
  - e.g. CPI, non-farm payrolls, pending home sales, ...

1. Notional values: $1,000,000, $750,000 and $500,000, resp.

Investors code daily portfolio rules...

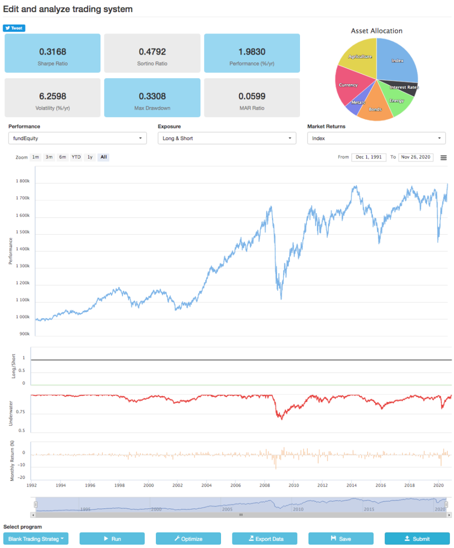
Edit and analyze trading system

Select program

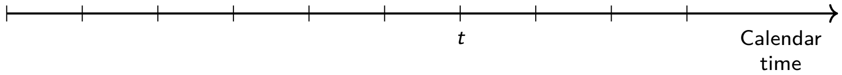
Blank Trading S ▾ | ▶ Run | Optimize | Export Data

```
### Quantiacs Trading System Template

# import necessary Packages below:
import numpy
#import pandas
#import scikit.learn
#import sciPy

def myTradingSystem(DATE, OPEN, HIGH, LOW, CLOSE, VOL, OI, P, R, RINFO, exposure, equity, settings):
    '''Define your trading system here.
    See the example trading system for a starting point.
    The function name "myTradingSystem" should not be changed. We evaluate this function on our server.
    Your system should return a normalized set of weights for the markets you have defined in settings['markets']. '''

    # this strategy implements a simple buy and hold strategy
    nMarkets = CLOSE.shape[1]
    pos = numpy.ones((1, nMarkets))
    pos = pos / numpy.sum(abs(pos))

    return pos, settings


def mySettings():
    '''Define your market list and other settings here.

    The function name "mySettings" should not be changed.

    Default settings are shown below.'''

    settings={}

    # Futures Contracts
    settings['markets'] = ['F_ES', 'F_MD', 'F_NQ', 'F_RU', 'F_XX',
        'F_YM', 'F_AX', 'F_CA', 'F_LX', 'F_VX', 'F_AE', 'F_DM',
        'F_AH', 'F_DZ', 'F_FB', 'F_FM', 'F_FP', 'F_FY', 'F_NY',
        'F_PQ', 'F_SH', 'F_SX', 'F_GD', 'F_FV', 'F_TU', 'F_TY',
        'F_US', 'F_DT', 'F_UB', 'F_UZ', 'F_GS', 'F_CF', 'F_GX',
```

… and observe historical performance prior to contest entry



Platform evaluates performance out-of-sample (OOS)



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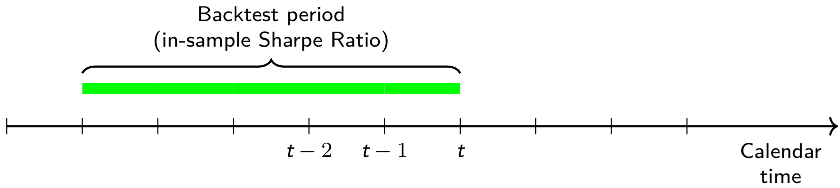

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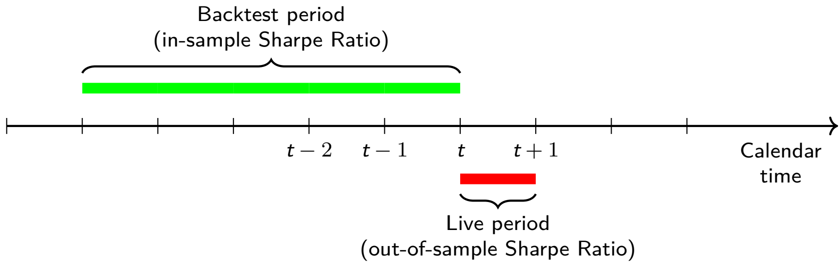

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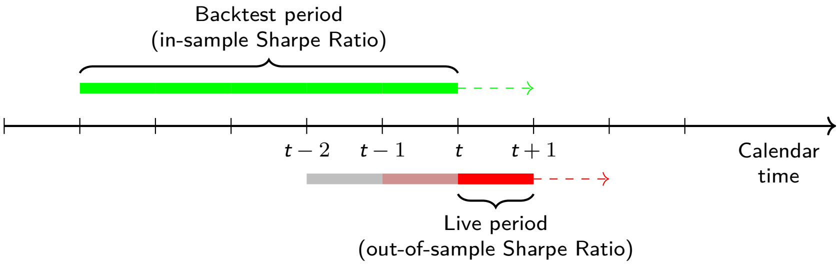


Contestants are publicly scored based on performance

QUANTIACS

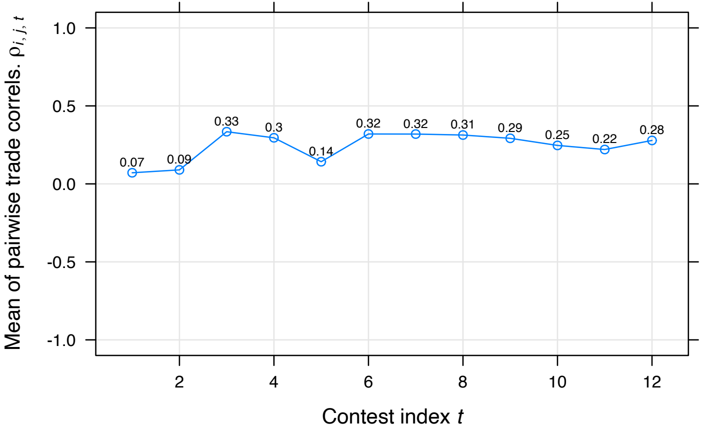
BECOME A QUANT | COMPETITIONS | SYSTEMS | BLOG

BACKTEST | LIVE TEST JANUARY 2019 TO APRIL 30 2019

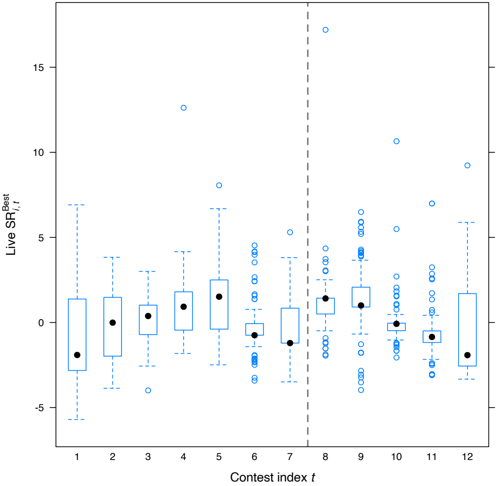
Rank Name	Score Upload Date Trading System	Yearly Perf.	Yearly Vola. Sharpe Ratio Sortino Ratio	Performance	Volatility Sharpe Ratio Sortino Ratio
Rank: 51 KOBAS Q12 CONTEST	1.72 12/13/2018 00:53 181212OR0S0FKJJ16	15.15%	11.89% 1.72 2.91	11.60%	0.00% 2.69 4.38
Rank: 52 mwalimudan Q12 CONTEST	1.71 12/01/2018 04:51 IWantToBe50	20.93%	12.79% 1.71 2.89	5.92%	0.00% 1.74 3.02
Rank: 53 stevefoeldvari Q12 CONTEST	1.71 12/09/2018 12:40 sf0013	25.11%	11.05% 2.35 3.89	6.51%	0.00% 1.71 2.83
Rank: 54 vsujith Q12 CONTEST	1.70 12/16/2018 23:47 1206Dilbert	4.02%	1.87% 2.22 3.70	0.76%	0.00% 1.70 2.76

Model disagreement is high

- Within a contest, all systematic traders access the same dataset
- ⇒ Heterogeneity should be due to model disagreement (Cookson and Niessner 2020), not heterogeneous information
- Low average correlation (i.e. agreement) of trading activity, within-contest ⇒ high model disagreement

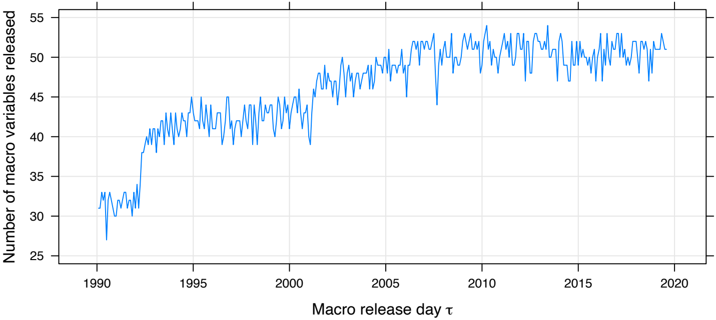


Such model disagreement impacts performance outcomes



Confirming model disagreement is due to differences of opinion (1/3)

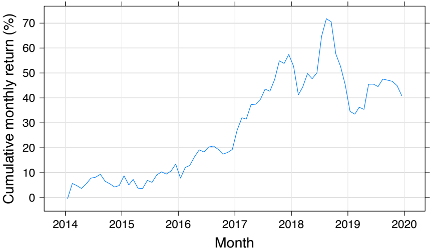
- To analyze how trades respond to information, I exploit institutional variation in variable release dates on the Quantiacs trading platform
- Macroeconomic variables are updated once a month...
- ... But not all the 54 indicators are consistently updated:



- ⇒ Variation in the aggregate informativeness of macro release days
- Use interpretable machine learning techniques to measure the out-of-sample predictive informational content of each macro release day

Confirming model disagreement is due to differences of opinion (2/3)

- Repeatedly train a Random Forest on actual macro data from platform
  - Gu, Kelly, and Xiu (2020); Van Binsbergen, Han, and Lopez-Lira (2023)
- Time-varying model fits, matched to contest Live periods
  - Take care to avoid look-ahead bias – just like the trading strategies
  - Models detect economically significant OOS return predictability:



- Informativeness$_\tau$ index: calculate additive SHAP values (Lundberg and Lee 2017) per variable & model fit, then aggregate them up over the subset of macro indicators released on a specific day τ
- Time series regressions measure the sensitivity β_i of each strategy i's (standardized) trading volume across macro release days τ:

$$\text{Volume}_{i,\tau} = \alpha_i + \beta_i \times \text{Informativeness}_\tau + \epsilon_{i,\tau} \tag{1}$$

Confirming model disagreement is due to differences of opinion (3/3)

$$\underbrace{-\rho_{i,j}}_{\substack{\text{Trading}\\\text{activity}\\\text{dissimilarity}}} \quad = \quad \gamma \;\times\; \underbrace{\delta(\widehat{\beta}_i, \widehat{\beta}_j)}_{\substack{\text{Disagreement}\\\text{about macro}\\\text{predictive info.}}} \quad + \quad \phi_t \quad + \quad \epsilon_{i,j} \qquad (2)$$

Dependent Variable:	$-\rho_{i,j}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\lvert\widehat{\beta}_i - \widehat{\beta}_j\rvert)$	0.0486***	0.0508***				
	(0.0030)	(0.0026)				
$\log(1 + \lvert\widehat{\beta}_i - \widehat{\beta}_j\rvert)$			0.2423***	0.2866***		
			(0.0225)	(0.0362)		
$\text{arcsinh}(\lvert\widehat{\beta}_i - \widehat{\beta}_j\rvert)$					0.1952***	0.2307***
					(0.0170)	(0.0258)
Intercept	✓		✓		✓	
Contest FEs		✓		✓		✓
Observations	19,640	19,640	21,512	21,512	21,512	21,512
R^2	0.343	0.380	0.338	0.420	0.345	0.428
Within R^2		0.371		0.416		0.424

Note: standard errors (in parentheses) are clustered by contest and contestant.

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

In search of a behavioral explanation

- The strength of disagreement is somewhat puzzling
  - Investors observe daily prices & monthly macro indicators going back to 1990 $\Rightarrow$ long timeseries of observations
  - Yet, clear lack of convergence over calendar time
- Investigate presence of behavioral bias in how investors use predictive information
- If true, likely to dissipate with experience
  - Inexperienced investors are more prone to behavioral biases (e.g. List 2003, ...)
  - Prediction: within-contest, experienced investors should outperform inexperienced investors

Inexperienced investors *do* perform worse

- Holds within contest; i.e. fixing a common dataset
- Holds within investor; i.e. accounting for unobserved skill

	Dependent variable:			
	Backtest $\text{SR}_{i,t}^{Best}$		Live $\text{SR}_{i,t}^{Best}$	
	OLS	*panel linear*	*OLS*	*panel linear*
	(1)	(2)	(3)	(4)
Contests experienced$_{i,t}$	1.161***	1.338***	0.445**	1.261***
	(0.055)	(0.505)	(0.178)	(0.456)
Intercept	✓		✓	
Contest FEs		✓		✓
Contestant FEs		✓		✓
Observations	874	874	874	874
R^2	0.156	0.024	0.035	0.040

Note: standard errors (in parentheses) are clustered by contest and contestant. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Investors' models agree more as investors gain experience

- $\rho_{i,j,t}$ measures trading activity similarity between investors i, j for entries made in contest t, computed on daily turnovers from 1990+
- Again, holds within contest; i.e. fixing a common dataset

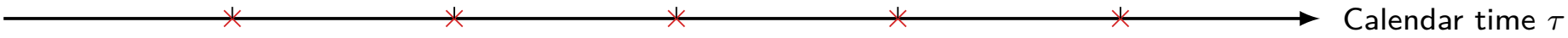
Dependent Variable:	$\rho_{i,j,t}$		
	(1)	(2)	(3)
Contests experienced$_{i,j,t}$	0.0625***	0.0640***	0.0929*
	(0.0176)	(0.0182)	(0.0436)
(Intercept)	0.3087***		
	(0.0207)		
Contest FEs		✓	✓
Contestant i FEs			✓
Observations	25,829	25,829	25,829
R^2	0.00112	0.00939	0.30492

Note: standard errors (in parentheses) are clustered by contest and contestant. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Data usage

- So far, we've seen evidence that inexperienced investors, i.e. those who are more prone to behavioral biases,
  - disagree more, and
  - perform worse
- How are their models of the world (mis)specified?
  - In what ways do inexperienced investors fail to make optimal use of the data they are endowed with?
- Empirically, focus on the 42 macroeconomic indicator inputs, which are available during later contests

Empirical strategy to measure usage of data



- Macro variables are released at a lower frequency (monthly/quarterly) than portfolios are updated (daily)
- Compare portfolio turnovers on macro release days vs. not
- Include a placebo test for earlier contests

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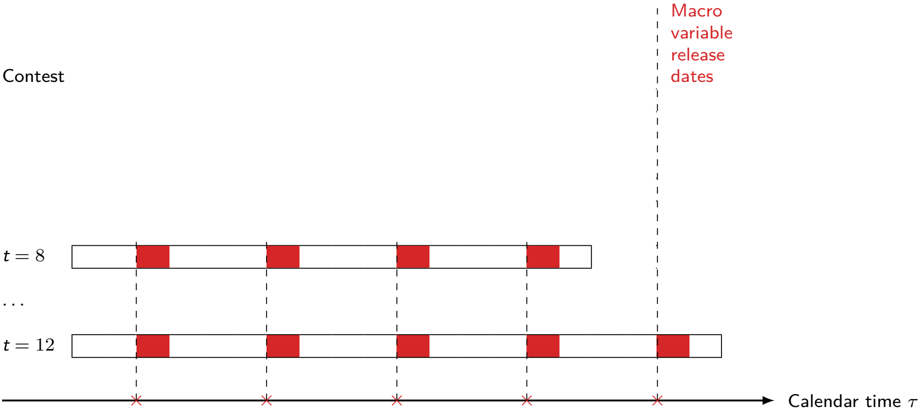

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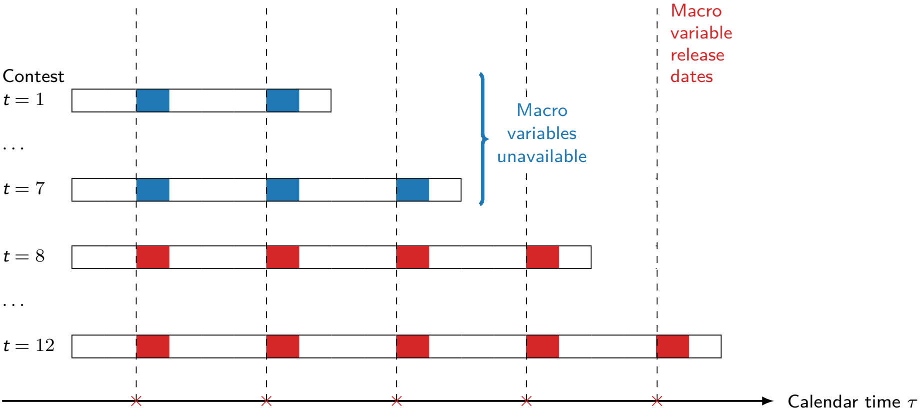

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Inexperienced investors respond weakly to data availability

	Volume$_{i,\tau}$			
	With data availability		*Placebo group*	
	(1)	(2)	(3)	(4)
(Intercept)	0.002***	0.003***	0.002***	0.002***
	(0.0004)	(0.0001)	(0.001)	(0.001)
Macro release$_\tau$	$-$0.009***	$-$0.011***	0.0002	0.0002
	(0.003)	(0.002)	(0.012)	(0.012)
Experienced$_{i,t}$		$-$0.009		0.0001
		(0.007)		(0.001)
Macro release$_\tau$ $\times$ Experienced$_{i,t}$		0.076**		0.001
		(0.036)		(0.017)
Observations	3,234,115	3,234,115	2,059,615	2,059,615
R^2	0.00000	0.00001	0.000	0.000

Std. errs. are clustered by contest & contestant: *p<0.1; **p<0.05; ***p<0.01.
Volume is standardized (i.e. z-score) within-trading strategy.

Inexperienced investors underweight genuine predictors

Dependent Variable:		$\text{Volume}_{i,\tau}$	
	(1)	(2)	(3)
$\text{Experienced}_{i,t}$	0.0673**		-0.3229*
	(0.0184)		(0.1208)
$\text{Informativeness}_{\tau}$		0.6774**	0.6348*
		(0.2132)	(0.2362)
$\text{Experienced}_{i,t} \times \text{Informativeness}_{\tau}$			1.025**
			(0.2357)
Intercept	✓		
Model Year FEs		✓	✓
Observations	142,332	142,332	142,332
R^2	0.00014	0.00034	0.00054

Note: standard errors (in parentheses) are clustered by contest and contestant. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Investors are influenced by their prior familiarity

- Familiarity: mentions in Factiva news articles or Google Books
- Finding is consistent with
  - availability heuristic (Tversky and Kahneman 1973, 1974)
  - recognition heuristic (Goldstein and Gigerenzer 1999, 2002)

Dependent Variable:	$\text{Volume}_{i,\tau}$				
Familiarity Index:		News Articles		Books	
	(1)	(2)	(3)	(4)	(5)
$\text{Experienced}_{i,t}$	0.0673** (0.0184)		-0.3381 (0.3085)		-0.1500 (0.2425)
$\text{Familiarity}_{\tau}$		0.0027*** (0.0003)	0.0026*** (0.0003)	0.0026*** (0.0005)	0.0026*** (0.0005)
$\text{Experienced}_{i,t} \times \text{Familiarity}_{\tau}$			0.0043 (0.0031)		0.0023 (0.0024)
Intercept	✓				
Benchmark Year FEs		✓	✓	✓	✓
Observations	142,332	142,332	142,332	142,332	142,332
R^2	0.00014	0.00019	0.00034	0.00014	0.00029

Note: standard errors (in parentheses) are clustered by contest and contestant.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Gains from access to (Bigger) Data

- We've seen evidence that inexperienced investors, i.e. those who are more prone to behavioral biases, make poor use of the macroeconomic indicators:
  - They seem to underweight genuine predictors
  - And rely instead on familiar variables
- Do they nevertheless gain *some* benefit from having access to these additional macroeconomic predictive variables?
- No! Inexperienced investors, who tend to mis-specify their models of the world, fail to benefit from access to Bigger Data

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Empirical strategy to measure gains from Big(ger) Data

The experimental ideal

- Each investor randomly assigned to an information regime: with/without the 54 new predictive macro variables
- Compare performance with/without, across investor groups

The reality of the contest setting

- During each contest, all investors have access to the same set of predictive variables (and have identical risk preferences, horizon, ...)
  - Contests 1-7: no investor could access the macro variables
  - Contests 8-12: all investors could access them
- Due to attrition, few investors participate in both regimes

⇒ Compare investors' performance across information regimes

- Major confounders already controlled by Quantiacs setting
- Compare OOS SR in excess of a benchmark portfolio
- Assumption: similar investor populations (see next slide) ⇒ differences in excess performance attributed to data availability
- Two-stage "Heckit" model (e.g. Seru, Shumway, and Stoffman 2010) to rule out selection effects as driver

Population balance: before vs. after macro variables added

Investor-contest-level balance

	Control (N=289)		Treatment (N=502)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p value
Contests experienced$_{i,t}$	1.0796	0.3183	1.1058	0.3985	0.0262	0.3108
Percentile(Score$^{Best}_{i,t-1}$)	0.6445	0.2570	0.7102	0.2588	0.0657	0.3592

Contest-level balance

	Control (N=6)		Treatment (N=4)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p value
Mean$_t$(Contests experienced$_{i,t}$)	1.2092	0.0544	1.2191	0.0810	0.0099	0.8389
Fraction of first-time contestants at t	0.8415	0.0534	0.8580	0.0396	0.0165	0.5914
Fraction of last-time contestants at t	0.7813	0.0778	0.8542	0.0567	0.0729	0.1263

Note: excluding first & last contests, due to fraction calculations.

Benefits of data availability concentrate among experienced investors

	Dependent variable:		
	Excess Live $SR^{Best}_{i,t}$		
	(1)	(2)	(3)
(Intercept)	-2.181^{***}	-1.959^{***}	-1.470^{**}
	(0.566)	(0.525)	(0.626)
Contests experienced$_{i,t}$	1.030^{***}	1.003^{***}	0.589^{***}
	(0.263)	(0.240)	(0.186)
Macro variables available$_t$		-0.318	-1.352
		(0.609)	(1.069)
Contests experienced$_{i,t}$ $\times$ Macro variables available$_t$			0.908^{**}
			(0.439)
Observations	830	830	830
R^2	0.048	0.053	0.063

Note: standard errors (in parentheses) are clustered by contest and contestant.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Heckit estimates *negative* selection bias after new variables available

Stage		Live $SR^{Best}_{i,t}$		
		All contests	*Contests 1-7*	*Contests 8-12*
1. *Selection*	(Intercept)	1.95^{***}	2.38^{***}	1.50^{***}
		(0.18)	(0.29)	(0.34)
	Contests experienced$_{i,t}$	-0.88^{***}	-1.22^{***}	-0.77^{***}
		(0.05)	(0.10)	(0.05)
	Quantopian search index$_t$	-0.01^{**}	-0.00	-0.00
		(0.00)	(0.00)	(0.00)
	Ratio of entries to contest mean$_{i,t-1}$	0.23^{***}	0.24^{***}	0.22^{***}
		(0.04)	(0.08)	(0.04)
2. *Outcome*	(Intercept)	-0.42^{***}	-0.79^{**}	-0.04
		(0.13)	(0.32)	(0.17)
	Contests experienced$_{i,t}$	0.84^{***}	0.55	0.86^{***}
		(0.17)	(0.39)	(0.20)
	ρ	-0.39	0.17	-0.55
	σ	2.13	1.89	2.31
	Inverse Mills Ratio	-0.83^{***}	0.33	-1.27^{***}
		(0.32)	(0.54)	(0.41)
	R^2	0.04	0.07	0.04
	Num. obs.	1482	482	1000
	Censored	621	163	458
	Observed	861	319	542

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

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Stage		Live $SR^{Best}_{i,t}$		
		All contests	*Contests 1-7*	*Contests 8-12*
1. *Selection*	(Intercept)	1.95^{***}	2.38^{***}	1.50^{***}
		(0.18)	(0.29)	(0.34)
	Contests experienced$_{i,t}$	-0.88^{***}	-1.22^{***}	-0.77^{***}
		(0.05)	(0.10)	(0.05)
	Quantopian search index$_t$	-0.01^{**}	-0.00	-0.00
		(0.00)	(0.00)	(0.00)
	Ratio of entries to contest mean$_{i,t-1}$	0.23^{***}	0.24^{***}	0.22^{***}
		(0.04)	(0.08)	(0.04)
2. *Outcome*	(Intercept)	-0.42^{***}	-0.79^{**}	-0.04
		(0.13)	(0.32)	(0.17)
	Contests experienced$_{i,t}$	0.84^{***}	0.55	0.86^{***}
		(0.17)	(0.39)	(0.20)
	ρ	-0.39	0.17	-0.55
	σ	2.13	1.89	2.31
	Inverse Mills Ratio	-0.83^{***}	0.33	-1.27^{***}
		(0.32)	(0.54)	(0.41)
	R^2	0.04	0.07	0.04
	Num. obs.	1482	482	1000
	Censored	621	163	458
	Observed	861	319	542

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Heckit estimates *negative* selection bias after new variables available

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Investor behavior when solving a prediction problem

- We have evidence that investors can underweight genuine predictors, due to a behavioral bias
- What are the consequences of investor bias against predictive variables?
  - Because of unfamiliarity with these variables, for example
- I now show such a bias may lead investors to completely ignore genuinely predictive variables

Baseline prediction problem (1/2)

Investor's goal

- To maximize portfolio OOS Sharpe Ratio over fixed horizon:

$$\max_{\boldsymbol{w}} \frac{\boldsymbol{\mu}^T \boldsymbol{w}}{\sqrt{\boldsymbol{w}^T \boldsymbol{\Sigma} \boldsymbol{w}}} \tag{3}$$

- Focus on simple case of 1 asset with expected return μ
- Assume second moment is known (Merton 1980)
- Expected return μ must still be estimated

Investor can make use of historical data

- $\boldsymbol{v}$: historical mean returns from (similar but not identical) futures contracts that expired in the past
- $\boldsymbol{S}$: corresponding historical values of some predictive variables

Baseline prediction problem (2/2)

Simple prediction problem

- Expected return is linear in predictive signals:

$$\mu = \sum_{i=1}^{m} b_i s_i = \boldsymbol{s}\boldsymbol{b} \tag{4}$$

- So investor must infer $\boldsymbol{b}$ based on historical data $\boldsymbol{v}$ & $\boldsymbol{S}$
  - Similar to Martin and Nagel (2022)
- Both over- and under-estimates of μ can lead to sub-optimal Sharpe Ratios (Best and Grauer 1991), so penalize both
- Investor could solve this problem by picking $\widehat{\boldsymbol{b}}$ to minimize

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} ||\boldsymbol{v} - \boldsymbol{S}\boldsymbol{b}||_2 \tag{5}$$

Deviating from the rational baseline

- A biased investor who is averse to unfamiliar variables is modeled as fearing worst-case outcomes
  - In the spirit of Cao, Han, Hirshleifer, and Zhang (2011)
- Suppose Nature conspires to maximize the error by perturbing the historical signals, up to an uncertainty set $\boldsymbol{U}$
- The investor acts to minimize the worst-case error

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} \max_{\boldsymbol{U}\in\mathcal{U}} ||\boldsymbol{v} - (\boldsymbol{S}+\boldsymbol{U})\boldsymbol{b}||_2, \tag{6}$$

- This can lead to the biased investor underweighting (or even completely ignoring) genuinely predictive variables
- The next few slides show why, for the special case of a constant bias against variables

Two equivalencies, from ML & optimization literatures

Biased investor's learning problem (6) & the "square-root lasso"

- Assumption on the form of $\boldsymbol{U}$ that the investor perceives: that column-wise perturbations have ℓ_2-norms bounded by δ
- So the investor will solve

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} ||\boldsymbol{v} - \boldsymbol{S}\boldsymbol{b}||_2 + \delta||\boldsymbol{b}||_1 \tag{7}$$

- Due to Xu, Caramanis, and Mannor (2010)

The "square-root lasso" (7) & the lasso

- They're equivalent; i.e. have the same regularization paths up to a one-to-one change of parameters δ for λ, for a fixed $\boldsymbol{v}, \boldsymbol{S}$
- So the investor will solve

$$\min_{\boldsymbol{b}\in\mathbb{R}^m} \frac{1}{2}||\boldsymbol{v} - \boldsymbol{S}\boldsymbol{b}||_2^2 + \lambda||\boldsymbol{b}||_1 \tag{8}$$

- See Tian, Loftus, and Taylor (2018) and Xu, Caramanis, and Mannor (2010)

Consequences of a bias against predictive variables

Sparse closed-form solution to the biased prediction problem

- Under an orthonormality assumption on $\boldsymbol{S}$, the investor's estimates of each element k of $\boldsymbol{b}$ incorporate sparsity:

$$\widehat{b}_k = \mathrm{sign}(\boldsymbol{s}_k^T \boldsymbol{v}) \max\left\{|\boldsymbol{s}_k^T \boldsymbol{v}| - \lambda, 0\right\}, \tag{9}$$

- $\lambda \geq 0$ bounds the magnitude of perturbations she fears Nature will inject $\Rightarrow$ captures the effect of the investor's bias
- Higher λ threshold $\Rightarrow$ fewer predictive variables incorporated by the investor into her (biased) learning problem

Test: (in)experience and variable usage

- Evidence that inexperienced investors are biased
- Do inexperienced investors actually use fewer predictive variables?
- Test this by numerical estimation on investor daily returns

Estimating investors' usage of predictive variables

- Tackle this by estimating the lasso:

$$\min_{\boldsymbol{b} \in \mathbb{R}^m} ||\boldsymbol{v} - \boldsymbol{S}\boldsymbol{b}||_2^2 + \lambda ||\boldsymbol{b}||_1 \tag{10}$$

- Back out an investor's estimated $\widehat{\boldsymbol{b}}$ using Friedman, Hastie, Höfling, and Tibshirani (2007)'s min. algorithm, and $\widehat{\lambda}$ by cross-validation

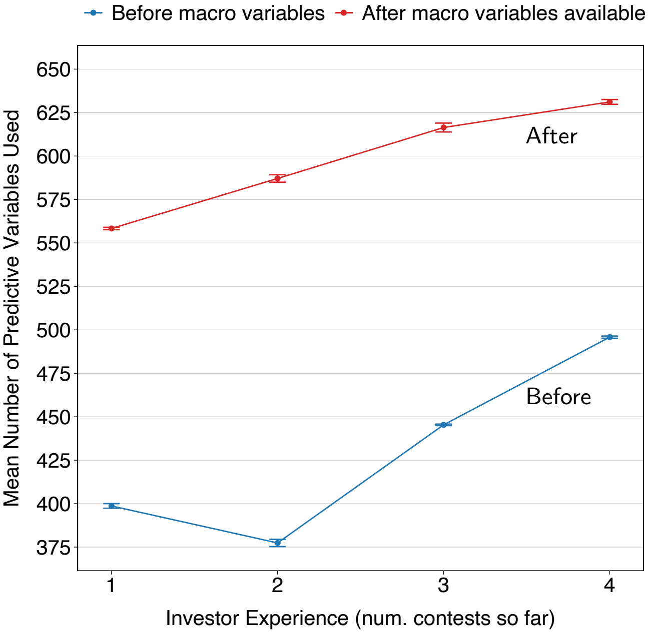
- $\boldsymbol{S}$: 880 lagged predictive variables based on daily futures market data, and the values of the additional 54 macroeconomic variables when available

- $\boldsymbol{v}$: daily portfolio returns of the investor

- Estimate at the investor-contest level

- Report the number of non-zero $\widehat{\boldsymbol{b}}$ values, i.e. variables used

Inexperienced investors ignore more predictive variables



Main takeaways

- When investors face a prediction problem, their behavioral biases play an important role in how they use data
  - They overly rely on familiar variables...
  - ... even for "hard" information that they are endowed with
  - Big(ger) Data is not necessarily helpful
- Corollaries:
  - Investors mis-specify their models of the world
  - Machine traders encode human biases
- Investors who *do* overcome their biases (with experience) benefit substantially from data availability
  - Economically significant: up to 2 units of OOS SR
  - Involves assigning a higher weight to genuine predictors

Thank you!

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