

**Wisdom or Whims**  
**Decoding the Language of Retail Trading**  
**with Social Media and AI**

by Chen, Peng and Zhou

Discussion by J. Anthony Cookson  
(CU Boulder)

# How to think about *retail* investment strategies?

**Retail traders have become more important.**

- Rise in past decade in retail trading
- Concurrent rise in investor social media

**Their strategies are not *that* well understood.**

- AP anomalies as strategies
- Disposition effect, horizon differences
- Knowledge, to date, pretty indirect

# How can we learn about investment strategies?

## **Existing work has used self-declaration**

- My own paper (Cookson and Niessner 2020) looked at *static* strategies, disclosed in StockTwits user profiles

## **Static strategies are not useful for looking at adoption of strategies**

- Enter this paper, which marries LLMs and social media to tackle this question

# What this paper does

- **Develops LLM classifiers** about whether a tweet 1) is about a strategy, 2) if so, is that strategy “technical,” “fundamental,” or “other.”
- Studies the **incidence** of and **covariates** of these strategies as well as the **return performance** to following these signals, as well as **retail trading** following them.

# What this paper finds

- Three main results stood out:
  - **Strategy malleability.** Users go “in and out” of technical versus fundamental strategies.
  - **Return differences.** Following technical sentiment signals underperforms while following fundamental sentiment outperforms.
  - **Retail trading patterns.** All kinds of sentiment correspond to retail trading, but retail trading is more informed if it follows fundamental sentiment.

# My take and discussion

## Take

- Impressive work combining social media data and LLM classification
- Takeaways that resonate well and are non-trivial

## Discussion

- Nature of Differences
- Stability of Differences.
- Classification and measurement questions

# Comment 1

## *Understanding the Nature of the Tech/Fund Difference*

Main result is in a simple one-day-forward regression:

	Return <sub><i>i,t+1</i></sub> (%)				
	(1)	(2)	(3)	(4)	(5)
Sentiment <sub><i>i,t</i></sub> <sup>TA</sup>	-0.016** [-2.19]				-0.015** [-2.25]
Sentiment <sub><i>i,t</i></sub> <sup>FA</sup>		0.014** [2.17]			0.017*** [2.88]
Sentiment <sub><i>i,t</i></sub> <sup>OS</sup>			-0.027*** [-3.57]		-0.026*** [-3.73]
Sentiment <sub><i>i,t</i></sub> <sup>NS</sup>				-0.003 [-0.56]	-0.002 [-0.30]
Attention <sub><i>i,t</i></sub>	-0.056*** [-5.47]	-0.056*** [-5.50]	-0.056*** [-5.46]	-0.056*** [-5.48]	-0.056*** [-5.47]
Stock Characteristics	Yes	Yes	Yes	Yes	Yes
Lagged Returns	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
N	2,974,304	2,974,304	2,974,304	2,974,304	2,974,304
R <sup>2</sup>	0.089	0.089	0.089	0.089	0.089

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Aside from being “other” strategy, why not emphasize this difference?



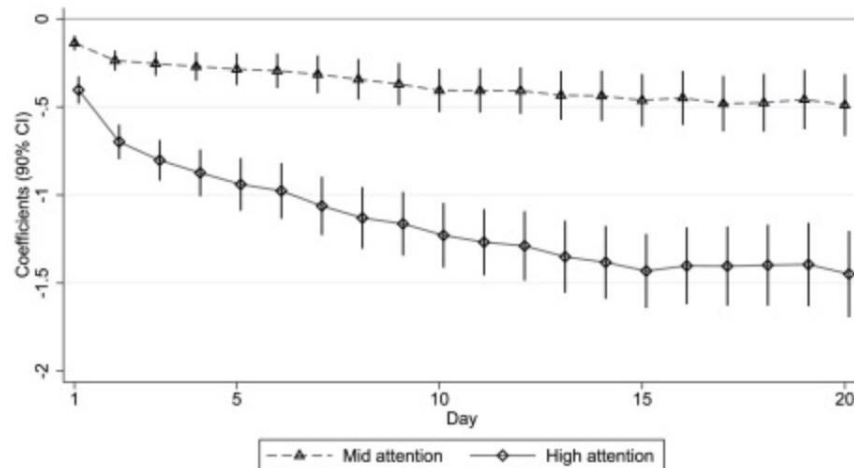
# Comment 1

## *Understanding the Nature of the Tech/Fund Difference*

Focus on tech/fund difference is well motivated, but still multiple reasons why?

- Paper addresses these questions using trading, but can do more with returns

*We faced a similar issue with “The Social Signal”*



(b) Attention signal

# Comment 1

## *Understanding the Nature of the Tech/Fund Difference*

**Day t analysis** helped point to a reversal

Table 7. How do same-day returns and retail trading relate to social signals?

	Dependent var.:					
	AR <sub><i>i,t</i></sub> (%)		RT imbalance <sub><i>i,t</i></sub> (%)		RH user ratio <sub><i>i,t</i></sub> (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Sentiment PC1<sub><i>i,t</i></sub> (z)</b>	1.591*** (0.036)	1.498*** (0.033)	0.781*** (0.046)	0.655*** (0.043)	1.373 (1.025)	1.182 (1.055)
<b>Attention PC1<sub><i>i,t</i></sub> (z)</b>	3.630*** (0.734)		1.084*** (0.214)		7.033*** (1.701)	
<b>Mid attention<sub><i>i,t</i></sub></b>		1.496*** (0.058)		2.000*** (0.089)		1.897*** (0.531)
<b>High attention<sub><i>i,t</i></sub></b>		4.049*** (0.155)		3.969*** (0.143)		5.976*** (1.337)

# Comment 1

## Nature of Tech/Fund Differences

Suggestions:

1. Worth contrasting with what happens concurrently or in a window.
2. May also be worth understanding what drives patterns with “other strategies” especially given the larger magnitudes and stronger persistence.
3. Interesting (important?) to break attention out separately by different categories.
  - Does technical message volume exhibit stronger return reversal?

# Comment 2

## GameStop Analysis is *striking*

	Return <sub><math>i,t+1 \rightarrow t+5</math></sub> (%)		Return <sub><math>i,t+6 \rightarrow t+10</math></sub> (%)		Return <sub><math>i,t+11 \rightarrow t+15</math></sub> (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Sentiment <sub><math>i,t</math></sub> <sup>TA</sup>	-0.060*** [-3.65]	0.284*** [3.03]	-0.056*** [-3.65]	0.252*** [2.64]	-0.016 [-1.09]	0.144 [1.62]
Sentiment <sub><math>i,t</math></sub> <sup>FA</sup>	0.052*** [3.88]	0.132** [2.15]	-0.002 [-0.12]	0.024 [0.40]	-0.001 [-0.08]	-0.061 [-0.89]
Sentiment <sub><math>i,t</math></sub> <sup>OS</sup>	-0.091*** [-5.30]	-0.019 [-0.23]	-0.046*** [-2.73]	0.238*** [2.64]	-0.036** [-2.28]	0.281*** [3.37]
Sentiment <sub><math>i,t</math></sub> <sup>NS</sup>	-0.027** [-2.37]	-0.045 [-0.75]	-0.001 [-0.12]	0.138** [2.04]	0.007 [0.64]	0.089 [1.39]
Sentiment <sub><math>i,t</math></sub> <sup>TA</sup> × Post-GameStop Episode		-0.455*** [-3.20]		-0.468*** [-3.39]		-0.295** [-2.12]
Sentiment <sub><math>i,t</math></sub> <sup>FA</sup> × Post-GameStop Episode		-0.176* [-1.83]		-0.173* [-1.84]		-0.043 [-0.44]
Sentiment <sub><math>i,t</math></sub> <sup>OS</sup> × Post-GameStop Episode		-0.219* [-1.67]		-0.455*** [-3.28]		-0.491*** [-3.85]
Sentiment <sub><math>i,t</math></sub> <sup>NS</sup> × Post-GameStop Episode		-0.113 [-1.25]		-0.345*** [-3.65]		-0.220** [-2.30]
Attention <sub><math>i,t</math></sub>	-0.164*** [-8.91]	-0.026 [-0.13]	-0.083*** [-6.05]	0.046 [0.32]	-0.065*** [-5.34]	0.119 [1.00]
Stock Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Returns	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

# Comment 2

## (In)stability over time?

	Return <sub><i>i,t+1</i>→<i>t+5</i></sub> (%)		Return <sub><i>i,t+6</i>→<i>t+10</i></sub> (%)		Return <sub><i>i,t+11</i>→<i>t+15</i></sub> (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Sentiment <sub><i>i,t</i></sub> <sup>TA</sup>	-0.060*** [-3.65]	0.284*** [3.03]	-0.056*** [-3.65]	0.252*** [2.64]	-0.016 [-1.09]	0.144 [1.62]
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Stock Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Returns	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

# Comment 2

## Instability over time

Suggestions:

1. Explore how the coefficients change yearly or for two-year windows within the sample.
2. Might returns to following technical be less stable than fundamental?
  - To extent that technical rules take advantage of anomalies, could relate to Farmer, Schmidt and Timmerman's "pockets of predictability"?
3. Might be worth relating to other events aside from GameStop (a flexible picture of how the loading change over time would help inform this...)

# Comment 3

## Evidence of Malleable Strategies

- I like the validation of the LLM classification against self-reported strategies & other characteristics:

Panel A. Determinants of Technical Analysis Usage						
	(1)	(2)	(3)	(4)	(5)	(6)
Technical Investor <sub>j</sub>	0.103*** [19.74]	0.075*** [17.50]	0.076*** [17.60]	0.068*** [17.42]		
Swing or Day Trader <sub>j</sub>		0.020*** [3.39]	0.022*** [3.89]	0.022*** [4.22]		
Long-Term Investor <sub>j</sub>		-0.028*** [-6.10]	-0.028*** [-6.44]	-0.023*** [-5.65]		
Professional <sub>j</sub>		0.047*** [6.45]	0.044*** [6.23]	0.033*** [5.30]		
Novice <sub>j</sub>		-0.022*** [-7.46]	-0.018*** [-6.21]	-0.013*** [-5.31]		
Abnormal Turnover <sub>i,t</sub>			-0.003*** [-2.99]	-0.005*** [-6.37]	-0.003*** [-7.45]	-0.003*** [-8.10]
Abnormal News <sub>i,t</sub>			-0.006*** [-9.73]	-0.005*** [-11.86]	-0.003*** [-12.15]	-0.002*** [-10.15]
Technical <sub>i,j,t,n</sub> <sup>TF-IDF</sup>			0.825*** [40.95]	0.798*** [40.26]	0.683*** [42.09]	0.653*** [39.56]
Fundamental <sub>i,j,t,n</sub> <sup>TF-IDF</sup>			-0.664*** [-27.39]	-0.632*** [-26.73]	-0.533*** [-28.29]	-0.498*** [-28.52]
Log(Number of Words <sub>i,j,t,n</sub> )			0.047*** [16.62]	0.049*** [18.92]	0.044*** [28.62]	0.043*** [26.76]
Date FEs	No	No	No	Yes	Yes	Yes
Stock FEs	No	No	No	Yes	Yes	No
Investor FEs	No	No	No	No	Yes	No
Stock × Investor FEs	No	No	No	No	No	Yes
N	21,641,362	21,641,362	21,641,362	21,641,218	21,623,813	20,630,883
R <sup>2</sup>	0.022	0.030	0.063	0.084	0.213	0.287



# Evidence of Malleable Strategies

- I like the validation of the LLM classification against self-reported strategies & other characteristics.
- The visualization is compelling too:





# Evidence of Malleable Strategies

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- The visualization is compelling too:

Cookson and Niessner (2020)



Panel A: Most Salient Words Used by Approach	
Approach	Most Common Unique Words
Fundamental	eps, sales, growth, sentiment, read, revenue, earnings, million, quarter, consensus, billion, share, cash, results, analysts
Technical	chart, support, nice, break, looking, looks, gap, move, day, stop, calls, daily, close, resistance, bounce
Momentum	play, calls, time, via, week, day, news, squeeze, hod (high of day), hit, shares, cover, highs, run, money
Value	view, attempts, bulls, rising, aboard, stair, intraday, correction overextended, breakdown, fresh, mayb, steak, moved, rollout

# Comment 3

## Evidence of Malleable Strategies

- I like the validation of the LLM classification against self-reported strategies & other characteristics.
- The visualization is compelling, but why phrase “strategies” this way when StockTwits has value, growth, momentum...?

You have a deep understanding of the language of social media and financial markets. Please analyze the message from an investor social media platform. Please parse the message along two dimensions. 1)

Presence of investment strategy (e.g., technical analysis, fundamental analysis, event-driven strategy, arbitrage strategy). If true, please answer 1, otherwise 0. 2) if a strategy is identified, please specify the strategy

Output in JSON format: {"has\_strategy":, "strategy\_type": }.

# Comment 3

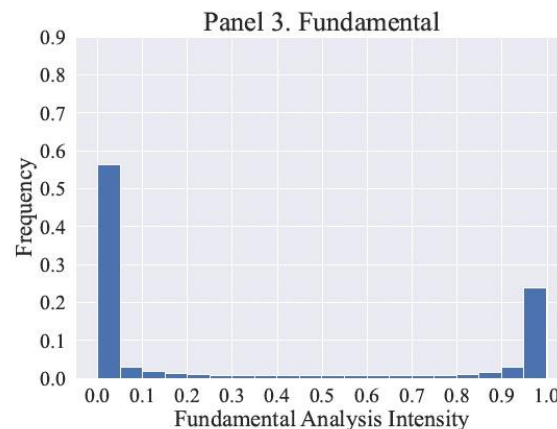
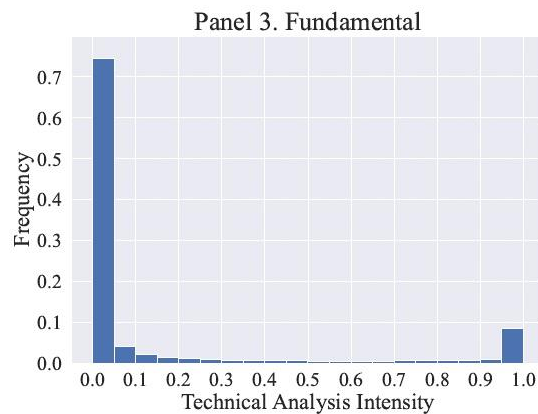
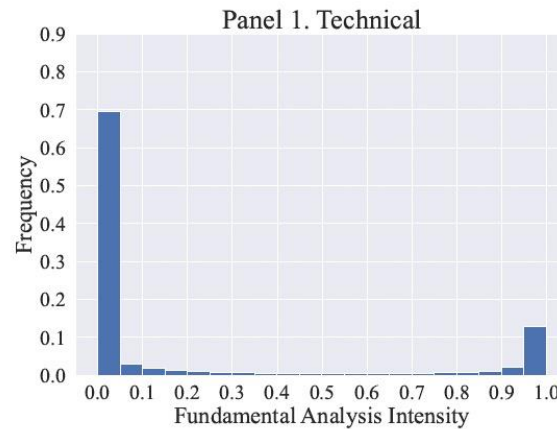
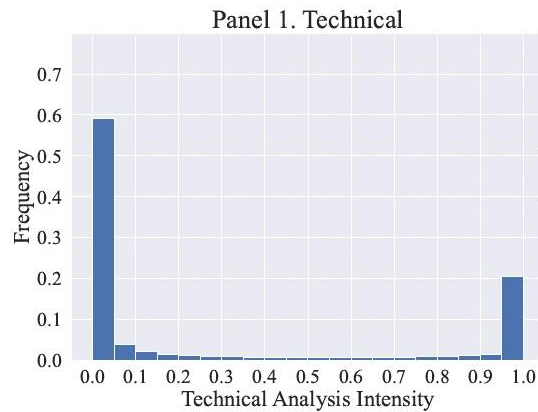
## Evidence of Malleable Strategies

- I like the validation of the LLM classification against self-reported strategies & other characteristics.
- The visualization is compelling, but why exclude value, growth, momentum...?
- This is particularly puzzling because “other” seems to have some interesting return predictability.
  - Is “other” absorbing some of these other strategies OR do fundamental/technical mostly absorb those?

# Comment 3

## Evidence of Malleable Strategies

Another cut at this same idea (Figures 1 and 4):



Main “insights” have to do with the height of the masses at 1, but...

- The big mass at zero draws a lot of attention.

Two possible interps:

- About 10% of posts are misclassified.
- Strategies are *truly* malleable.

# Comment 3

## Evidence of Malleable Strategies

Suggestions:

- Highlighting anecdotes where truly fundamental users make blatantly technical statements (or vice versa).
- Perform an analysis of “technical messages made by so-called fundamental users” (and vice versa)
  - Do these look different than the typical fundamental post?

# Summing up

- Ambitious project with some truly novel results.
- Questions about nature and stability of this difference have no “wrong answers,” but they’ll make the paper more complete.
- Looking forward to seeing the next draft.