Comprehending the Influence of Oil Shock News

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Comprehending Human Languages

- Machine learning techniques developments:

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  - Large language models (*LLM*)

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- **Comprehending human languages is a text-specific task:**
  - Example: The word "*strike*," whih can have a **negative** connotation in a labor context but a **positive** one in a sports context.

Comprehending Human Languages

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Comprehending Human Languages

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  - **FinGPT** (Yang et al., 2023)
- *How do LLMs help us comprehend human language text compared to conventional dictionary methods, and does the comprehensibility of the text matter?*

1. Background
2. Methodology and Data
3. Results and Discussions

Data

- Oil shock news from 1986 to 2019

Data

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  - From financial newspapers and wire feeds, Financial Times, New York Times, Wall Street Journal, Dow Jones Institutional News, Weekly Energy News

U.S. Stocks Give Up Gains After Jobless Claims

Publication info: Dow Jones Institutional News ; New York [New York]23 Apr 2020.

https://login.ezproxy.lib.ou.edu/login?url=https://search.proquest.com/docview/2393956017?accountid=12964

Abstract: None available.

Links: http://libraries.ou.edu/eresources/resolver.aspx?rft.genre=article&rft.atitle=U.S.+Stocks+Give+Up+Gains+After+Jobless+Claims&rft.au=&rft.volume=&rft.issue=&rft.spage=&rft.date=2020&rft.btitle=&rft.jtitle=Dow+Jones+Institutional+News&rft.issn=&rft.isbn=&sid=ProQ%3Aabidateline_

http://libraries.ou.edu/eresources/resolver.aspx?rft.genre=article&rft.atitle=U.S.+Stocks+Give+Up+Gains+After+Jobless+Claims&rft.au=&rft.volume=&rft.issue=&rft.spage=&rft.date=2020&rft.btitle=&rft.jtitle=Dow+Jones+Institutional+News&rft.issn=&rft.isbn=&sid=ProQ%3Aabidateline_

Full text: By Caitlin Ostroff and Joanne Chiu
U.S. stocks pared gains Thursday as investors digested the latest coronavirus news and the Labor Department said the weekly number of Americans applying for jobless benefits eased slightly.
The Dow Jones Industrial Average rose 39 points, or 0.2%, giving up much of the 400 points they had gained earlier in the session. The S&P 500 slipped less than 0.1%, and Nasdaq Composite was essentially flat as of the 4 p.m. close of trading in New York.
All three indexes are on course for modest weekly losses, following a sharp selloff to start the week when turmoil in the oil market pulled U.S. crude prices negative for the first time ever.
Stocks lost some of their momentum in afternoon trading on reports that cast doubt on the effectiveness of remdesivir, the Gilead Sciences drug under investigation as a potential treatment for Covid-19. Gilead shares dropped 4%.
Stocks have swung wildly since the coronavirus pandemic effectively brought the economy to a halt. The Dow and S&P 500 have rebounded sharply since late March but remain down more than 13% for the year. The Nasdaq Composite, on the other hand, is off just 5% in 2020 as big technology stocks have powered much of the recent rebound.
"The markets completely lack direction," said Agnes Belaisch, chief European strategist at Barings

Methodology and Data

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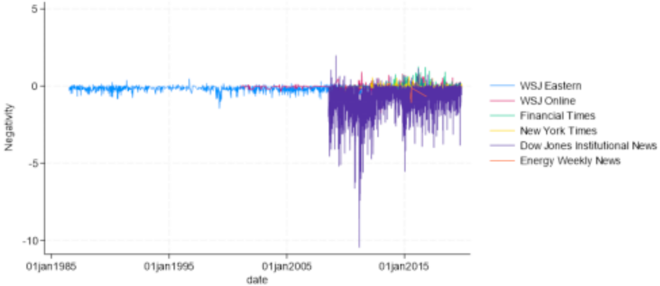
  - Sentiment: **Prompt asks FinGPT "What is the probability of classifying the news as positive, negative, or neutral?"**

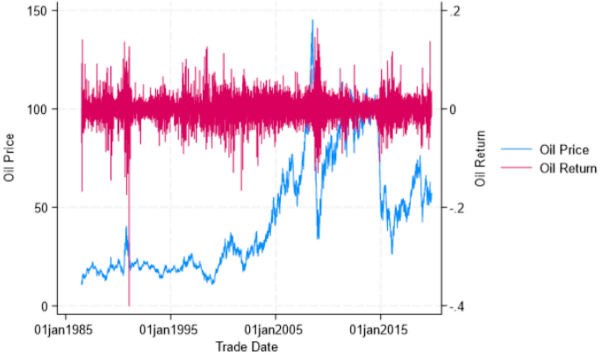
$$\text{Sentiment\_GPT} = P(\text{negative}) - P(\text{positive}).$$

$$\text{Sentiment}_t = \sum_{n=1}^{N} \text{Sentiment}_{n,t},$$



Methodology and Data

- Daily oil price returns: WTI nearest-term futures prices from CME



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- **Number:** the percentage of numerical text in the news article, e.g. 10, 2, 34.3

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$$R_t = \beta_0 + \beta_1 \,\text{Sentiment}_t + \Delta_t + \sum_{i=1}^{4} \theta_i \, R_{t-i} + \sum_{i=1}^{3} \gamma_i \,\text{Sentiment}_{t-i} + \varepsilon_t \quad (1)$$

Oil Return	**Fog Index**			**Sureness**			**Number**		
	Coef.	**S.E.**	**p**	**Coef.**	**S.E.**	**p**	**Coef.**	**S.E.**	**p**
Sentiment	-1.776	0.673	0.008 ***	-1.665	0.061	0.006 ***	-0.102	0.057	0.075 *
Moderator	-0.043	0.010	0.000 ***	-4.307	9.785	0.004 ***	-0.263	0.060	0.000 ***
Interaction	-0.006	0.003	0.030 **	-0.631	0.220	0.004 ***	-0.575	0.177	0.001 ***

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- Difficulty to read, sureness in tones, and percentage of numerical text reinforce the impacts of FinGPT sentiments on oil returns

Comparing Techniques: Predicting Powers

Mean prediction errors *(compare median)*	**(1)** *Full sample*	**(2)** *Readability<*	**(3)** *Sureness<*	**(4)** *Number>*
Observations	3,915	2,638	1,296	2,643
LMP	1.244	-6.229	6.075	-0.887
HL	0.854	-2.195	5.970	1.956
GPT	1.212	-1.246	4.983	1.504

- Comparing the LLM technique with conventional dictionary methods: Three sentiments measured (negativity-positivity):

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  - Less sureness in tones: GPT lowest prediction errors
  - Higher percentage of numerical text: medium prediction errors

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  - Controlling: Day of week and the dummy News Day=1 for coverage days

Impacts of Sentiments on Return Responses

$$AR_t/CAR_t = \beta_0 + \beta_1\,\text{Sentiment}_t + \Delta_t + Dummy_{NewsDay} + \varepsilon_t \quad (2)$$

Regressions	**AR**			**CAR3**			**CAR5**		
	Coef.	**S.E.**	**p**	**Coef.**	**S.E.**	**p**	**Coef.**	**S.E.**	**p**
Sentiment	0.169	0.114	0.137	0.531	0.334	0.118	0.937	0.566	0.098 *
News Day	0.031	0.022	0.165	0.102	0.067	0.128	0.182	0.111	0.102
Day of Week	Yes			Yes			Yes		
Constant	0.026	0.003	0.000 ***	0.078	0.010	0.000 ***	0.130	0.016	0.000 ***
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- AR (FF4 alpha), CAR3/CAR5: cumulative 3/5-day alphas
- Regressing the (cumulative) abnormal returns on the FinGPT sentiment:
  - Sentiments does not lead to significant differences in the return responses to oil shock news

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