Paper Fong: Analysing the behaviour finance impact of 'fake news' phenomena on financial markets: a representative agent model and empirical validation

1)

How can we modelize fake news? And how it impacts the financial markets? (returns of a company)

2)

The authors made an empirical experiment to test their hypothesis:

As existing models and literature remain insufficient in fully explaining how fake news can contradict the efficient-market hypothesis and rationally have impacts on financial markets and prices, a new full model needs to be built to effectively achieve this.

As shown in the "Literature review" section, prior literature proves that fake news empirically generates initial price impacts on financial securities (defined in this paper as fake news' primary impact). As previously discussed, these represent price overreactions that contradict the efficient-market hypothesis—which this paper aims to formally rationalise through an economic model.

Prior literature and models of price underreactions and overreactions fail to satisfactorily fully explain why or how this primary impact can arise in financial markets. Therefore, to reconcile this with empirically-observed short-term underreactions to real news, this section proposes an original unified representative agent model of price underreaction/ overreaction. Motivated by established behavioural finance biases, the model is driven by bounded rationality over uncertainty in information veracity.

Setting up the model

The model uses a sole representative investor, which therefore sets the security's market prices based on their personal valuation, P.
News shocks are simplified to convey direct information on the security's exogenously generated true value.
For this model, this is akin to each investor simultaneously receiving each news shock through the same (and only) news outlet—so the only consideration is the actual shock itself.
The model additionally simplifies news shocks into two distinct extremes: real and fake. Real shocks in this model are accurate and unambiguous numerical indicators of a security's value, occurring whenever this value updates. Fake shocks in this model convey similar numerical indicators of a security's value, but are conversely purely spurious.
As this model's news shocks directly convey a security's numerical value, only one is ever contemporaneously accurate; the rest must be fake or outdated.

The model starts at time 0 with a real news shock, I_0, forming the initial P. This valuation evolves with subsequent news shocks, based on a weighted average.
News shock, I_n, occurs at period $t = n$, where n _ $\{0, . . . ,M\}$. M represents the period of the latest news shock. The model assumes a maximum of one news shock per period.

Information weight determinants: base model

The agent's security valuation, P, is a weighted average of news shocks, I_n, weighted by their weighted shares, θ_n:

$$P = \sum_{n=0}^{M} \underbrace{\theta_n}_{\text{Shares}} \underbrace{I_n}_{\text{News shock}}; \ \sum_{n=0}^{M} \theta_n = 1$$

The weighted shares for individual news shocks are determined by the size of their information weights, S_n, relative to the sum of all information weights, so the weighted shares sum to 1:

$$\theta_n = \frac{\overbrace{S_n}^{\text{Size of their information weight}}}{\underbrace{\sum_{n=0}^{M} S_n}_{\text{Sum of all the information weight = 1}}}$$

The information weights, S_n, represent the relative importance of the different news shocks to the agent. Therefore, P represents a weighted average of the valuations conveyed by the news shocks, weighted by their relative importance to the agent.

We know gonna see three terms:

-base value (a)
-irrelevant factor (b)
-time decay factor (c)

(a)*(b)*(c) = information weight

Base value

The primary determinant of a news shock's information weight is its base value

This is determined by the binary variable representing the news shock I_n's nature, $\omega_n \in \{0, 1\}$, and the investor's ability to distinguish this nature, $\rho \in [0.5, 1]$:

$$S_n(base) = [\rho\omega_n + (1-\rho)(1-\omega_n)] \in [0, 1]$$

$\omega_n = 1$ indicates I_n is real
$\omega_n = 0$ indicates I_n is fake.
p= 1 indicates an agent perfectly able to distinguish between real and fake news,
p = 0.5 indicates an agent perfectly unable to distinguish between the two.

S_n(base) measures the agent's certainty of the news shock's veracity.
If agents are perfectly sure that I_n is real, they will value I_n fully as the security value => S_n(base) = 1.
If they are perfectly sure that I_n is fake, they will be certain of its spuriousness and ignore it => S_n(base) = 0.
Therefore, as p increases, agents place more weight on real news and less on fake news.
However, as p decreases towards 0.5, the agent grows more uncertain of which type they face, optimizing over this constraint by placing increasingly similar middling weights on both.

In this paper's model, real and fake news only differ in credibility, represented by ω_n

The model therefore assumes that real news shocks are fully credible ($\omega_n = 1$), while fake news shocks are completely non-credible ($\omega_n = 0$).

This paper therefore assumes that agents ideally fully rely on credibility, ω_n, to determine their value of a security, but are constrained by their ability to actually distinguish ω_n.
Thus, as p determines the agent's ability to distinguish ω_n. P determines how much agents rely on credibility to determine confidence.
Therefore, the lower an agent's p, the more constrained they are from relying on credibility; making them more underconfident in real news and overconfident in fake news.

Irrelevance factor or old news

With perfect ability to distinguish information veracity, p = 1 , previous news shocks should become immediately irrelevant once updated real information is introduced; or remain unaffected if new fake information is introduced.

without p = 1, agents are not certain of a shock's veracity.

old shocks grow increasingly irrelevant over time. For real news, this could be because updated real information's credibility remains persistently robust; so over time an updated real shock's veracity can be increasingly relied on.

Since older information naturally becomes harder to recall over time, after updated information is introduced. Therefore, older news shocks grow increasingly irrelevant, conditional on the agent's certainty in the updated shock's veracity.

These dynamics are modelled by an irrelevance factor:

$$S_n(irr.) = \left[\prod_{j>n}^{M} [\delta(1-\rho)]^{(t-t_j+1)[\rho\omega_j+(1-\rho)(1-\omega_j)]}\right] \in [0,1]$$

For each more updated news shock, $I_{j>n}$, introduced, I_n's weight is multiplied by an additional irrelevance term; which individually and jointly decrease (or at most maintain) I_n's weight, since each term $\in[0, 1]$.

Each irrelevance term can be decomposed into four components: the irrelevance multiplier, $\delta \in [0, 1]$; the investor's inability to distinguish between real and fake news, $(1 - p) \in [0, 0.5]$; the time since news shock $I_{j>n}$ was introduced, $(t - t_j + 1) \geq 1$; and the base value of updated news shock $I_{j>n}$, $[p\omega_j + (1 - p)(1 - \omega_j)] \in [0, 1]$.

An investor better at distinguishing information veracity relies less on past information, decreasing I_n's weight further for every new shock introduced, through a lower $(1 - p)$; which can be amplified by a non-unitary δ, to represent a greater bias against old news. At the limit, a perfectly competent agent with $(1 - p) = 0$, fully discounts I_n once a new real shock occurs.

This base value and $\delta(1 - p)$ are $\in [0, 1]$, so the irrelevance term increases towards 1 as certainty in $I_{j>n}$'s veracity decreases.

At the limit, with perfect certainty in $I_{j>n}$'s spuriousness, $I_{j>n}$'s base value equals 0, so $I_{j>n}$'s overall irrelevance factor equals 1; so, $I_{j>n}$ leaves I_n's information weight unaffected.

with perfect certainty in $I_{j>n}$'s veracity, $I_{j>n}$'s base value equals 1 and $(1 - p)$ equals 0, so I_n is fully discounted

This starts at 1 upon $I_{j>n}$'s introduction, since the introduction of new shocks immediately affects the relevance of old information.

Time decay factor of spurious information:

Spurious information's credibility decays over time since, without any solid supporting evidence, spurious rumours progressively lose believability.

empirically demonstrating that, even without outright debunking, fake news' average initial price impacts on small firms fully reverse within a year.
This is represented through a spurious information time decay factor, $\delta \in [0, 1]$:

$$S_n(time\ decay) = \left[\varphi^{(1-\omega_n)(t-t_n)}\right] \in [0, 1]$$

ω_n: credibility of the news

$\delta = 0$ => spurious information is perfectly temporary and decays after fully one period
$\delta = 1$ => spurious information suffers no additional time decay

This is modified by $(1 - \omega_n)$ in the exponent, neutralizing S_n(time decay) into 1, leaving I_n's information weight unaffected unless I_n is fake.
This factor is amplified by the $(t - t_n)$ term in the exponent, diminishing I_n's weight further as more time passes since I_n's introduction (if I_n is spurious).

Information weight determinants: fake-news specific

This paper also proposes an extended 'full' model, incorporating fake news-specific effects drawn from existing literature on fake news' characteristics. Therefore, two additional determinants of information weight are included for the full model: the virality factor, and the fake news uncertainty factor.

Virality factor of fake news

Fake news is structured to shock and convince, maximising initial impacts to spread faster and deeper than real news.

This is represented through a fake news virality factor, δ ≥1:

$$S_n(viral) = \left[\alpha^{(1-\omega_n)(1-\rho)}\right] \geq 1$$

α=1 => indicate that fake news in the model is unaffected by virality effects. This factor is also modified by (1-ωn) in the exponent.
This term ensures that, unless I_n is fake and $\_n = 0$, the entire S_n(viral) factor is neutralized to S_n(viral) = 1 , which thereby leaves I_n 's information weight unaffected.
This factor is also modified by the agent's inability to distinguish information veracity,(1 − p) , in the exponent; since less capable agents are more susceptible to fake news virality.
In comparison, the base model ignores fake news' differentiating characteristics from real news, and assumes that "strength" remains equal across both fake news and real news shocks of equal magnitude. As such, this is effectively represented in the full model by the virality factor, with fake news shocks having greater "strength" than real news shocks, as long as δ > 1.

Fake news uncertainty factor

As we know fake news decreases responsiveness to subsequent news shocks. This enters the model as an investor becoming less able to distinguish information veracity upon learning of fake news' presence.

This fake news uncertainty effect is modelled through a new equation for the investor's ability to distinguish between real and fake news, p:

$$\rho = \left[1 - \left[0.5\left(\frac{1-\rho_0}{0.5}\right)^{1-\gamma\mu}\right]\right] \in [0.5, 1]$$

Where:

-pO ∈ [0.5, 1] is initial ability
-(1 − p_0) ∈ [0, 0.5] measures initial inability
- γ ∈{0, 1} is a binary variable indicating fake news' signaled presence in the security
-μ ∈ [0, 1] represents the fake news uncertainty factor

This therefore models the fake news uncertainty effect as a simple modifier affecting the investor's percentage inability, from which the new investor ability can be rederived.

(1 − γμ) determines the magnitude of the fake news uncertainty effect, depending on the agent becoming aware of fake news' presence.

If γ= 0, fake news' presence is not signaled, transforming the uncertainty exponent to 1, so investor ability remains unchanged po=p

γ = 1 indicates fake news' signaled presence, so the uncertainty exponent would be ∈[0, 1]

If both the uncertainty exponent and the percentage investor inability are ∈ (0, 1) , this increases the percentage investor inability, decreasing $p < p_0$.

The rate of decrease depends on μ. As μ increases, the uncertainty exponent decreases, further decreasing p. If μ = 1, discovering fake news renders the agent perfectly unable to distinguish information veracity. If μ = 0, this has no effect.

Complete Model

The representative agent's security valuation, P , is formed as follows:

$$P = \sum_{n=0}^{M} \theta_n I_n; \quad \theta_n = \frac{S_n}{\sum_{n=0}^{M} S_n}$$

Base model

Table 1 Model terms

P	Security valuation for the representative agent
t	Time period
I_n	News shock conveying an unambiguous security value at time n
$n \in \{0, \ldots, M\}$	Period, $t = n$, when news shock I_n occurred
$j \in \{0, \ldots, M \| j \rangle n\}$	Period, $t = j$, when news shock $I_{j>n}$ occurred
$\theta_n \in [0, 1]$	Weighted share of news shock I_n; $\sum_{n=0}^{M} \theta_n = 1$
$S_n \geq 0$	Information weight of news shock I_n
$\omega_n \in \{0, 1\}$	Real or fake news indicator for I_n; information credibility
$\rho \in [0.5, 1]$	Ability to distinguish between real and fake news
$\rho_0 \in [0.5, 1]$	Initial ability to distinguish between real and fake news
$\delta \in [0, 1]$	Irrelevance multiplier of old news shocks
$\varphi \in [0, 1]$	Time decay factor of spurious information
$\alpha \geq 1$	Virality factor of fake news
$\gamma \in \{0, 1\}$	Signalled presence of fake news indicator
$\mu \in [0, 1]$	Fake news uncertainty factor

$$S_n = [\rho\omega_n + (1-\rho)(1-\omega_n)]\left[\varphi^{(1-\omega_n)(t-t_n)}\right]\left[\prod_{j>n}^{M}[\delta(1-\rho)]^{(t-t_j+1)[\rho\omega_j+(1-\rho)(1-\omega_j)]}\right]$$

Full model:

The full model's information weight, formed by the determinants in the "Information weight determinants: base model" section, and the fake news-specific determinants in the "Information weight determinants: fake news" section, is given as:

$$S_n = [\rho\omega_n + (1-\rho)(1-\omega_n)]\left[\alpha^{(1-\omega_n)(1-\rho)}\right]\left[\varphi^{(1-\omega_n)(t-t_n)}\right]$$
$$\left[\prod_{j>n}^{M}[\delta(1-\rho)]^{(t-t_j+1)[\rho\omega_j+(1-\rho)(1-\omega_j)]}\right]$$
$$\rho = 1 - \left[0.5\left(\frac{1-\rho_0}{0.5}\right)^{1-\gamma\mu}\right]$$

Impulse-response functions :

- A real news shock, I_1
- A fake news shock, I_1
- A fake news shock, I_1 , followed by a debunking real news shock, I_2

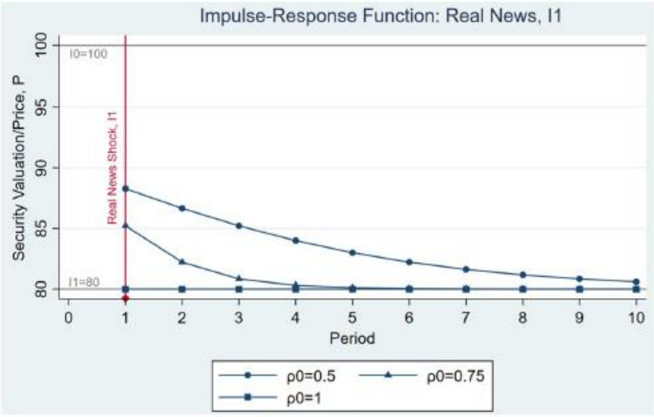

Fig. 1 Impulse-response function: real news, I1

$I_0 = 100$, so P starts at 100
$I_1 = 80$
$I_2 = 100 = I_0$

A debunking shock, I_2 , is used, since debunking represents a subsequent real news shock which contradicts prior fake news, and signaling the presence of prior fake news; thereby activating the fake news uncertainty factor.

The impulse-response functions are modelled with varying initial investor ability, ρ_0

Base Model:
- $\delta = 1$; no additional bias against old news
- $\varphi = 0.6$

Full Model :
- $\alpha = 5$
- $\gamma = 1$; after debunking shock, I_2, signals fake news' prior presence; $\gamma = 0$ otherwise
- $\mu = 0.5$

One real news shock

Fig. 1, display an initial shift (down from $I_0 = 100$) in P when the real news shock occurs, for all values of ρ_0 . This is a full shift to $I_1 = 80$ when $\rho_0 = 1$; with increasing underreaction for lower values of ρ_0.

Underreaction is resolved over time, moving P towards $I_1 = 80$. The rate this occurs at increases with larger ρ_0 values.

This matches the model's theorised dynamics, where less capable investors underreact more to real news, due to conservatism bias from uncertainty over I_1's veracity and qualitatively matches empirical underreactions to real news shocks.

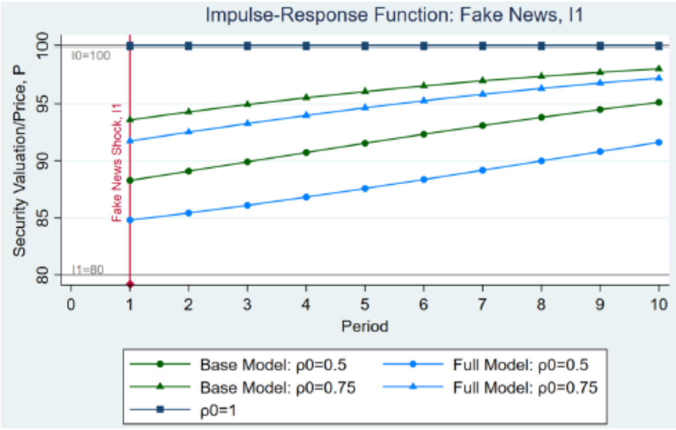

Fig. 2 Impulse-response function: fake news, I1

One fake news shock

Both models are identical when _0 = 1 as the agent is perfectly unaffected by fake news;
P remains at $I_0 = 100$.

the full model (light blue) only adds the virality multiplier, α. This amplifies the fake shock's information weight, compared to the base model (green); weighting the full model closer to $I_1 = 80$ in each period and p_0 value.

Fig. 2, display an initial shift (down from $I_0 = 100$) in Pwhen the fake news shock occurs, for $P_0 < 1$; representing an overreaction to fake news.
This decreases in p_0 , as more capable investors overreact less to fake news, due to greater certainty in I_1's spuriousness; matching the "Information weight determinants: base model" section's theorised dynamics.

The initial shifts for the base model are weaker at every _0 , compared to Fig. 1's shifts under equivalent real news; except when _0 = 0.5 , where agents cannot distinguish information veracity, and initial shifts are equal.

$P_0 > 0.5$, as they show that fake news' initial price effects are empirically smaller than equivalent real news'; indicating that agents empirically can partially distinguish information veracity. Comparatively, the full model is amplified by virality, so the initial shift could be greater than equivalent real news', depending on α.

the initial overreaction reverses over time; moving P back towards $I_0 = 100$. Here, the time decay factor,φ , overrides the irrelevance factor in I_0's information weight,
degrading the fake I_1's credibility over time

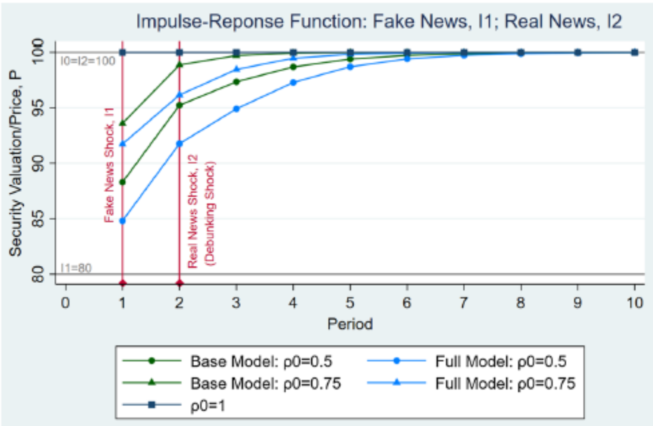

Fig. 3 Impulse-response function: fake news, I1; real news, I2

One fake news shock and one real news shock

Both models are identical when $\_0 = 1$ as the agent is perfectly unaffected by fake news;
P remains at $I_0 = 100$.

For a fake shock followed by debunking, the full model (light blue) adds both the virality multiplier, α , and the fake news uncertainty factor. α enters first, amplifying the full model's fake shock information weights, compared to the base model (green), identically to Fig. 2. After debunking, I_2 , occurs and signals fake news' prior presence, the uncertainty factor enters the full model. This weakens the reversion to I_0 for $p_0 = 0.75$, as awareness of fake news' presence renders the agent less able to distinguish information veracity; so $p < p_0$. The uncertainty factor has no effect when $p_0 = 0.5$ or 1 , as perfectly competent agents are unaffected by fake news and perfectly incompetent agents cannot worsen.

when $\_0 < 1$, this recursion is not immediate. P persistentlydeviates from I_0 several periods after debunking, as agents underreact to I_2 due to conservatism bias from uncertainty over I_2 's veracity.

Underreaction to I_2 increases with weaker spurious information time decay, φ, and lower initial investor capability, p_0 ; as well as with the full model's fake news-specific effects. Specifically, greater fake news virality, α , and greater fake news uncertainty effects, μ , increase underreactions to the debunking real news shock; by persistently boosting the prior fake shock's information weight, and worsening the agent's ability to distinguish information veracity (upon awareness of fake news), respectively.
Therefore, the full model (driven by these fake news-specific effects) predicts a novel secondary fake news impact: that fake news in a security amplifies underreactions to all subsequent real news for the security.

Data description
The 2019 Chinese ADR delisting threat

This paper identifies the 2019 Chinese ADR Delisting Threat as a clear example of fake news and debunking.
This specific event and data set was used, as it was one of the only events which allowed for the full model to be evaluated over a large sample of testable security price data.

The event's timeline proceeds as follows:

11:36am EDT, Friday, September 27, 2019 A Bloomberg News article states that the Trump administration is considering "delisting Chinese companies from U.S. stock exchanges", citing an anonymous source "close to the deliberations"

5:06 pm EDT, Saturday, September 28, 2019 A Bloomberg News article states that U.S. Treasury official Monica Crowley publicly announced via email that "the administration is not contemplating blocking Chinese companies from listing shares on U.S. stock exchanges at this time" debunking Friday's rumour.

This was a high-profile event, which would have reasonably affected all Chinese companies with U.S.-listed shares, of which there were 156 as of February 25, 2019. Therefore, this was an unambiguous example of fake news impacting a large number of public equities, before subsequent debunking.

Event study methodology:

Estimating normal returns

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it};\ E(\varepsilon_{it}) = 0,\ var(\varepsilon_{it}) = \sigma^2_{\varepsilon_i}$$

R_{it} is security i 's return at time t.
R_{mt} is the market return at time t
ε_{it} is a zeromeanerror term.
α_i and β_i are parameters of the market model that would be estimated via OLS regression in the estimation window prior to the event window.
$\sigma^2_{\varepsilon i}$ represents the market model variance.

Abnormal returns and cumulative abnormal returns

$$AR_{it} = R_{it} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{mt}\right) = \hat{\varepsilon}_{it}$$

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it}$$

AR_{it} is security i 's abnormal return at time t .
$CAR_i(t_1, t_2)$ is security i 's cumulative abnormal return, covering t_1 to t_2 .

$\left(\hat{\alpha}_i + \hat{\beta}_i R_{mt}\right)$ is the estimated market model relationship predicting security i 's normal return at time t

The cross-sectional average abnormal returns (AARs) and cumulative average abnormal returns (CAARs) across N sample firms, are calculated as:

$$\overline{AR}_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it};\quad \overline{CAR}(t_1, t_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(t_1, t_2)$$

$\overline{AR}_t$ is the AAR at time t, and $\overline{CAR}(t_1, t_2)$ is the CAAR covering t_1 to t_2.

Hypothesis testing

The traditional t-test statistics for the ARs, CARs, AARs, and CAARs are calculated by dividing their respective values by their respective standard deviations

$$\sigma^2_{AR_i} = \hat{\sigma}^2_{\varepsilon_i} + \frac{1}{L_1}\left[1 + \frac{(R_{mt} - \bar{R}_m)^2}{\hat{\sigma}^2_m}\right]$$

$$\lim_{L_1 \to \infty} \sigma^2_{CAR_i(t_1,t_2)} = (t_2 - t_1 + 1)\sigma^2_{\varepsilon_i}$$

$$\sigma^2_{\overline{AR}_t} = \frac{1}{N^2}\sum_{i=1}^{N}\sigma^2_{AR_i}; \quad \sigma^2_{\overline{CAR}(t_1,t_2)} = \frac{1}{N^2}\sum_{i=1}^{N}\sigma^2_{CAR_i(t_1,t_2)}$$

AR variance is the market model sample variance
$\hat{\sigma}^2_{\varepsilon_i}$ adjusted for forecast error
L_1 is the length of the estimation window
$\bar{R}_m$ average market return over the estimation window
$\hat{\sigma}^2_m$ sample market variance over the estimation window

With large estimation windows, the forecast error asymptotically converges to zero,.

$\sigma^2_{AR_i}$ converges to $\hat{\sigma}^2_{\varepsilon_i}$.

To test for fake news' cross-sectional abnormal price impacts over time and postdebunking, this paper focuses on testing CAARs. The CAAR t-test statistic, covering t_1 to t_2

$$t_{\overline{CAR}(t_1,t_2)} = \frac{\overline{CAR}(t_1,t_2)}{\sqrt{\sigma^2_{\overline{CAR}(t_1,t_2)}}} \sim N(0,1)$$

Under the null hypothesis, CAARs theoretically have zero-mean normal distributions.
This test statistic standardized the CAARs, to compare against the standard normal twotailed critical values.
If $t_{CAR(t_1,t_2)}$'s absolute value exceeds the critical values, the null hypothesis (that $t_{CAR(t_1,t_2)}$ is insignificant) can be rejected, and the event's cumulative effect can be shown as persistently significant until t_2.

Results

Table 2 Chinese ADR delisting threat event study results

Event day	Cross-sectional results		Cross-sectional cumulative test statistics			Bootstrapped normal distributions means and two-tailed 95% crit. values		
	AAR	CAAR	T-Test	Z Patell	Adj. Z Patell	T-Test	Z Patell	Adj. Z Patell
0	−0.016799	−0.016799	**−4.511603***	**−6.313699***	**−1.632980**	−7.50e−08 ± 3.910770	3.69e−07 ± 4.647513	9.55e−08 ± 1.202036
1	−0.003293	−0.020091	**−3.815459***	**−4.411101***	**−1.140890**	−2.79e−08 ± 3.272632	3.41e−07 ± 3.639121	8.81e−08 ± 0.941225
2	0.008693	−0.011399	−1.767461*	−1.591624	−0.411659	3.2e−08 ± 3.243619	1.65e−07 ± 3.333734	4.27e−08 ± 0.862239
3	0.017480	0.006081	0.816564	1.725958*	0.446403	−1.84e−08 ± 2.772181	1.24e−07 ± 3.260866	3.20e−08 ± 0.843398
4	0.006830	0.012911	1.550669	2.701564***	0.698735	2.01e−08 ± 2.665905	1.18e−07 ± 3.045232	3.06e−08 ± 0.787621
5	−0.012358	0.000553	0.060595	0.573809	0.148410	−5.87e−09 ± 2.560256	1.33e−07 ± 2.929651	3.43e−08 ± 0.757727
6	−0.002246	−0.001693	−0.171863	0.124803	0.032279	−5.44e−09 ± 2.686922	1.58e−07 ± 2.915622	4.09e−08 ± 0.754099
7	−0.001201	−0.002894	−0.274744	−0.017087	−0.004419	−4.02e−08 ± 2.552700	2.08e−07 ± 2.939094	5.38e−08 ± 0.760169
8	−0.003742	−0.006636	−0.594052	−0.388312	−0.100433	−1.06e−08 ± 2.542586	2.08e−07 ± 2.897774	5.39e−08 ± 0.749482
9	−0.003491	−0.010127	−0.860067	−0.380519	−0.098418	−1.13e−08 ± 2.753750	2.30e−07 ± 3.189146	5.95e−08 ± 0.824845
10	0.008476	−0.001651	−0.133654	0.513696	0.132863	1.30e−08 ± 2.620065	2.04e−07 ± 3.032666	5.29e−08 ± 0.784371
11	0.004845	0.003194	0.247628	0.735337	0.190188	2.04e−08 ± 2.589723	1.02e−07 ± 2.843265	2.63e−08 ± 0.735384
12	−0.000492	0.002702	0.201271	0.622304	0.160953	2.71e−08 ± 2.680568	1.14e−07 ± 2.859409	2.96e−08 ± 0.739560
13	0.000964	0.003666	0.264595	0.756633	0.195696	2.82e−08 ± 2.856353	1.63e−07 ± 3.085974	4.21e−08 ± 0.798158
14	0.001016	0.004703	0.326066	0.745946	0.192932	1.99e−08 ± 2.761991	1.53e−07 ± 2.907198	3.96e−08 ± 0.751920
15	−0.005060	−0.000358	−0.024014	0.190392	0.049243	2.89e−08 ± 2.802960	1.22e−07 ± 2.891613	3.15e−08 ± 0.747889

Statistical significance at: 10% Level = *, 5% Level = **, 1% Level = ***, Bootstrapped 5% Level = Bolded

The Adjusted Patell test results with bootstrapped critical values, in Table 2, can be interpreted as testing fake news' abnormal price effect, cumulative over the debunking shock, for significance over time.

Graphed in Fig. 4, these results confirm significant abnormal price effects. Specifically, the Adjusted Patell test values on September 27 and 30 are − 1.63 and − 1.14 respectively, exceeding their bootstrapped two-tailed 95% critical values (± 1.20 and ± 0.94 respectively); represented in Fig. 4, as both results fall below the bootstrapped region.

All subsequent results fall within the bootstrapped region, so their insignificance cannot be rejected; implying that the initial fake news abnormal price effect is neutralised after September 30. Table 2 indicates that these dynamics are all also supported by the weaker t-test and Patell test results.

indicates that fake news generates a significant initial abnormal negative price effect. This gradually reverses but remains significant for three calendar days post-debunking.

This robustly indicates a significant initial overreaction to fake news, and significant underreaction to debunking; qualitatively matching the model dynamics.

the empirical results suggest that the post-debunking underreaction is too protracted to be accounted for solely by the base model. According to the base model, fake news' initial price impact should be significantly smaller than equivalent real news' initial price impact, if $p_0 > 0.5$

The empirical evidence thus supports the full model's predicted secondary fake news impact: that fake news in a security amplifies underreactions to subsequent real news in the security. Combined with the qualitative accuracy of the model's dynamics for debunked fake news shocks, and standalone real and fake news shocks, this validates this paper's model of underreaction/overreaction, and its explanation of fake news' financial impacts.

Opinion on the result

Thanks to the results we can see how the financial markets reacts to the real/fake news (reactions). And how the model can predict the impact of the fake news in the financial markets (economic explanation).

Contributions

This paper seeks to provide a formal economic explanation of how fake news can generate impacts in financial markets, through a combination of theory and empirics.

Propose an original formal economic model to explain the empirically- proven impacts that fake news can have on financial markets. An extended version of the model also provides a hypothesis for an additional novel impact of fake news in financial markets which has not been formally analysed by prior literature—which is validated along with the overall model's qualitative accuracy through empirical testing.

Established behavioural finance biases are introduced to explain and reconcile empirically observed price overreactions to fake news with empirically observed price underreactions to real news.

Second This model is then extended with established fake news-specific characteristics and predicts a new secondary impact of fake news: that fake news in a security amplifies underreactions to subsequent real news for the security.

Then the model's dynamics and predictions are evaluated through a large-sample empirical event study. This is conducted as a novel event study over the 2019 Chinese ADR Delisting Threat fake news and debunking event.

The empirical results indicate statistically significant price overreactions to fake news and price underreactions to debunking over the event and provide qualitative support for the model's prediction including the proposed secondary fake news effect.

Critiques:

Great paper that thanks to statistical method prove how fake news impact the financial market and how investors react to it (debunking).