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

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Abstract

This paper proposes an original behavioural finance representative agent model, to explain how fake news' empirical price impacts can persist in finance despite contradicting the efficient-market hypothesis. The model reconciles empirically-observed price overreactions to fake news with empirically-observed price underreactions to real news, and predicts a novel secondary impact of fake news: that fake news in a security amplifies underreactions to subsequent real news for the security. Evaluating the model against a large-sample event study of the 2019 Chinese ADR Delisting Threat fake news and debunking event, this paper finds strong qualitative validation for its model's dynamics and predictions.

Keywords: Behavioural finance, Fake news, Representative agent model, Event study, Bootstrapping

Introduction

Context and motivation

Intentional disinformation, or 'fake news' is defined as "false stories that appear to be news, spread on the internet or using other media, usually created to influence political views or as a joke" (Cambridge Dictionary 2021). Though disinformation in the media has long existed in a myriad of forms, the modern fake news phenomenon has garnered significant attention recently due to its pronounced pervasiveness and impact in the social media era. Commonly linked to several major recent world events, such as the US elections and Brexit, modern fake news has had significant and well-documented influence in contemporary politics and society—and has subsequently received substantial attention, both in popular discourse and academic research.

In addition, though less commonly discussed, recent studies have shown fake news similarly capable of significantly impacting security prices and financial markets (Clarke 2018; Kogan et al. 2019). For instance, Clarke et al. (2018) and Kogan et al. (2019) both analyse the fake news articles on Seeking Alpha which were identified by a 2017 SEC

crackdown to have artificially inflated certain stock prices. In another high-profile case, a series of fake WhatsApp messages shared on Twitter incited a bank run on the UK-based Metro Bank in May 2019—and are associated with the subsequent plunge that hit Metro Bank's share price (Makortoff et al. 2019).

However, despite fake news' recent general popularity as a research focus, the amount of research available on fake news' impacts specifically in financial markets remains notably limited. The overwhelming majority of studies remain focused on fake news' political and social impacts, and these are additionally largely isolated to methods for detecting and countering fake news. In particular, while prior literature has proven that fake news can have statistically significant impacts on financial markets (Clarke et al. 2018; Kogan et al. 2019), no research currently exists to formally provide an economic rationale or model for how this is at all possible.

According to the tenets of the efficient-market hypothesis (a popular base economic model for financial markets), fake news should not be able to impact market prices as it conveys spurious information that should be rejected by rational agents in an efficient market (Fama 1970). This implies that fake news' observed impacts in financial markets are irrational and should not exist as they contradict the efficient-market hypothesis—despite the empirical proof to the contrary.

Yet, in spite of this stark disjoint between economic theory and empirical evidence, no existing literature or model currently provides an applicable and effective explanation for how fake news' impacts could rationally persist in financial markets in contradiction of the efficient-market hypothesis. As such, this paper aims to initiate this research by proposing a novel theoretical base model that provides a formal and rigorous economic explanation covering the primary drivers of how fake news generates statistically-significant impacts in financial markets—as well as empirical validation for the model's dynamics and predictions. By providing a formalised starting point, this paper additionally hopes to stimulate future research to build upon this base model, to account for further conditions and variables, and more fully explain fake news' financial impacts.

Paper outline and 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—and offers several novel contributions to the literature. As previously described, this primarily centres around proposing 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.

The paper progresses as follows. First, 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. This occurs through the structure of a novel unified representative agent model, driven by bounded rationality over uncertainty in information veracity. 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.

Next, 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—one of the only large-sample events which allows the full model (including the novel hypothesised secondary fake news effect) to be tested. Using the Adjusted Patell test with bootstrapped normal critical values, the event study accounts for cross-sectional correlation, unrepresentative excessively volatile observations, and non (standard) normal distributions—ensuring the robustness of the empirical test.

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 predictions—including the proposed secondary fake news effect. As such, the empirical results validate this paper's model, and reinforce the robustness of the paper's proposed formal economic explanation of fake news' impacts in finance.

Literature review

As previously mentioned, there is a distinct scarcity of literature on fake news in financial markets—and a complete lack of literature explaining the economic rationale of fake news' impacts on financial markets and prices. This shortage of prior literature on the subject serves as one of the primary motivations for this paper, but also limits the relevance of inferences that can be directly drawn from prior studies.

However, in building an original economic model and explanation for fake news' impacts in financial markets, this paper still draws inferences from three sets of existing literature. These include literature characterising fake news' impacts on agents and communities (specifically in comparison to real news, and on financial markets), studies on established behavioural finance effects and biases, and existing formalised models of price underreaction and overreaction (relative to the predictions of the efficient-market hypothesis).

Fake news and financial markets

The majority of recent literature on fake news focuses on its characteristics in politics and society. The most recent and numerous of these studies are even more specifically tailored to detecting and countering fake news—fields which are not relevant to the objective of this paper. However, in building an effective model for fake news' financial impacts, it is important to understand the defining characteristics of how fake news impacts agents and communities, in comparison to real news—which are provided by several key papers.

One of these papers, Allcott and Gentzkow (2017), build a model of media markets and content producers to explain how fake news in society can arise in equilibrium, and hypothesise that fake news is more convincing than real news due to its relative extremity in tone and content. This is supported by Vosoughi et al's (2018) work in analysing the comparative dynamics of real and fake news spread across Twitter—which finds that fake news is more novel than real news, and inspired “fear, disgust, and surprise in replies”, indicating a strong shock factor which corroborates with Allcott and Gentzkow's

(2017) hypothesis. Vosoughi et al. (2018) also demonstrate empirical proof of fake news' enhanced impact compared to real news, finding that fake news "diffused significantly farther, faster, deeper, and more broadly than the truth in all categories of information". This accelerated spread was also empirically attributed to human action, as opposed to due to bot involvement, indicating the strong viral characteristic of fake news' impact on agents and communities. This is additionally supported by the research on fake news detection, as a common method of detection is through non-physical news content analysis—indicating that fake news' non-physical content "like purpose, sentiment, and news topics" are detectably different than real news (Zhang and Ghorbani 2020). For instance, "fake news creators often use exaggerated title[s] to attract readers' attention", and sentiment scores measuring the intensity and emotional posture of news articles are recognised as powerful tools for fake news detection (Zhang and Ghorbani 2020). Therefore, this emphasises fake news' relative extremity compared to real news, and further supports Allcott and Gentzkow's (2017) hypothesis.

Allcott and Gentzkow (2017) also show that fake news can incur social costs, and could render agents more sceptical to all news—including legitimate news. This is reinforced by Aymanns et al. (2017) who analyse the spread of fake news through a social learning game imposed on a network model. After training a neural network to optimise strategies within the model, they find that agents aware of the existence (or even the potential) of fake news are likely to "give less weight to their private signals which might be biased". This indicates that agents aware of fake news become more wary of all incoming information, real or fake.

These papers help characterise and differentiate fake news' general impacts on agents, relative to real news; however, the specific dynamics of fake news would be significantly different within the financial markets. For instance, agents in financial markets are typically more sophisticated, valuing true information for profit-making and financial self-preservation. These agents can also more easily test for and discern the truth of financial news, from the granular, quantitative detail available in finance—for instance through financial statements or equity research reports, against which financial news can be independently analysed by any agent. Therefore, this hinders fake news' impacts (and study) in finance, which is supported by Vosoughi et al. (2018) who find subdued fake news effects in the financial markets compared to the political sphere.

Despite this—and despite the relative scarcity of research on fake news in finance—there have been several papers that have statistically proven fake news' ability to have significant impacts on financial markets and prices. For instance, Kogan et al. (2019) and Clarke et al. (2018) both provide analyses on fake news impacts using the SEC crackdown on fake stock promotion articles on Seeking Alpha (a financial crowd-sourced news platform) in April 2017. Kogan et al. (2019) demonstrate 8% average initial fake news price impacts on small firms. These fully reverse within a year, indicating fake news' temporary credibility even without debunking. Clarke et al. (2018) also demonstrate fake news generating significant abnormal trading volumes and initial price impacts, which are smaller than equivalent real news; indicating that agents partially discount fake news. Kogan et al. (2019) additionally support Aymanns et al. (2017) and Allcott and Gentzkow's (2017) theory that fake news awareness increases wariness towards subsequent news, showing that exposing fake news' presence decreases abnormal trading volumes

significantly for subsequent news. It is important to remember though, that research on fake news in financial markets is a relatively young and niche field, with limited existing literature. Both papers study the impacts of the similar events and similar financial fake news articles, which primarily influenced small firms. This lack of external validity therefore limits the overall inferences that previous literature can provide.

These papers therefore characterise fake news' impacts on agents, relative to real news, and empirically support fake news' capability to statistically impact financial markets and prices. However, pre-existing literature remains insufficient in providing a formal economic rationale which reconciles the contradiction between fake news' statistical impacts on financial prices and the efficient-market hypothesis; the provision of which forms this paper's primary objective and original contribution.

Behavioural finance effects

As previously described, the efficient-market hypothesis dictates that security prices should fully, and correctly, reflect all available information (Fama 1970). Fake news should therefore be ignored by rational agents and market prices, as fake news conveys spurious information. As seen in the "[Fake news and financial markets](#)" section though, several papers statistically prove this as empirically violated. This results in a contradiction between economic theory and empirical evidence, rendering fake news' impacts on financial markets and prices seemingly economically irrational. As such, providing a formal economic model explaining how fake news can rationally have statistically significant impacts on financial markets and prices is the primary objective of this paper, as this has so far not been reconciled by any prior literature.

However, significant literature does exist from several modern economic schools of thought that consider such 'irrational' contradictions to the efficient-market hypothesis as phenomena which are simply poorly or incompletely represented by traditional models. These schools of thought believe that these contradictions can be explained as perfectly economically rational outcomes and actions with the appropriate constraints and models. This has led to significant research dedicated to formally modelling and rationalising observed exceptions to the base efficient-market hypothesis model.

One of the most prominent of these schools of thought, the field of behavioural finance, explains deviations from the efficient-market hypothesis as due to bounded rationality over constraining cognitive, psychological, and behavioural factors. As such, to explain fake news' impacts on financial markets and prices, this paper uses established behavioural finance biases of conservatism and confidence effects.

Analysed in psychology with empirical proof by Edwards (1968), conservatism bias represents when agents insufficiently update their beliefs (relative to optimal Bayesian updating) against new information. Linking this to financial agents, Barberis et al. (1998) rely heavily on conservatism bias in their popular behavioural finance model explaining price underreactions and overreactions, relative to the efficient-market hypothesis.

Similarly, confidence as a behavioural bias was studied in psychology by Griffin and Tversky (1992), who decompose information into two characteristics: "strength" and "weight"; which generate empirical under/overconfidence effects based on which characteristic agents value more. According to Griffin and Tversky (1992), this is because "strength" represents information's qualities of tone and extremity, and "weight"

represents information's credibility. They theorise that more rational agents should derive confidence in information from its credibility—as agents which are more confident in (and therefore are more likely to act on) more credible information, make more rational decisions in line with the efficient-market hypothesis. On the other hand, less rational agents relying less on credibility and more on “strength” factors, would lead to overconfidence in information with low credibility and high “strength”, and underconfidence in the reverse (Griffin and Tversky 1992). Confidence effects are also employed by several popular behavioural finance models of price underreactions and overreactions, including Daniel et al. (1998) and Barberis et al. (1998).

As such, this research establishes conservatism and confidence as empirically-robust behavioural finance effects that can be used to help explain how fake news has statistically significant impacts on financial markets and prices. However, neither effect on its own is capable of sufficiently reconciling the ostensible contradiction between the efficient-market hypothesis and fake news' empirical financial impacts. Additionally, existing models that rely on each behavioural finance effect rely on particularly narrow interpretations of each effect, which apply poorly to fake news. For instance, Barberis et al.'s (1998) model relies on conservatism bias, but only considers conservatism against real news shocks that may be potentially temporary; this is a very specific context that is not directly applicable to fake news' impacts. Therefore, a new model would need to be built, to reconcile conservatism, confidence, and fake news effects, to effectively explain fake news' dynamics.

Models of underreaction and overreaction

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. Therefore, to construct such a formal behavioural finance model, key inferences were drawn from the main models of price underreaction and overreaction that exist in behavioural finance literature.

Hong and Stein (1999) represent price underreactions and overreactions as outcomes of interactions between heterogeneous agents, which react purely to news shocks and historical price trends respectively, with non-instantaneous information diffusion.

Daniel et al. (1998) build a representative agent model of price underreactions and overreactions, relying on overconfidence and self-attribution; where overconfident agents disproportionately misinterpret public signals to support initial private signals.

Barberis et al. (1998) build a representative agent model of price underreactions and overreactions, based on conservatism and representativeness biases; where agents misinterpret random-walk information shocks, as either mean-reverting or continuous trends.

These form the main behavioural finance explanations for price underreactions/overreactions. However, they remain largely inapplicable to fake news, as they assume (at least partial) information veracity, and would immediately reject fake news' purely spurious information. Additionally, contradicting this paper's empirical findings in the “Empirical evidence” section, Daniel et al. (1998) and Barberis et al.'s (1998) models would imply that prices would not underreact at all to debunking—since debunking

represents real and accurate news which unambiguously discredits prior fake news, and cannot be misinterpreted.

Only Hong and Stein's (1999) model of non-instantaneous information diffusion could partially explain this underreaction to debunking. However, to achieve this, Hong and Stein's (1999) model would need to rely on unreasonably strong assumptions of similarity between real and fake news' impacts. This renders Hong and Stein's (1999) model similarly inappropriate for explaining the empirical underreaction to debunking fake news—as in reality, and as shown in the “[Fake news and financial markets](#)” section, fake news' impacts on agents have distinctly different characteristics compared to real news. Such differences should therefore indicate heterogenous price underreaction or overreaction patterns in reaction to fake and real news. However, Hong and Stein's (1999) non-instantaneous information diffusion model would instead predict homogenous, albeit mirrored, patterns in reaction to both fake news and subsequent debunking (which represents real news). Furthermore, non-instantaneous information diffusion loses relevance with high-profile events in increasingly-digitalised financial markets—as modern technology minimises information diffusion delays, particularly in fast moving environments like the stock market.

Consequently, existing behavioural finance models remain inappropriate for explaining fake news' impacts on financial markets and prices. As such, inspired by such models, this paper proposes a new alternative representative agent model of price underreactions and overreactions, based on information veracity uncertainty, to explain fake news' empirical price dynamics.

Model

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.

Extending the model with fake news-specific characteristics, this section subsequently predicts a new secondary fake news impact: that fake news in a security amplifies underreactions to all subsequent real news concerning that security.

It is important to note though that, as a completely novel economic model for a nascent field of research, this model merely aims to serve as a base model explaining the primary drivers of fake news' empirical impacts on financial markets and prices. As such, this model is not intended to be a comprehensive representation of every possible variable or contributing factor in fake news' financial impacts—but rather, a formal model containing multiple simplifications which enable a clearer and more direct understanding of the key levers influencing fake news' price impacts. By providing such preliminary

research into this field, this paper aims to inspire future research to build and expand upon this base model—enabling subsequent more complex models in future papers, that account for a greater set of variables and conditions, and explore fake news' financial impacts in greater depth and across a wider range of scenarios.

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 . Similar to Hong and Stein's (1999) "news-watchers", the simplified agent forms P purely by internalising news shocks, and does "not condition on current or past prices".

News shocks are simplified to convey direct information on the security's exogenously generated true value. As these news shocks are considered exogenous, their generation and conveyance are similarly considered exogenous in the model, and therefore not included in the model. 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, and not the transmission mechanism to each agent. In reality, the outlet and transmission mechanism of such news shocks would certainly influence the nuances of their credibility and impacts on agents. However, for parsimoniousness and the purposes of isolating the main drivers of how fake news impacts financial markets and prices, this simplification will be used to focus directly on the nature of each news shock in the model. As such, the security's modelled market price dynamics will depend solely on how the agent values each news shock.

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. Again, it is important to note that this is a simplified model. In reality, most news shocks will convey information on contributing factors to a security's value, as opposed to its direct numerical value (i.e. information on a company's operating performance and brand perception, as opposed to information on what the true dollar value of their shares is). As such, multiple news shocks would be able to remain contemporaneously accurate. However, for the purposes of isolating the main drivers of fake news' impacts on financial markets and prices, the model simplifies news shocks this way to focus directly on the impact of each type of news shock.

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 $n \in \{0, \dots, M\}$. 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 :

$$P = \sum_{n=0}^M \theta_n I_n; \quad \sum_{n=0}^M \theta_n = 1$$

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:

$$\theta_n = \frac{S_n}{\sum_{n=0}^M S_n}$$

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.

The following sections explain the three terms determining each news shock's information weight: the base value, the irrelevance factor, and the time decay factor. The information weight is the product of these terms.

Base value of a news shock

The primary determinant of a news shock's information weight is its base value, as standalone information, to the agent. 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, $\rho \in [0.5, 1]$:

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

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

Combined, $S_n(\text{base})$ 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; $S_n(\text{base}) = 1$. Conversely, if they are perfectly sure that I_n is fake, they will be certain of its spuriousness and ignore it; $S_n(\text{base}) = 0$. Therefore, as ρ increases, agents place more weight on real news and less on fake news. However, as ρ decreases towards 0.5, the agent grows more uncertain of which type they face, optimising over this constraint by placing increasingly similar middling weights on both.

This links to Griffin and Tversky's (1992) paper on confidence. As previously discussed, Griffin and Tversky's (1992) decompose information into "strength" (representing tone and extremity) and "weight" (representing credibility). Rational agents should derive confidence in information from its credibility; since relying less on credibility and more on "strength", leads to overconfidence in information with low credibility and high "strength", and underconfidence in the reverse (Griffin and Tversky 1992).

In this paper's model, real and fake news only differ in credibility, represented by ω_n . This stems from the understanding that real news—by definition—has inherently stronger credibility than fake news. Simplified to binary terms, the model therefore assumes that real news shocks are fully credible ($\omega_n = 1$), while fake news shocks are completely non-credible ($\omega_n = 0$). Assuming shocks of equal magnitude, the base

model also uses a simplification where “strength” remains equal across news shocks. It is important to note that, in reality, these factors would also be influenced by the transmission mechanism (i.e. the news outlets or mode of conveyance) through which these news shocks reach agents. However, the model considers news shocks as exogenously generated and instantaneously conveyed to agents. Therefore, a news shock’s transmission mechanism is not considered in the model—enabling such simplifications, which allow the model to focus on the news shocks and their direct impacts themselves.

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 ρ determines the agent’s ability to distinguish ω_n , ρ determines how much agents rely on credibility to determine confidence.

Therefore, the lower an agent’s ρ , the more constrained they are from relying on credibility; making them more underconfident in real news and overconfident in fake news.

Irrelevance factor of old news

With perfect ability to distinguish information veracity, $\rho = 1$, previous news shocks should become immediately irrelevant once updated real information is introduced; or remain unaffected if new fake information is introduced. However, without $\rho = 1$, agents are not certain of a shock’s veracity. With updated real shocks this would induce conservatism bias, preventing full discounting of past information, due to underconfidence in the new shock’s veracity. With new fake shocks, this would cause erroneous discounting of past real shocks, due to overconfidence in the new shock’s veracity.

This forms the core of this model’s underreaction/overreaction mechanism. Based on the information veracity uncertainty discussed in the “[Information weight determinants: base model](#)” section, agents are prevented from immediately switching, or maintaining, their valuation fully at the most updated real news shock.

However, 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. For instance, reports of a takeover become more credible as regulatory protocols are completed, equity swaps are offered, and finally as the actual takeover occurs. Alternatively, the availability heuristic, where agents place greater weight on information more ‘available’ or easier to recall (Schwarz 1991), could explain this; 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:

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

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, $(1 - \rho) \in [0, 0.5]$; the time since news shock $I_{j>n}$ was introduced, $(t - t_j + 1) \geq 1$; and the base value of updated news shock $I_{j>n}$, $[\rho\omega_j + (1 - \rho)(1 - \omega_j)] \in [0, 1]$.

These combine to influence I_n 's weight as follows:

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 $(1 - \rho)$; 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 $(1 - \rho) = 0$, fully discounts I_n once a new real shock occurs.

However, the less certain they are of $I_{j>n}$'s veracity, the less they discount old shocks. This modifies the irrelevance term, through the agent's base value of $I_{j>n}$ in the exponent. Both this base value and $\delta(1 - \rho)$ 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. Conversely, with perfect certainty in $I_{j>n}$'s veracity, $I_{j>n}$'s base value equals 1 and $(1 - \rho)$ equals 0, so I_n is fully discounted.

Finally, the time since $I_{j>n}$'s introduction increasingly amplifies I_n 's irrelevance through the exponent, the longer that passes since $I_{j>n}$'s introduction. 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.

Kogan et al. (2019) support this, 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, $\varphi \in [0, 1]$:

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

At the extremes, $\varphi = 0$ indicates that spurious information is perfectly temporary and decays fully after one period; $\varphi = 1$ indicates that spurious information suffers no additional time decay. This is modified by $(1 - \omega_n)$ in the exponent, neutralising $S_n(\text{time decay})$ 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

The model described so far qualitatively explains both the primary fake news impact and underreactions to real news, through an underreaction/overreaction mechanism driven by uncertainty in information veracity. However, 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 (Allcott and Gentzkow 2017; Vosoughi et al. 2018). This represents fake news' amplified virality relative to real news—which serves to magnify the weight that agents place on fake shocks.

This is represented through a fake news virality factor, $\alpha \geq 1$:

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

At the lower-bound, a value of $\alpha = 1$ would indicate that fake news in the model is unaffected by virality effects. This factor is also modified by $(1 - \omega_n)$ in the exponent. This term ensures that, unless I_n is fake and $\omega_n = 0$, the entire $S_n(viral)$ factor is neutralised 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, $(1 - \rho)$, in the exponent; since less capable agents are more susceptible to fake news' virality. This reconciles well with the previously discussed Griffin and Tversky (1992) decomposition of information, as more rational agents should have a greater inclination to ignore a news shock's "strength" when determining their confidence in a news shock, to instead more heavily rely on its credibility or "weight".

Indeed, as Griffin and Tversky (1992) characterise information "strength" as representing tone and extremity, and information "weight" as representing credibility, this virality factor serves as an effective representation of information "strength" in the model—and therefore helps ensure a more comprehensive model through its inclusion. 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. However, prior literature indicates that fake news should have specific characteristics of tonality and extremity which enhance its impacts on agents (Allcott and Gentzkow 2017; Vosoughi et al. 2018). 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 $\alpha > 1$.

Fake news uncertainty factor

Previous literature suggests and proves that awareness of fake news decreases responsiveness to subsequent news shocks (Allcott and Gentzkow 2017; Aymanns et al. 2017; Kogan et al. 2019).

This enters the model as an investor becoming less able to distinguish information veracity upon learning of fake news' presence. This could be attributed to the availability heuristic, which makes information that is easier to recall seem erroneously more likely (Schwarz et al. 1991). For instance, high-profile events, like plane crashes or fake news scandals, are easier to recall—which consequently often makes such events seem excessively likely for agents, regardless of their actual statistical likelihood. This could decrease the agent's ability to distinguish between real and fake

news, if their amplified concern leads them to misattribute possible signs of fake news to real news, diminishing their competence; or if the seemingly amplified fake news risk diminishes their confidence in accurately distinguishing information veracity.

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

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

$\rho_0 \in [0.5, 1]$ is initial ability, $(1 - \rho_0) \in [0, 0.5]$ measures initial inability, $\gamma \in \{0, 1\}$ is a binary variable indicating fake news' signalled presence in the security, and $\mu \in [0, 1]$ represents the fake news uncertainty factor.

This decomposes ρ into: initial investor inability, scaled as a percentage of maximum investor inability, $\left(\frac{1 - \rho_0}{0.5}\right)$; modified by the fake news uncertainty exponent, $(1 - \gamma\mu)$; then rescaled back to level inability terms (multiply by 0.5), and transformed back into ability (subtract from 1). 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.

This uncertainty exponent $(1 - \gamma\mu)$ determines the magnitude of the fake news uncertainty effect; depending on the agent becoming aware of fake news' presence. If $\gamma = 0$, fake news' presence is not signalled, transforming the uncertainty exponent to 1, so investor ability remains unchanged; $\rho_0 = \rho$. Conversely, $\gamma = 1$ indicates fake news' signalled presence, so the uncertainty exponent would be $\in [0, 1]$. If both the uncertainty exponent and the percentage investor inability are $\in (0, 1)$, this increases the percentage investor inability, decreasing $\rho < \rho_0$.

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

This affects percentage investor inability, and therefore leaves ρ unaffected, if ρ_0 starts at the extremes. This is because perfectly incompetent investors cannot worsen at distinguishing information veracity, and perfectly capable investors are invariably unaffected as they disregard fake news completely.

The 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

The base model's information weight, formed by the determinants in the “[Information weight determinants: base model](#)” section, is given as:

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
$n \in \{0, \dots, M\}$	Period, $t = n$, when news shock I_n occurred
$j \in \{0, \dots, M j > n\}$	Period, $t = j$, when news shock $I_{j>n}$ occurred
$\theta_n \in [0, 1]$	$\sum_{n=0}^M \theta_n = 1$ Weighted share of news shock $I_{m,n=0}$
$S_n \geq 0$	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:

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

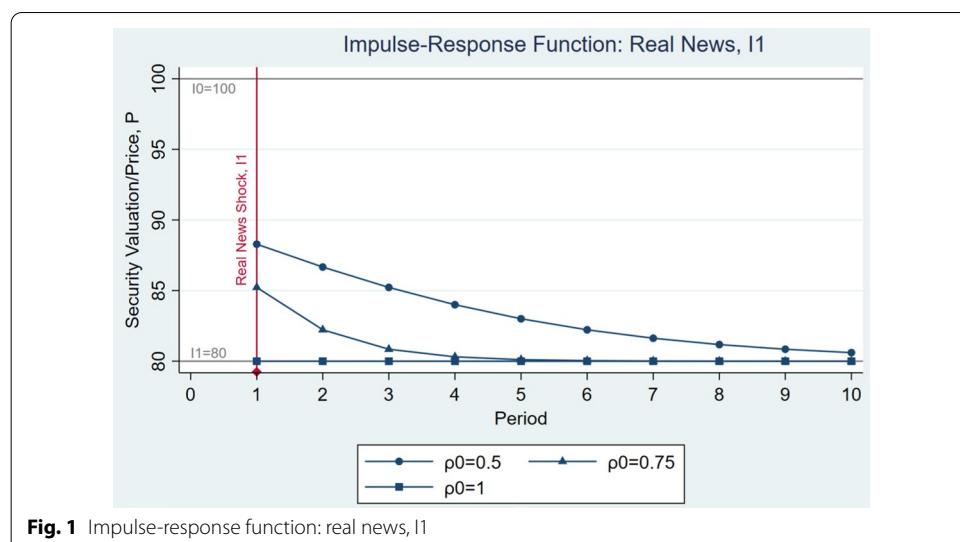
Glossary of model terms.

See Table 1.

Impulse-response functions

To explore model dynamics, this paper models three impulse-response functions for:

- 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



$I_0 = 100$, so P starts at 100. Each shock has an equal magnitude of difference: $I_1 = 80$, and $I_2 = 100 = I_0$. A debunking shock, I_2 , is used, since debunking represents a subsequent real news shock which contradicts prior fake news, and signalling 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 , and differ between the base and full model where applicable. All other variables are held constant at:

Base Model:

- $\delta = 1$; there is 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
- $\mu = 0.5$

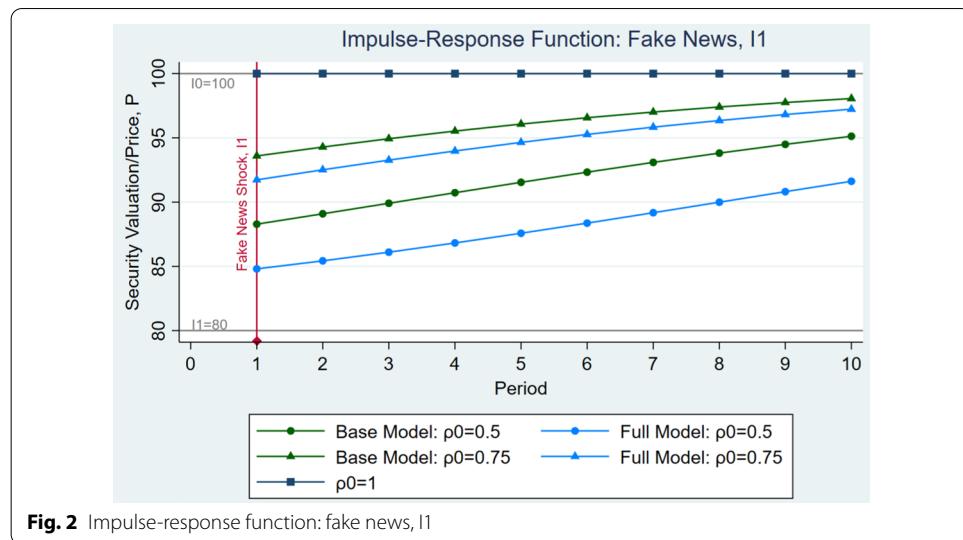
One real news shock

For standalone real shocks, both models are identical and are only determined by base value and irrelevance factors.

Impulse-response dynamics in 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 (Barberis et al. 1998; Daniel et al. 1998; Hong and Stein 1999).

One fake news shock

Both models are identical when $\rho_0 = 1$ as the agent is perfectly unaffected by fake news; P remains at $I_0 = 100$.

For standalone fake shocks, 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 ρ_0 value.

Impulse-response dynamics in Fig. 2, display an initial shift (down from $I_0 = 100$) in P when the fake news shock occurs, for $\rho_0 < 1$; representing an overreaction to fake news. This decreases in ρ_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 ρ_0 , compared to Fig. 1’s shifts under equivalent real news; except when $\rho_0 = 0.5$, where agents cannot distinguish information veracity, and initial shifts are equal. Notably, Clarke et al. (2018) support $\rho_0 > 0.5$, 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 .

In Fig. 2, 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_1 ’s information weight, degrading the fake I_1 ’s credibility over time. For relatively stronger irrelevance factors, reversion to I_0 could be much slower; or even increase the overreaction to I_1 over time, if the irrelevance factor is stronger than φ . However, Fig. 2’s dynamics, with φ stronger than the irrelevance factor, qualitatively matches empirics; as Kogan et al. (2019) show fake news’ initial price effects on small firms reversing fully within a year without debunking.

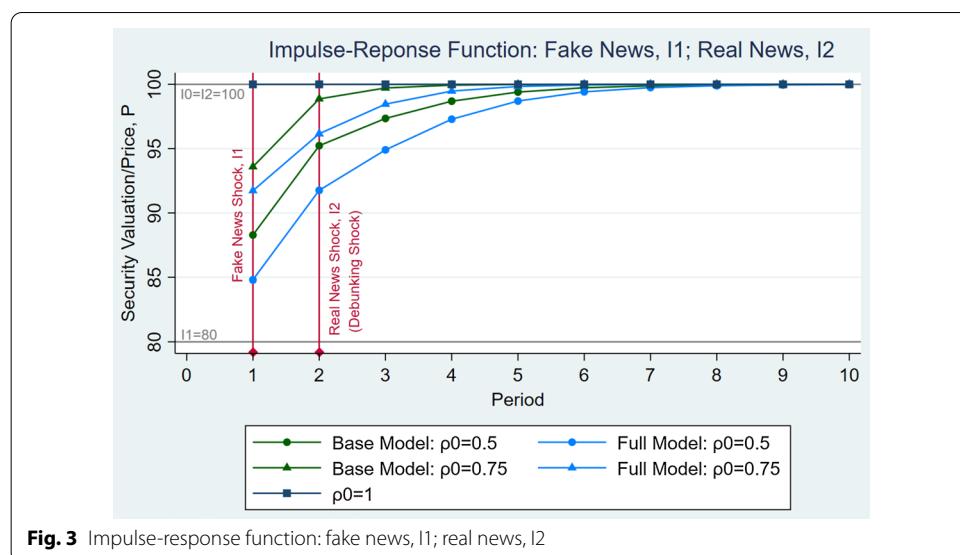


Fig. 3 Impulse-response function: fake news, I_1 ; real news, I_2

One fake news shock and one real news shock

Both models are identical when $\rho_0 = 1$ 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 $\rho_0 = 0.75$, as awareness of fake news' presence renders the agent less able to distinguish information veracity; so $\rho < \rho_0$. The uncertainty factor has no effect when $\rho_0 = 0.5$ or 1, as perfectly competent agents are unaffected by fake news and perfectly incompetent agents cannot worsen.

Impulse-response dynamics in Fig. 3, display the same initial overreaction to I_1 as Fig. 2. After I_2 occurs, this overreaction is partially reversed; P reverses towards I_0 at a faster rate than in Fig. 2, as Fig. 3 exhibits recursion pressure from both debunking and Fig. 2's time decay. However, when $\rho_0 < 1$, this recursion is not immediate. P persistently deviates 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, ρ_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.

Empirical evidence

The model constructed in the “[Model](#)” section predicts underreaction/overreaction dynamics following fake and real news shocks. The full model variant also predicts a new secondary fake news impact: that fake news in a security amplifies underreactions to all subsequent real news for that security.

Therefore, to evaluate both model variants, the following section empirically tests security price reactions to the 2019 Chinese ADR Delisting Threat fake news and debunking event. A debunked fake news event is specifically used because debunking is a subsequent real news shock, clearly signalling prior fake news, with an unambiguous theoretical value (i.e. immediate reversal of fake news’ primary impact).

Conducting a robust large-sample event study, accounting for potential cross-correlation bias, unrepresentative excessively volatile observations, and non (standard) normal distributions, the empirical results strongly validate the model’s qualitative predictions; including the modelled impulse-response dynamics and the predicted secondary fake news impact.

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. As previously mentioned, to evaluate both model variants, an empirical event was needed which introduced a fake news shock that should materially influence a security’s valuation, followed by a subsequent contradictory real news shock that also signalled the prior fake news’ existence. This combination of shocks would therefore logically be found in a debunked fake news event, because debunking is a subsequent real news shock which clearly signals prior fake news. To perform an effective statistical test the event would also need to have influenced a large number of securities to ensure a large sample test, since small-sample tests empirically suffer significant power loss (MacKinlay [1997](#)) —and should also have the debunking take place soon enough after the initial fake news event to prevent exogenous events from statistically interfering with the average security price. This narrows the candidate events and data sets for testing considerably. As the set of observed instances of effective fake news in finance is already notably limited, given the relatively recent widespread introduction of modern fake news, this leaves very few alternatives which are similarly as viable for the empirical evaluation of this paper’s model as the 2019 Chinese ADR Delisting Threat.

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” (Leonard and Donnan [2019](#)).

- *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” (Leonard et al. 2019), 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 (USCC 2019). Therefore, this was an unambiguous example of fake news impacting a large number of public equities, before subsequent debunking.

The event study event window starts on the fake news event date (Friday, September 27) as day 0, since fake news is immediately introduced with no opportunity for insider trading or pre-emption. The event window continues over subsequent trading days to Friday, October 18, covering 16 event window days total, over a period of 22 calendar days.¹

The event study estimation window covers 120 trading days from April 08 to September 26, 2019.

Data selection

The top 100 Chinese firms by market capitalisation, with sufficiently liquid U.S.-listed shares avoiding continuous periods of zero trading volume, over the estimation and event windows, are used as the event study sample.

The market model indices used are the NYSE and NASDAQ Composite indices, respective to each firm’s listing during the estimation and event windows.

U.S. daily closing prices, for each index and firm’s US-listed shares, from April 05 to October 18, 2019, were obtained from S&P Capital IQ and used to calculate respective log-returns from April 08 to October 18, 2019.

All returns data series are tested via Augmented Dickey-Fuller for stationarity. All tests reject the null of non-stationarity at 1% significance; indicating strong stationarity and the absence of spurious regressions that would invalidate inferences.

Event study methodology

Event studies “measure the impact of a specific event on the value of a firm” (MacKinlay 1997), through its impact on their securities’ returns.

The basic event study framework used in this paper follows MacKinlay’s (1997) traditional method. This first estimates “normal” returns over the event period, as if the event never occurred. Then, cumulative abnormal returns (CARs) over the event period are calculated. Finally, these CARs are tested for significance at each event date; using cross-sectional average CARs for a multi-firm sample.

Estimating normal returns

This paper estimates normal returns, through the market model, as a function of a representative wider market’s returns.

The market model is given as (MacKinlay 1997):

¹ Public equities do not trade on weekends and public holidays.

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

R_{it} is security i 's return at time t . R_{mt} is the market return at time t and ε_{it} is a zero-mean error 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. $\sigma_{\varepsilon_i}^2$ represents the market model variance.

Abnormal returns and cumulative abnormal returns

After predicting normal returns over the event window with the estimated market model, the abnormal returns (ARs) and CARs for each event day are calculated as (MacKinlay 1997):

$$\begin{aligned} AR_{it} &= R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt}) = \hat{\varepsilon}_{it} \\ CAR_i(t_1, t_2) &= \sum_{t=t_1}^{t_2} AR_{it} \end{aligned}$$

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 . $(\hat{\alpha}_i + \hat{\beta}_i R_{mt})$ 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 (MacKinlay 1997):

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

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

The variance of each statistic is calculated as (MacKinlay 1997):

$$\begin{aligned} \sigma_{AR_i}^2 &= \hat{\sigma}_{\varepsilon_i}^2 + \frac{1}{L_1} \left[1 + \frac{(R_{mt} - \bar{R}_m)^2}{\hat{\sigma}_m^2} \right] \\ \lim_{L_1 \rightarrow \infty} \sigma_{CAR_i(t_1, t_2)}^2 &= (t_2 - t_1 + 1) \sigma_{\varepsilon_i}^2 \\ \sigma_{\bar{AR}_t}^2 &= \frac{1}{N^2} \sum_{i=1}^N \sigma_{AR_i}^2; \quad \sigma_{\bar{CAR}(t_1, t_2)}^2 = \frac{1}{N^2} \sum_{i=1}^N \sigma_{CAR_i(t_1, t_2)}^2 \end{aligned}$$

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

window. With large estimation windows, the forecast error asymptotically converges to zero, and $\sigma_{AR_i}^2$ converges to $\hat{\sigma}_{\varepsilon_i}^2$.

The CAR variance (as the forecast error asymptotically goes to 0) is just the market model sample variance, $\hat{\sigma}_{\varepsilon_i}^2$, multiplied by the number of observations covered by the CAR, $(t_2 - t_1 + 1)$.

The AAR and CAAR variances are averages of the respective AR and CAR variances across N sample firms, assuming cross-sectional independence.

To test for fake news' cross-sectional abnormal price impacts over time and post-debunking, this paper focuses on testing CAARs. The CAAR t-test statistic, covering t_1 to t_2 , is (MacKinlay 1997):

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

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

Issues with the traditional event study method

Traditional event studies rely heavily on assumed asymptotic standard normality in their test statistics; which is a strong and empirically-flawed assumption. A non-exhaustive list of common and pertinent violations includes:

Cross-sectional correlation Traditional test statistic calculations assume cross-sectional independence. This is clearly violated in multi-firm event studies affected by the same event, with identical event and estimation windows (Kramer 1998). This clustering implies cross-sectional correlation across the event and estimation window observations, generating significant bias even with low levels of cross-correlation (Kolari and Pynnönen 2010); thereby invalidating traditional t-test statistics.

Non (standard) normal distributions Traditional event studies rely on excess returns being naturally normally distributed, or on large enough samples to assume their asymptotic normality through central limit theory (CLT), for (asymptotically) standard normal test statistics.

However, Brown and Warner (1985) and Ford and Kline (2006) show that daily excess returns are inherently non-normally distributed. Furthermore, Kramer (1998) proves that no finite sample could feasibly satisfy the conditions necessary for asymptotic standard normality in traditional event study test statistics.

This implies that traditional test statistics are non (standard) normally distributed, suggesting significant bias and invalidating traditional event study hypothesis testing; as Kramer (1998) empirically proves for sample sizes up to 200.

Event study extensions and robustness measures

To resolve the issues in the “[Issues with the traditional event study method](#)” section, and to strengthen this paper’s inferences, several extensions and robustness measures are employed.

Patell test

Patell ([1976](#)) corrects for outliers with excessive volatility, that may misrepresent the event’s impact. They standardise all ARs by their respective standard deviations (adjusted for forecast error), cumulate them across the event days, then aggregate them over the N sample firms to form aggregate cumulative standardised abnormal returns (ACSARs):

$$\text{ACSAR}(t_1, t_2) = \sum_{i=1}^N \sum_{t=t_1}^{t_2} \frac{\text{AR}_{it}}{\sqrt{\sigma_{\text{AR}_i}^2}} \sim N\left(0, \sigma_{\text{ACSAR}(t_1, t_2)}^2 = \sum_{i=1}^N \left[\frac{L_i - 2}{L_i - 4} (t_2 - t_1 + 1) \right] \right)$$

Since standardised ARs theoretically have unit variance, an ACSAR’s variance is just its number of event days covered, multiplied by a factor penalising short estimation window lengths, cumulated across the N sample firms (Patell [1976](#)).

The Z_{Patell} statistic can then be formed to test cross-sectional cumulative effects between t_1 and t_2 (Patell [1976](#)):

$$Z_{\text{Patell}}(t_1, t_2) = \frac{\text{ACSAR}(t_1, t_2)}{\sqrt{\sigma_{\text{ACSAR}(t_1, t_2)}^2}}$$

Assuming cross-sectional independence, this statistic is theoretically asymptotically standard normal (Patell [1976](#)), and so can be tested against standard normal critical values, similar to the traditional method.

Adjusted Patell test

Kolari and Pynnönen ([2010](#)) correct the Patell test for the flawed assumption of cross-sectional independence. They accomplish this through a correction factor, taking advantage of the theoretically equal variance all sample firms’ cumulated standardised ARs have, assuming equal estimation window lengths. Taking $\bar{\rho}$ as the average correlation coefficient between ARs, this correction factor is (Kolari and Pynnönen [2010](#)):

$$\frac{1}{\sqrt{(1+(N-1)\bar{\rho})}}.$$

The $\text{Adj. } Z_{\text{Patell}}$ statistic, covering t_1 to t_2 , is given as (Kolari and Pynnönen [2010](#)):

$$\text{Adj. } Z_{\text{Patell}}(t_1, t_2) = Z_{\text{Patell}}(t_1, t_2) \left[\frac{1}{\sqrt{(1 + (N - 1)\bar{\rho})}} \right]$$

Accounting for cross-sectional correlation, this is more robustly standard normally distributed, and can be tested against standard normal critical values.

Bootstrapping

To resolve potential non (standard) normal distributions, Kramer ([1998](#)) uses bootstrapping to generate representative distributions for the test statistics’ null hypotheses, that

the test statistics can be compared against with no power loss; assuming that the original bootstrapping sample robustly represents the population.

This paper modifies Kramer's (1998) methodology, to accommodate cumulative $Adj.Z_{Patell}$ test statistics and multi-day event windows.

The bootstrap method used in this paper proceeds as follows:

1. ARs/SARs (across all sample firms and event window days) are de-means, to robustly represent the null hypothesis' zero-mean, to produce the original bootstrapping sample.²
2. The original sample is randomly drawn from, with replacement, to produce a new sample of ARs/SARs for each firm and event day, equal in size to the original.
3. Cross-sectional cumulative test statistics are calculated for the new sample, using the relevant variances and the Kolari-Pynnönen correction factor, which would be constant for each firm for test statistics relating to the same time periods.
4. Steps 2–3 are repeated 1000 times,³ for each test, to generate full normal distributions representative of the test statistics under their null hypotheses.
5. The distribution values are arranged smallest to largest, with the 25th largest and smallest values in each distribution representing the two-tailed 95% significance critical values for that test statistic.
6. If a test statistic's absolute value exceeds their bootstrapped critical values, the null hypothesis (that the event's cross-sectional cumulative impact over the period covered by the test statistic is insignificant) can be rejected.

Results

See Table 2.

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. The most robust of the empirical tests conducted, these results account for potential cross-correlation bias, unrepresentative excessively volatile observations, and non (standard) normal distributions.

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.

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

² To preserve the standardised observations the (Adjusted) Patell test relies on, de-means SARs are used for those bootstraps.

³ 1000 repetitions are sufficient for robustness, with more repetitions showing "no marked change in results" (Kramer 1998).

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	-0.02091	-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 ± 3.243819	1.65e-07 ± 3.333334	4.27e-08 ± 0.862239
3	0.017480	0.006081	0.816564	1.725958*	0.446403	-1.84e-08 ± 2.772181	1.24e-07 ± 3.260886	3.20e-08 ± 0.843398
4	0.006630	0.012911	1.550669	27.015644***	0.698735	2.01e-08 ± 2.6665905	1.18e-07 ± 3.045232	3.06e-08 ± 0.783621
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	-0.17853	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	2.39e-07 ± 3.189146	5.95e-08 ± 0.824843
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 ± 0.733384
12	-0.000492	0.002702	0.201271	0.622304	0.160953	2.71e-08 ± 2.830568	1.14e-07 ± 2.859409	2.96e-08 ± 0.735660
13	0.000984	0.003686	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	0.326086	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**

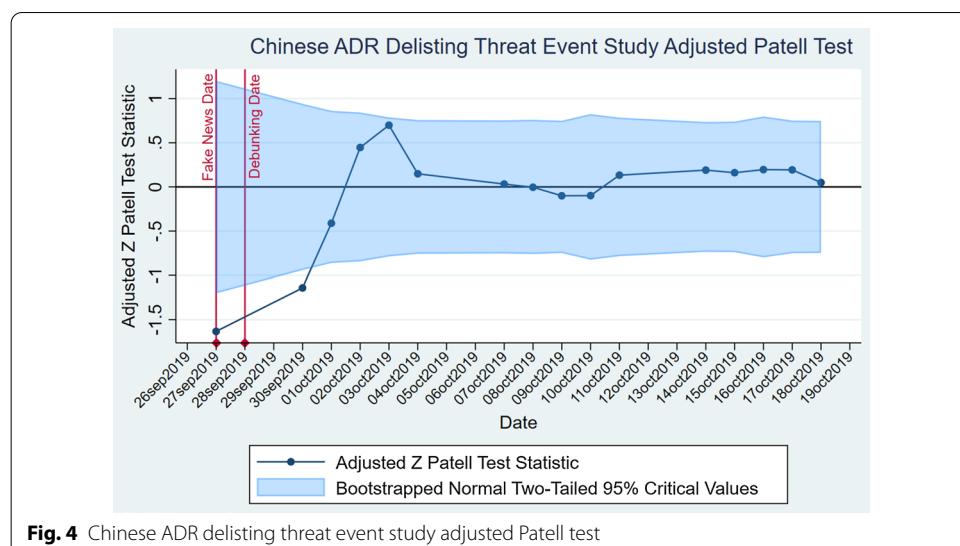


Fig. 4 Chinese ADR delisting threat event study adjusted Patell test

post-debunking (or four, according to the t-test at 10% significance), when it should have reversed fully upon debunking. This robustly indicates a significant initial overreaction to fake news, and significant underreaction to debunking; qualitatively matching the model dynamics explored in the “One fake news shock and one real news shock” section and Fig. 3.

However, 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 $\rho_0 > 0.5$; which Clarke et al. (2018) empirically support. Fake news and debunking are equivalent, but contradictory; therefore, under the base model, debunking should reverse fake news’ initial impact much faster than the three (or four) days that it empirically takes. Figure 3’s impulse-response dynamics support this as, under the base model, debunking sharply reverses fake news’ initial impacts to (near) insignificance within a day, at all levels of $\rho_0 > 0.5$; let alone over three days (or four). Therefore, the full model, which includes fake news-specific effects that amplify and prolong the underreaction, more appropriately explains the persistent post-debunking underreaction; and remains consistent with existing literature on fake news’ characteristics.

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.

Conclusion and discussion

This paper proposed a unified representative agent model of underreaction/overreaction, to explain how fake news is able to have statistically significant impacts on financial markets and prices, despite contradicting the efficient-market hypothesis. Centring around behavioural finance biases of conservatism and confidence, the base model reconciled fake news' empirically-observed initial price impacts with empirically-observed underreactions to real news, through a model driven by bounded rationality over uncertainty in information veracity.

The full model extended this model to a greater level of representative accuracy, by incorporating established fake news-specific characteristics, and also predicted a novel secondary impact of fake news, driven by fake news' virality and uncertainty effects: that fake news in a security amplifies underreactions to subsequent real news for the security.

To validate the model, a large-sample empirical event study was conducted on the 2019 Chinese ADR Delisting Threat fake news and debunking event. Using the Adjusted Patell test with bootstrapped normal critical values, this robustly accounted for cross-sectional correlation, unrepresentative excessively volatile observations, and non (standard) normal distributions.

The resultant empirical dynamics qualitatively matched the modelled dynamics. They were also found more appropriately represented by the full model variant, supporting the full model's predicted secondary fake news effect. Combined with the model's qualitatively accurate representation of price underreactions/overreactions to standalone real and fake news, these results strongly validated this paper's proposed model and explanation of fake news' impacts in the financial markets.

It is important to note though, that this paper's model is a simplified one, relying on several assumptions. The objective of this paper's model was to initiate the research into this field, and provide a base model which could provide a formal economic rationale for the primary drivers of fake news' financial impacts. By initiating this research, this paper aims to inspire future research into expanding the model, allowing for deeper and wider exploration of the variables and conditions under which fake news is able to significantly impact financial markets.

For instance, future model extensions could include heterogenous agents with varying abilities to distinguish information veracity, ρ , or agents which condition on historical price trends—both of which are closer to reality, but were simplified in this model for the sake of parsimoniousness and isolating the main factors driving fake news' financial impacts. This is because, in reality, the model's sole representative agent would actually be several heterogenous agent types, with inter-agent influences and interactions, that would further amplify, compound, and influence the factors discussed in this paper—and so this would be a good area for further research. Additionally, extensions examining the influence of information transmission mechanisms (i.e. news outlets or the means through which news shocks reach agents) would be valuable. This is because, while this paper's model simplified news shocks as exogenously generated to focus on the fake or real nature of each shock, transmission mechanisms undeniably influence how news shocks influence agents. Furthermore, incorporating other applicable behavioural finance effects (e.g. herding and confirmation bias), and estimating precise empirical values for the model's variables to

evaluate its quantitative accuracy, would be valuable to more accurately understand fake news' dynamics.

Additionally, the empirical robustness measures ensured strong internal validity, but external validity of the empirical results would also be ideally confirmed with alternate debunked fake news events. However, as previously discussed, the general scarcity and nicheness of debunked financial fake news prevented this, as the few alternate examples only affected single firms; and small-sample event studies empirically suffer significant power loss (MacKinlay 1997), which would therefore impede any statistical tests conducted. Therefore, confirming the empirical results' external validity, through additional tests on alternate datasets as more large-sample debunked fake news events occur, would be an invaluable area for further research.

Appendix: Dataset of event study sample firms

Company name	Ticker	Market cap. (\$mm)
Alibaba Group Holding Limited	NYSE: BABA	521,936.2
PetroChina Company Limited	NYSE: PTR	108,050.4
China Life Insurance Company Inc	NYSE: LFC	100,698.2
China Petroleum and Chemical Corporation	NYSE: SNP	73,017.6
JD.com Inc	NASDAQ: JD	60,722.4
Pinduoduo Inc	NASDAQ: PDD	54,408.2
CNOOC Limited	NYSE: CEO	50,745.4
NetEase Inc	NASDAQ: NTES	41,630.7
Baidu Inc	NASDAQ: BIDU	33,208.4
TAL Education Group	NYSE: TAL	29,528.0
China Telecom Corporation Limited	NYSE: CHA	27,941.2
ZTO Express (Cayman) Inc	NYSE: ZTO	22,270.4
Tencent Music Entertainment Group	NYSE: TME	21,341.8
New Oriental Education and Technology Group Inc	NYSE: EDU	19,028.9
Yum China Holdings Inc	NYSE: YUMC	17,454.9
Trip.com Group Limited	NASDAQ: TCOM	14,216.2
iQIYI Inc	NASDAQ: IQ	12,002.4
BeiGene Ltd	NASDAQ: BGNE	10,870.6
VipShop Holdings Limited	NYSE: VIPS	10,220.8
Huazhu Group Limited	NASDAQ: HTHT	9442.7
China Eastern Airlines Corporation Limited	NYSE: CEA	9106.6
Autohome Inc	NYSE: ATHM	8839.1
Bilibili Inc	NASDAQ: BILI	8684.0
China Southern Airlines Company Limited	NYSE: ZNH	8579.1
Huaneng Power International Inc	NYSE: HNP	8222.7
GDS Holdings Limited	NASDAQ: GDS	8217.8
Weibo Corporation	NASDAQ: WB	7921.6
58.com Inc	NYSE: WUBA	7662.6
Aluminum Corporation of China Limited	NYSE: ACH	6027.6
Sinopec Shanghai Petrochemical Company Limited	NYSE: SHI	5062.3
Zai Lab Limited	NASDAQ: ZLAB	4511.9
Momo Inc	NASDAQ: MOMO	4497.6

Joyy Inc	NASDAQ: YY	4191.7
China Biologic Products Holdings Inc	NASDAQ: CBPO	4045.8
51job Inc	NASDAQ: JOBS	3854.9
Nio Limited	NYSE: NIO	3345.7
HUYA Inc	NYSE: HUYA	3316.5
Hutchison China MediTech Limited	NASDAQ: HCM	2887.5
Guangshen Railway Company Limited	NYSE: GSH	2160.6
SinaCorporation	NASDAQ: SINA	2145.9
BEST Inc	NYSE: BEST	1999.9
Baozun Inc	NASDAQ: BZUN	1806.4
Noah Holdings Limited	NYSE: NOAH	1602.2
21Vianet Group Inc	NASDAQ: VNET	1599.0
360 Finance Inc	NASDAQ: QFIN	1500.3
LexinFintech Holdings Ltd	NASDAQ: LX	1373.0
Sogou Inc	NYSE: SOGO	1322.8
GreenTree Hospitality Group Ltd	NYSE: GHG	1289.5
Fanhua Inc	NASDAQ: FANH	943.4
Bitauto Holdings Limited	NYSE: BITA	826.1
OneSmart International Education Group Limited	NYSE: ONE	781.5
Huami Corporation	NYSE: HMI	766.9
Bright Scholar Education Holdings Limited	NYSE: BEDU	765.5
Cango Inc	NYSE: CANG	754.9
Daqo New Energy Corp	NYSE: DQ	689.7
JinkoSolar Holding Co. Ltd	NYSE: JKS	659.1
Niu Technologies	NASDAQ: NIU	636.1
Qutoutiao Inc	NASDAQ: QTT	624.4
111 Inc	NASDAQ: YI	595.5
Changyou.com Limited	NASDAQ: CYOU	576.0
FinVolution Group	NYSE: FINV	544.2
China Online Education Group	NYSE: COE	519.2
Puxin Limited	NYSE: NEW	485.6
CooTek (Cayman) Inc	NYSE: CTK	441.9
Uxin Limited	NASDAQ: UXIN	422.7
Yintech Investment Holdings Limited	NASDAQ: YIN	412.9
Qudian Inc	NYSE: QD	406.0
Viomi Technology Co. Ltd	NASDAQ: VIOT	403.1
Up Fintech Holding Limited	NASDAQ: TIGR	381.4
Puyi Inc	NASDAQ: PUYI	367.9
Yiren Digital Ltd	NYSE: YRD	348.7
Sohu.com Limited	NASDAQ: SOHU	293.8
Cheetah Mobile Inc	NYSE: CMCM	271.6
CNFinance Holdings Limited	NYSE: CNF	267.5
Aurora Mobile Limited	NASDAQ: JG	266.2
Ruhnn Holding Limited	NASDAQ: RUHN	262.3
Tarena International Inc	NASDAQ: TEDU	253.0
Leju Holdings Limited	NYSE: LEJU	248.4
RISE Education Cayman Ltd	NASDAQ: REDU	247.5
China Distance Education Holdings Limited	NYSE: DL	246.6
Jumei International Holding Limited	NYSE: JMEI	227.2
Xunlei Limited	NASDAQ: XNET	214.8
Nam Tai Property Inc	NYSE: NTP	190.0
500.com Limited	NYSE: WBAI	187.9

Kandi Technologies Group Inc	NASDAQ: KNDI	180.7
LAIX Inc	NYSE: LAIX	167.5
Secoo Holding Limited	NASDAQ: SECO	157.3
Jianpu Technology Inc	NYSE: JT	155.3
X Financial	NYSE: XYF	152.3
Xinyuan Real Estate Co. Ltd	NYSE: XIN	133.2
MOGU Inc	NYSE: MOGU	112.8
Phoenix New Media Limited	NYSE: FENG	101.2
Tuniu Corporation	NASDAQ: TOUR	96.4
Fang Holdings Limited	NYSE: SFUN	92.4
RYB Education Inc	NYSE: RYB	74.8
Pintec Technology Holdings Limited	NASDAQ: PT	49.6
TD Holdings Inc	NASDAQ: GLG	49.5
ReneSola Ltd	NYSE: SOL	48.3
Jupai Holdings Limited	NYSE: JP	38.8
Gulf Resources Inc	NASDAQ: GURE	37.0

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Authors' contributions

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Availability of data and materials

The data used in this paper is available from S&P Capital IQ, and is described in the "Appendix". The specific codes and dataset analysed for this paper are also available upon reasonable request.

Declarations

Competing interests

The author(s) declare that they have no competing interests.

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