

# Fake News & Fact Checking: Impact on News Consumption and Dissemination

Jiding Zhang

*joint work with*

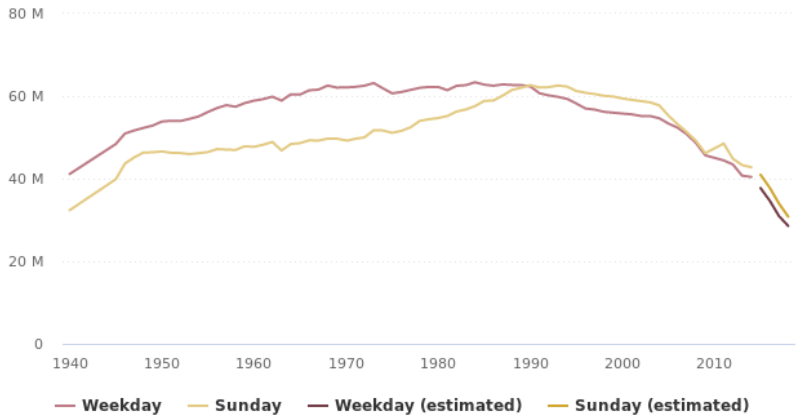
Ken Moon, Senthil Veeraraghavan

The Wharton School



# The “Newsvendor’s Problem”

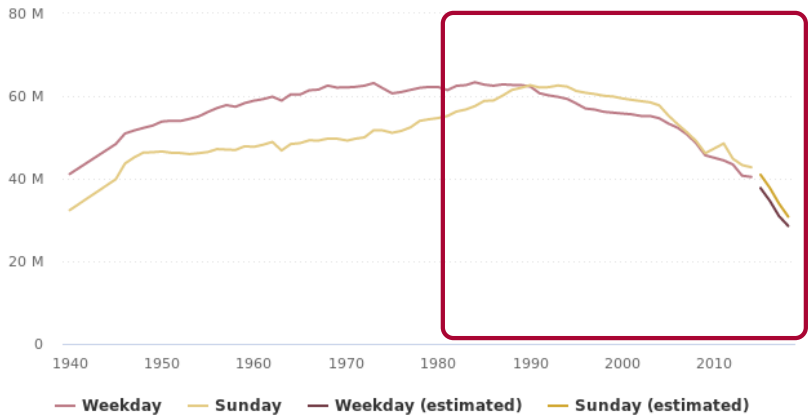
total circulation of US newspapers





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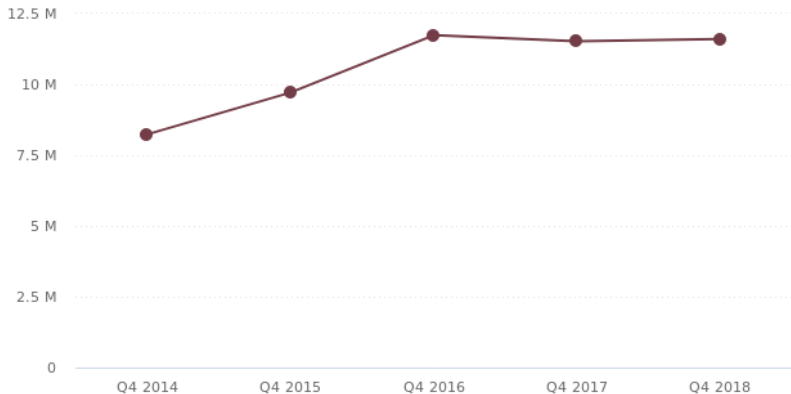
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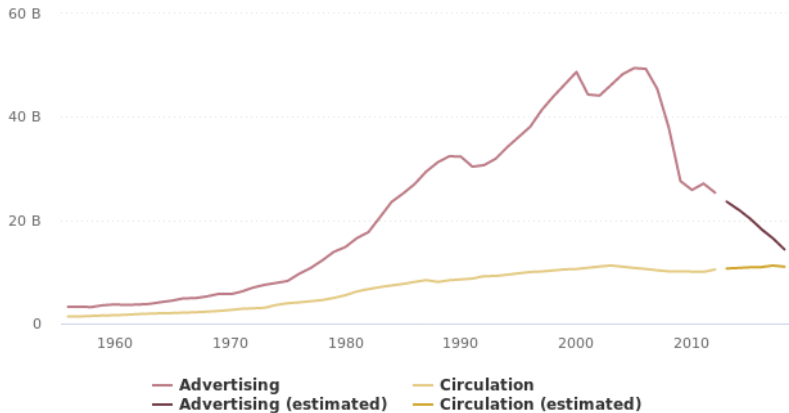
avg. monthly unique visitors to top US newspaper websites





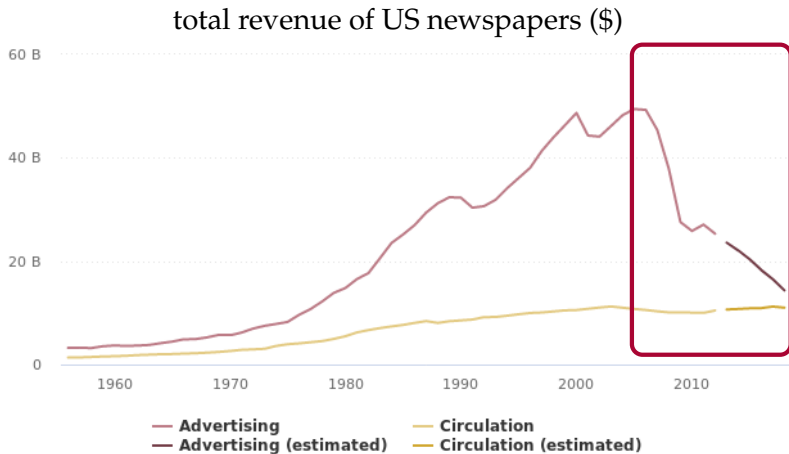
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total revenue of US newspapers (\$)



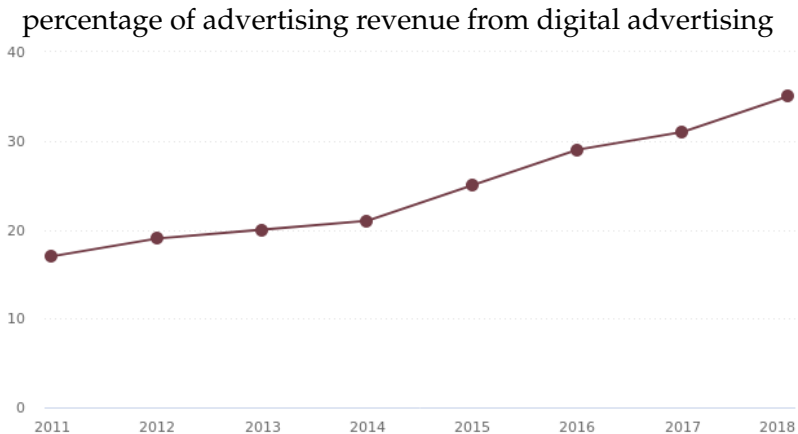


# The “Newsvendor’s Problem”





# The “Newsvendor’s Problem”





# The “Newsvendor’s Problem”

Facts:

- ↓ circulation volume of traditional newspapers
- ↑ digital news readership
- ↓ revenues
- ↑ revenue dependence on digital channel

We need:

- deeper understanding of the news operations

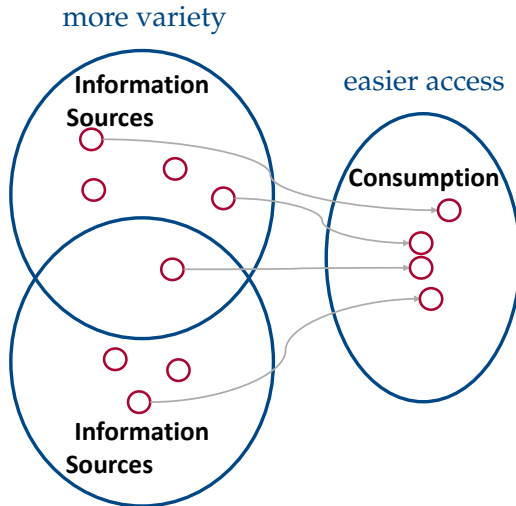




**Consumers**

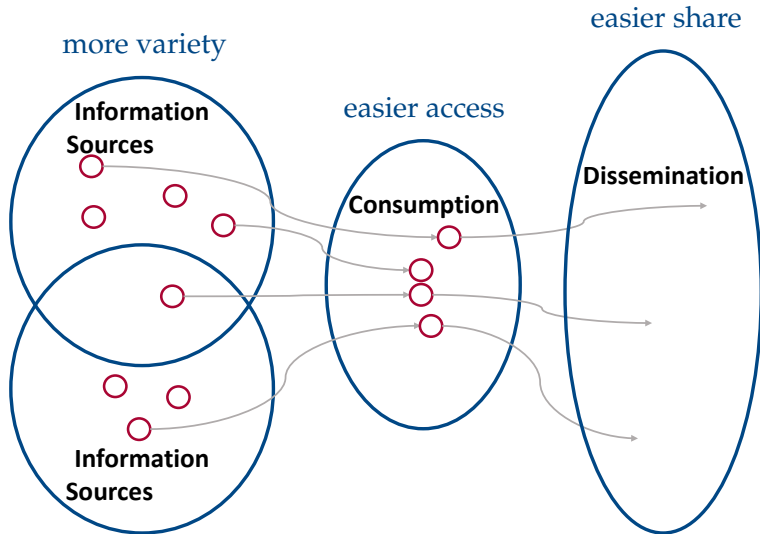


# News Consumption and Dissemination



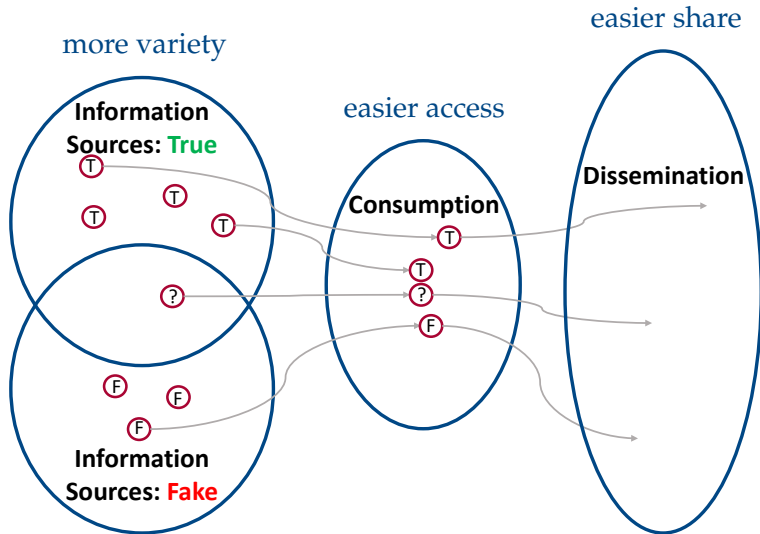


# News Consumption and Dissemination



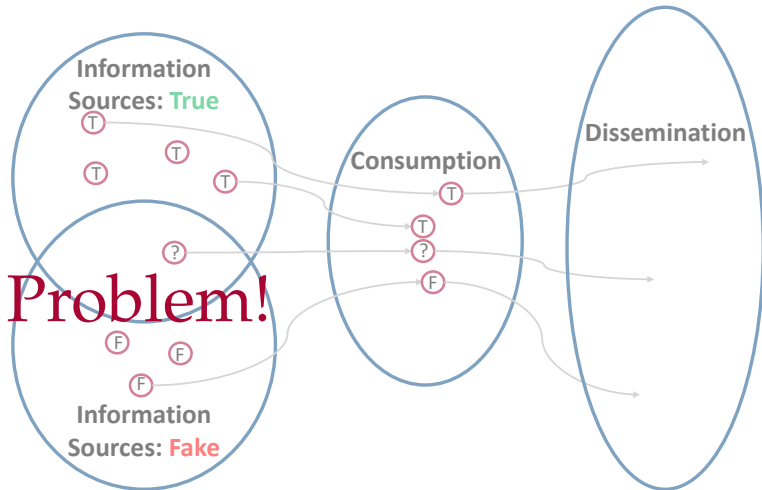


# News Consumption and Dissemination





# News Consumption and Dissemination





## Burned to death because of a rumour on WhatsApp

By Marcos Martínez  
BBC Monitoring

12 November 2018

f b t e Share

- violence



A host of mobile phones were raised aloft to capture the moment Ricardo and Alberto were set on fire



- violence
- public health

## A viral fake news story linked trans health care to 'thousands' of deaths

Hormone blockers used by some transgender people have multiple uses, including treating prostate cancer in terminally ill patients.

Sept. 27, 2019, 6:16 PM EDT

By Tim Fitzsimons

A recent article published by Catholic news outlet LifeSiteNews alleged that the drugs used to treat gender dysphoria in some transgender children are linked to “thousands” of deaths.

The story went viral on right-wing news websites such as the [Christian Post](#) and the [Daily Wire](#). According to CrowdTangle, a social media metric platform, these posts – including shares by Daily Wire founder [Ben Shapiro](#) and commentator [Matt Walsh](#) – are currently some of the top performing LGBTQ-related content on Facebook and Twitter.

The problem is: the “thousands” of people who die while taking these drugs are likely the terminally ill cancer patients who receive hormone blockers to fight hormone-sensitive cancers, like prostate cancer, according to experts.

### Sponsored Stories

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### 15 Cheapest Countries for Retirement



EXPERTS IN MONEY



- violence
- public health
- politics

## Social Media and Fake News in the 2016 Election

Hunt Allcott

Matthew Gentzkow

JOURNAL OF ECONOMIC PERSPECTIVES  
VOL. 31, NO. 2, SPRING 2017  
(pp. 211-36)

[Download Full Text PDF](#)  
(Complimentary)

Article Information

Comments (0)

### Abstract

Following the 2016 US presidential election, many have expressed concern about the effects of false stories ("fake news"), circulated largely through social media. We discuss the economics of fake news and present new data on its consumption prior to the election. Drawing on web browsing data, archives of fact-checking websites, and results from a new online survey, we find: 1) social media was an important but not dominant source of election news, with 14 percent of Americans calling social media their "most important" source; 2) of the known false news stories that appeared in the three months before the election, those favoring Trump were shared a total of 30 million times on Facebook, while those favoring Clinton were shared 8 million times; 3) the average American adult saw on the order of one or perhaps several fake news stories in the months around the election, with just over half of those who recalled seeing them believing them; and 4) people are much more likely to believe stories that favor their preferred candidate, especially if they have ideologically segregated social media networks.





# What We Study

- How do people consume news?



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- How do people consume “true” news and fake news?
- Fake news is harmful, but to whom?

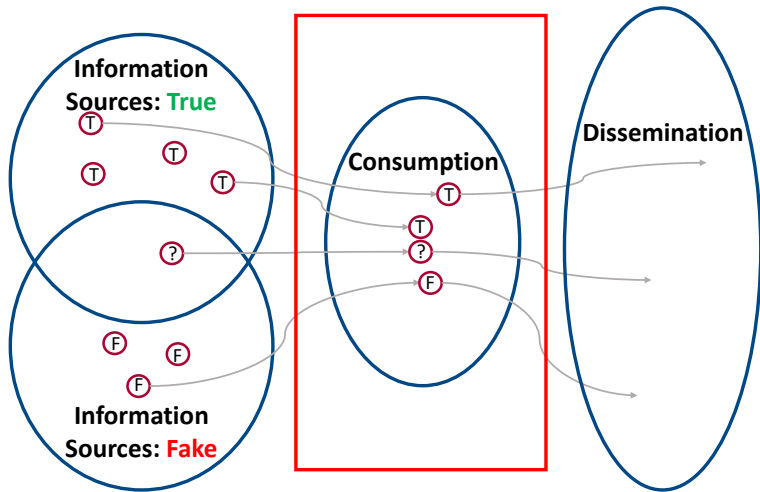


# What We Study

- How do people consume news?
- How do people consume “true” news and fake news?
- Fake news is harmful, but to whom?
- What’s the role of fact-checking in digital news?



# A Conceptual Look of News Consumption





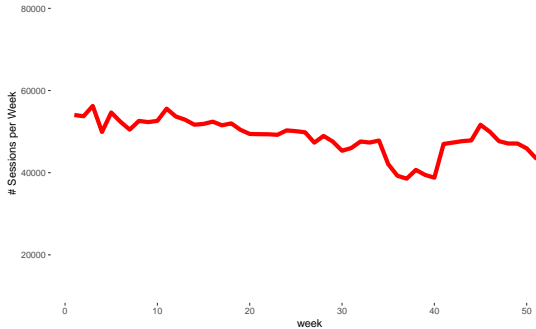
Existing research:

- **Economics, Social Science and Information Systems:**  
Allcott et al. (2019a), Allcott et al. (2019b), Gentzkow and Shapiro (2010), Gentzkow and Shapiro (2008), Acemoglu et al. (2001), Vosoughi et al. (2018), Goel et al. (2015), etc.
- **Computer Science:**  
Bakshy et al. (2011), Romero et al. (2011), Wen et al. (2015), Wang et al. (2018), etc.
- **Operations:**  
Papanastasiou (2018)

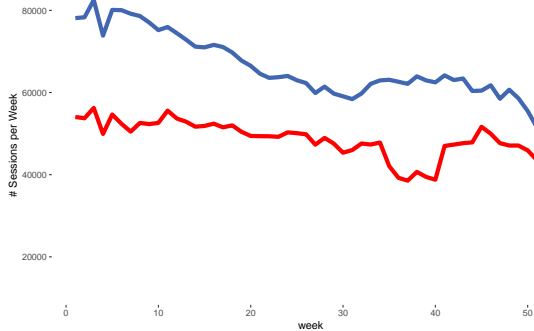
**Our Research:** the fundamental question of **preference** and **consumption**

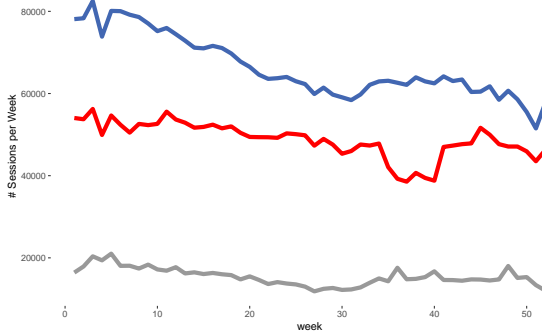


- individual (household) level web-browsing behavior on personal computers
- > 30,000 households in the United States
- from January 1, 2017 to December 31, 2017
- demographics: highest education, household oldest age, whether have children, zip code, household income











# True News vs. Fake News: Classification

- **True News:** Top 12 authentic news sites according to Alexa traffic: *cnn.com*, *nytimes.com*, *wsj.com*, *washingtonpost.com*, etc.



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- **Fake News:** Top 15 fake news sites according to Alexa traffic: *dailywire.com*, *ijr.com*, etc. (same list as provided in Allcott et al. (2019))



# True News vs. Fake News: Classification

## Las Vegas Shooting: 59 Killed and More Than 500 Hurt Near Mandalay Bay



— Concertgoers flee the Route 91 Harvest country music festival in Las Vegas on Sunday. David Becker / Getty Images



## MORGUE EMPLOYEE CREMATED BY MISTAKE WHILE TAKING A NAP



1M



Beaumont, Texas | An employee of the Jefferson County morgue died this morning after being accidentally cremated by one of his coworkers.

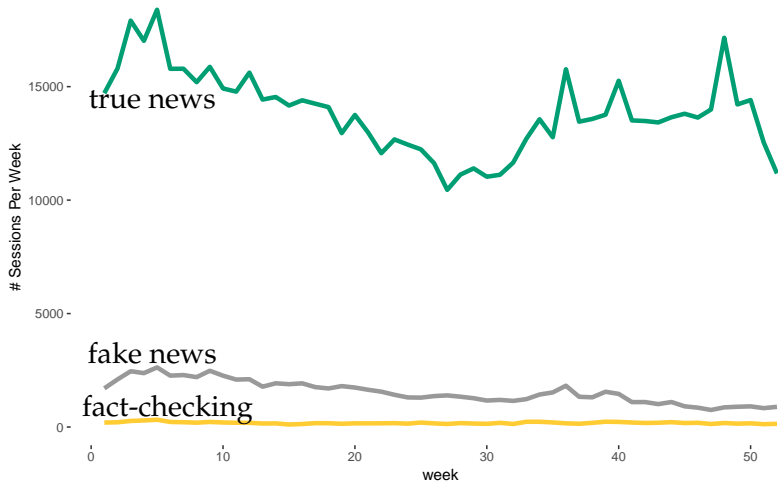


# True News vs. Fake News: Classification

- **True News:** Top 12 authentic news sites according to Alexa traffic: *cnn.com*, *nytimes.com*, *wsj.com*, *washingtonpost.com*, etc.
- **Fake News:** Top 15 fake news sites according to Alexa traffic: *dailywire.com*, *ijr.com*, etc. (same list as provided in Allcott et al. (2019))
- **Fact Checking:** Top 3 fact checking sites: *snopes.com*, *factcheck.org*, *politifact.com*



# Consumption: True News vs. Fake News





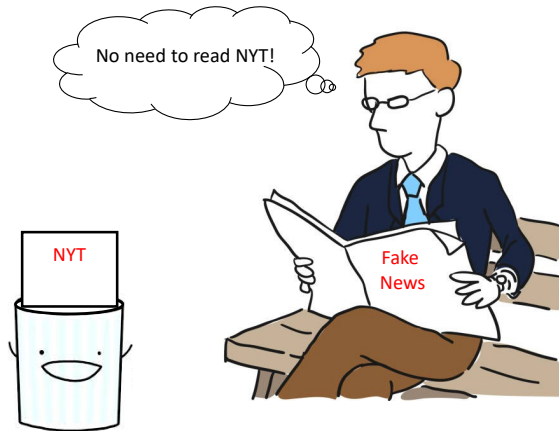


# Does Fake News Suppress True News?



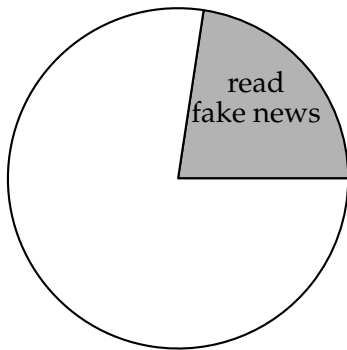


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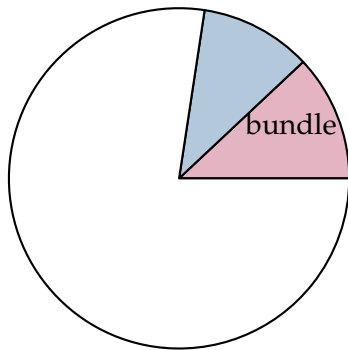


Among people who read true news, 24.6% read fake news.



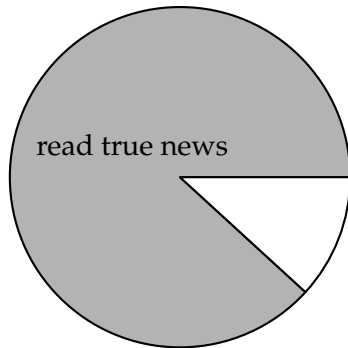


Among people who read true news, 24.6% read fake news, and 12.0% read fake news in same periods of time (bundle).



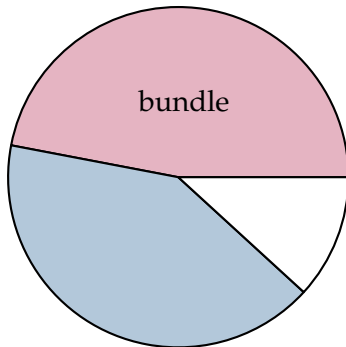


Among people who read fake news, 88.2% read true news.





Among people who read fake news, 88.2% read true news, and 47.0% read true news in same periods of time (bundle).





# Mechanisms: Reading Both in Same Periods

*Correlation-driven*  
*("love news in general")*

*Complementarity-driven*  
*("opera-and-football")*



*Correlation-driven*  
*("love news in general")*

- **Similarity** in the consumption patterns between readers
- Promote News: **Reduced** consumption of fake news

*Complementarity-driven*  
*("opera-and-football")*

- **Heterogeneity** in the consumption patterns across readers
- Promote News: **Increased** consumption of fake news





# Utility-Based Choice Model

Utility of for consumer  $i$  to consume news type  $j$  at time  $t$  for  $j \in \{Fake, Checking, True\}$ :

$$u_{ijt} = \delta_j + X_i\beta_j + \nu_{ij}$$

- $\nu_{ij}$ : idiosyncratic taste for different news types
- $\nu_{ij}$  modeled as random effect:  $\nu_{ij} \sim N(0, \Sigma_\nu)$



# Utility-Based Choice Model

Utility of consuming the bundle  $B \in 2^{\{Fake, Checking, True\}}$ :

$$u_{iBt} = \underbrace{\sum_{j \in B} u_{ijt}}_{\text{utility from each item}} +$$



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$$u_{iBt} = \underbrace{\sum_{j \in B} u_{ijt}}_{\text{utility from each item}} + \underbrace{X_i \Gamma_B}_{\text{"opera-and-football" utility boost}} +$$

- $\Gamma_j = 0$  for  $j \in \{F, C, T\}$ ,  $\Gamma_{F\&T\&C} = \Gamma_{F\&T} + \Gamma_{T\&C} + \Gamma_{F\&C}$



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- idiosyncratic error  $\epsilon$  follows the Type I extreme value distribution



# Correlation or Complementarity?

*Correlation-driven*  
*("love news in general")*

October

	1	2	3	4	5	6
7	8	9	10	11	12	13
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- True news and fake news are **complements**.

Estimators on Complementarity ( $\Gamma$ )

	F & C	C & T	F & T
Education	-0.088***	0.011	-0.057***
No Kid	0.185***	-0.048*	0.024**
Age 39-	-0.065	0.208***	-0.0579
Age 65+	-0.017	-0.101	0.066***
Baseline Complementarity	0.758***	1.849***	0.116***



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- Fact-checking websites might drive consumption of fake news.

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# A Natural Experiment

**facebook** Newsroom


Like 631K Share

Search in Newsroom

Home News Company Info Directory Media Gallery Inside Feed Public Policy Investor Relations

August 18, 2017

## Blocking Ads From Pages that Repeatedly Share False News



By Satwik Shukla, Product Manager & Tessa Lyons, Product Manager

Over the past year we have taken several steps to reduce false news and hoaxes on Facebook. Currently, we do not allow advertisers to run ads that link to stories that have been marked false by third-party fact-checking organizations. Now we are taking an additional step. If Pages repeatedly share stories marked as false, these repeat offenders will no longer be allowed to advertise on Facebook.

### Contact Us

press@fb.com

---

### Categories

- Company News
- Product News
- Data & Privacy
- Innovation
- Integrity & Security
- Safety & Well-Being
- Social Impact


---

### Archives

Select year

---

### Featured News





# Instrumenting for Fake News Supply

$$True_{it} = Fake_{it} + Fake_{it} : Demo_i + \eta_i + e_{it}$$

<i>Dependent variable: True</i>				
Fake	0.184*** (0.007)	0.205*** (0.024)	0.779*** (0.147)	1.687*** (0.602)
Fake:hoh_most_education		0.046*** (0.008)		0.069 (0.177)
Fake:factor(census_region)2		-0.062*** (0.024)		-0.269 (0.634)
Fake:factor(census_region)3		0.084*** (0.022)		-1.375** (0.537)
Fake:factor(census_region)4		-0.005 (0.027)		-0.012 (0.594)
Fake:hoh_oldest_age		-0.005 (0.003)		-0.074 (0.066)
Fake:children		-0.021 (0.015)		-0.075 (0.325)
Fake:household_income		0.018*** (0.004)		-0.095 (0.090)
Instrument: week $\geq$ 35			Y	Y



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Fake:household_income		0.018*** (0.004)		-0.095 (0.090)
Instrument: week $\geq$ 35			Y	Y



- We develop a utility-based choice model to study the consumption pattern of news.
- We disentangle bundling driven by correlation and complementarity.
- True news and fake news are complements. There is reader level heterogeneity in such complementarity.
- Fact-checking is a strong complement to fake news.





Thank you!

Fake News & Fact Checking:  
Impact on News Consumption and Dissemination  
(work in progress)

Jiding Zhang, Ken Moon, Senthil Veeraraghavan

[jiding@wharton.upenn.edu](mailto:jiding@wharton.upenn.edu)