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Consumer sentiment: The influence of social media

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A B S T R A C T

Since the late 1940s consumer sentiment has been used by policy makers, companies and investors as an indicator of economic mood. However, the rapid growth and spread of social media has changed the landscape of the consumer. By using a unique hand-collected dataset of more than 11 million influencers' posts, we test whether consumer sentiment is related to social media influencer sentiment. We find consumer sentiment, after testing for endogeneity concerns, is robustly related to different categories of influencer sentiment across different groupings of individuals.

1. Introduction

By using a unique hand-collected dataset, we analyze the impact of social media influencers on consumer sentiment. Consumer sentiment has been seen as a key indicator for business, investors and policymakers since Michigan University developed its consumer sentiment index in the late 1940s. The rapid development and spread of social media suggest the impact of influencers on consumer sentiment needs to be considered.

The growth (see Fig. 1) and sheer scale of social media is remarkable. For example, Instagram has approximately 2 billion monthly active users worldwide and 200 million businesses. Influencers have been found, perhaps not surprisingly, to significantly affect the consumption intentions of their followers, as they are perceived as being expert, prestigious, authentic, informative, and intimate, thereby establishing themselves as opinion and taste leaders (Ki and Kim, 2019). The long term director of the Michigan Consumer Sentiment Index identified the potential impact of social networks on consumer sentiment, stating:

> "*Every upturn as well as every downturn in consumer sentiment is driven at some point by social forces that caused cascading optimism or pessimism across the population*" (Curtin, 2019, p. 209).

We contribute to the literature that studies the role of social media in shaping economic and financial decision-making (e.g., Kuchler and Stroebel, 2021) by showing that consumer sentiment is significantly related to social media influencer sentiment. Previous studies have shown that social connectedness, as estimated through social media networks, affects expectations and decisions related to the housing market (Bailey et al., 2018), income tax credit claiming behavior (Wilson, 2022), and insurance decisions (Hu, 2022).

2. Data and methodology

Our dependent variable is the Michigan Consumer Sentiment Index (CS) from 2012 to 2019, stratified by age, income, and education (see Table 1). Our major explanatory variable is social media influencer sentiment obtained from Instagram's top influencers' posts from 2012 to 2019.[1] Using Supermetrics API through Google Data Studio, we web-crawled 11,274,838 Instagram posts from influencers who have more than 1 million followers.[2] Of the 5,686 influencer profiles in our sample, 39.7 % belong to artists, including actors, singers, and musicians, and 16 % are general individuals who have garnered substantial followings on social media platforms by sharing content, opinions and engaging with audiences. Company profiles make up the third-largest category (15.7 %), followed by athletes (8.1 %) and models (3.6 %).

We used the VADER[3] method by Hutto and Gilbert (2014) for the

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[1] See the Online Appendix for more details on the construction and features of the influencer sentiment variable.

[2] One potential concern is that the text analysis techniques employed to derive sentiment are solely applied to the captions of posts, neglecting the transcripts of videos. However, during our sample period, images were the primary post type on Instagram, as opposed to videos (see https://www.quintly.com/blog/instagram-study-2019). In addition, we partially capture the sentiment of video posts, as we leverage the captions of these posts.

[3] https://github.com/cjhutto/vaderSentiment.

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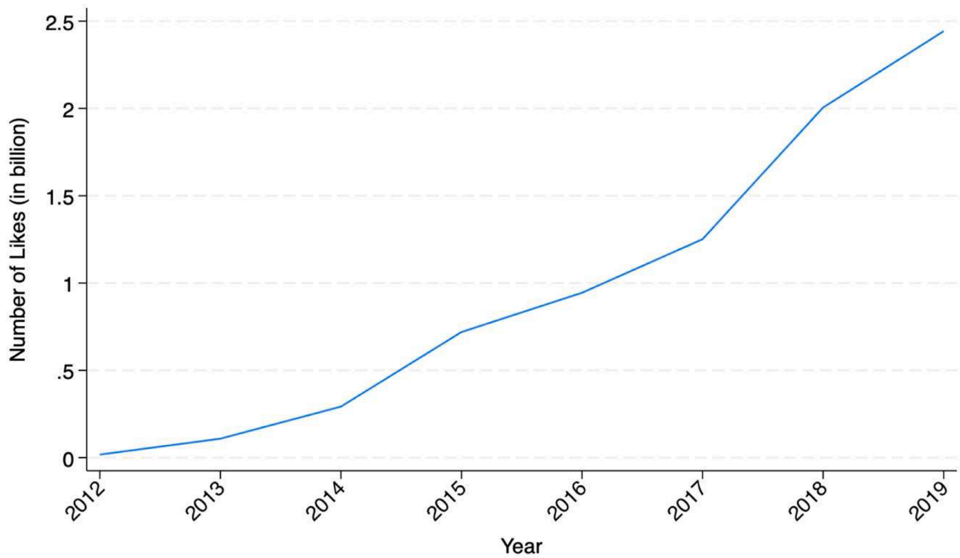

Fig. 1. Total number of Instagram likes by year.

Table 1
Summary statistics.

	N	Mean	Std. Dev.	p25	Median	p75
Panel A: Dependent variables						
CS_(Young_Age)	96	0.992	0.071	0.963	1.001	1.035
CS_(Middle_Age)	96	0.919	0.086	0.852	0.946	0.991
CS_(Low_Income)	96	0.817	0.084	0.734	0.840	0.886
CS_(High_Income)	96	0.968	0.087	0.916	0.986	1.034
CS_(No_Degree)	96	0.884	0.108	0.803	0.894	0.979
CS_(Degree)	96	0.929	0.069	0.879	0.948	0.977
Panel B: Key regressors						
IS_Total	96	0.344	0.052	0.328	0.362	0.377
IS_Listed	96	0.382	0.057	0.364	0.398	0.418
IS_Total_US	96	0.331	0.049	0.317	0.348	0.361
IS_Listed_US	96	0.375	0.061	0.350	0.389	0.414
Panel C: Controls						
Disposable_Income	96	0.002	0.007	0.001	0.003	0.004
Interest_Rate	96	0.006	0.007	0.001	0.005	0.010
Inflation	96	0.001	0.001	0.000	0.001	0.002
Unemployment	96	−0.001	0.001	−0.001	0.000	0.001
Personal_Consumption	96	0.002	0.002	0.001	0.002	0.003
EPU	96	0.982	0.360	0.719	0.897	1.175

textual analysis.[4] Influencer Sentiment (IS) is either computed on all 11, 274,838 influencers' posts (which we label as **IS_Total**) or on a subset of influencers' posts exclusively linked to listed companies (**IS_Listed**).[5] To provide insights into the potential "local" effect on consumer sentiment, Influencer Sentiment (IS) is also computed either on the subset of all posts shared by US-based influencers (**IS_Total_US**) or on the subset of US-based influencers' posts exclusively linked to listed companies (**IS_Listed_US**).[6] Influencer Sentiment is hence calculated by equal weight for each post in day *d*, and then by equally weighting for (the mean value of) each day in month *t*.

Table 2
ADF and Granger causality tests (*p*-values).

Panel A: ADF Tests		
Dependent variables		
CS_(Young_Age)	0.000	
CS_(Middle_Age)	0.043	
CS_(Low_Income)	0.034	
CS_(High_Income)	0.014	
CS_(No_Degree)	0.016	
CS_(Degree)	0.012	
Key regressors		
IS_Total	0.013	
IS_Listed	0.001	
IS_Total_US	0.021	
IS_Listed_US	0.008	
Panel B: Granger Causality Tests (with two lags) – full sample		
	H_0: IS does not cause CS	H_0: CS does not cause IS
CS_(Young_Age)	0.021	0.875
CS_(Middle_Age)	0.022	0.762
CS_(Low_Income)	0.080	0.312
CS_(High_Income)	0.001	0.830
CS_(No_Degree)	0.000	0.764
CS_(Degree)	0.005	0.535
Panel C: Granger Causality Tests (with two lags) – US-based Influencers only		
	H_0: IS does not cause CS	H_0: CS does not cause IS
CS_(Young_Age)	0.024	0.907
CS_(Middle_Age)	0.015	0.606
CS_(Low_Income)	0.094	0.341
CS_(High_Income)	0.001	0.370
CS_(No_Degree)	0.000	0.487
CS_(Degree)	0.004	0.354

[4] See Shapiro et al. (2022) for a recent application.

[5] In addition to using posts linked to listed companies, we explored a more comprehensive approach to detect sponsored content, specifically by identifying posts that include hashtags such as #ad, #adv, #sponsor, #sponsored, #paidpartnership, or hashtags with the sponsor's name followed by the term "partner" (e.g., #nikepartner). We repeated our analysis, regressing consumer sentiment on influencer sentiment and controls, using influencer sentiment derived from posts with the specified hashtags. Results remained qualitatively unchanged when compared to the results obtained through a similar analysis using influencer sentiment computed on posts linked to listed companies. We have chosen to use the subset of posts linked to listed companies as a proxy for sponsored posts, rather than the subset of posts with the specified hashtags; this decision is based on data availability, as the latter method is more likely to overlook many sponsored posts. See the Online Appendix for more details.

[6] US-based influencers account for 50% of all influencers in our sample.

Table 3
The effect of influencer sentiment on consumer sentiment.
This table shows OLS-estimation results for Eq. (3). IS_Total is the influencer sentiment computed on all influencers' posts. IS_Listed is the influencer sentiment computed on a subset of posts exclusively linked to listed companies. All specifications include month fixed-effects. Heteroscedasticity-robust standard errors are clustered at the month level. *t*-statistics in parentheses. Intercepts included but not reported. Number of monthly observations: 96. *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively.

	(1) Young_Age	(2) Middle_Age	(3) Low_Income	(4) High_Income	(5) No_Degree	(6) Degree
Panel A						
IS_Total	**0.685*****	**1.305*****	**1.334*****	**1.262*****	**1.889*****	**0.832*****
	(6.81)	**(13.13)**	**(14.49)**	**(11.44)**	**(17.32)**	**(13.14)**
Dispostable_Income	0.606	0.474	0.495	1.038	0.012	0.629
	(1.26)	(0.69)	(0.82)	(1.23)	(0.03)	(1.00)
Interest_Rate	1.687	−2.639***	−1.831**	−2.047**	−4.725***	−0.281
	(1.41)	(−3.34)	(−2.33)	(−2.61)	(−5.05)	(−0.32)
Inflation	−8.903*	−0.726	−2.862	0.990	−2.773	−0.821
	(−1.82)	(−0.16)	(−0.56)	(0.21)	(−1.00)	(−0.19)
Unemployment	−2.090	4.172	−0.518	0.423	4.140	−1.590
	(−0.44)	(1.00)	(−0.13)	(0.12)	(0.80)	(−0.97)
Personal_Consumption	1.432	−1.920	−1.840	0.250	−0.360	−0.962
	(0.70)	(−0.91)	(−0.84)	(0.17)	(−0.21)	(−0.58)
EPU	−0.043**	−0.041	−0.004	−0.062**	−0.005	−0.063**
	(−2.57)	(−1.79)	(−0.17)	(−2.27)	(−0.27)	(−2.91)
Adjusted-R^2	0.512	0.605	0.532	0.629	0.667	0.596
Panel B						
IS_Listed	**0.561*****	**1.108*****	**1.125*****	**1.053*****	**1.600*****	**0.683*****
	(6.52)	**(9.19)**	**(8.69)**	**(8.48)**	**(11.83)**	**(9.55)**
Dispostable_Income	0.824	0.895	0.925	1.443	0.622	0.894
	(1.62)	(0.90)	(1.00)	(1.33)	(0.73)	(1.10)
Interest_Rate	1.641	−2.789**	−1.971**	−2.163**	−4.934***	−0.340
	(1.31)	(−3.02)	(−2.24)	(−2.32)	(−4.51)	(−0.36)
Inflation	−8.759	−0.629	−2.728	1.166	−2.613	−0.654
	(−1.75)	(−0.14)	(−0.60)	(0.24)	(−0.81)	(−0.15)
Unemployment	−1.805	4.502	−0.138	0.843	4.644	−1.253
	(−0.40)	(1.12)	(−0.03)	(0.27)	(0.94)	(−0.69)
Personal_Consumption	1.069	−2.696	−2.617	−0.461	−1.475	−1.406
	(0.50)	(−1.12)	(−1.02)	(−0.26)	(−0.72)	(−0.72)
EPU	−0.059***	−0.071**	−0.034	−0.091***	−0.048**	−0.083***
	(−3.80)	(−3.02)	(−1.57)	(−3.36)	(−2.99)	(−4.01)
Adjusted-R^2	0.480	0.558	0.474	0.571	0.601	0.545

$$Daily\ IS = \sum Post\ Sentiment_p \Big/ Total\ Number\ of\ Posts_d \quad (1)$$

$$Monthly\ IS = \sum Daily\ IS \Big/ Number\ of\ Days\ in\ Month_t \quad (2)$$

We, therefore, estimate the following OLS-regression model:

$$CS = \alpha + \beta\ Monthly\ IS + \gamma\ controls_t + \varepsilon \quad (3)$$

The controls are chosen on the basis of prior literature (e.g., Öztürk and Stokman, 2019) and are downloaded from Federal Reserve Economic Data. **Disposable_Income** is the monthly growth rate of real disposable personal income. **Interest_Rate** is the market yield on U.S. Treasury securities at 10-year constant maturity deflated by the consumer price index. **Inflation** is the personal consumption deflator calculated as the monthly growth rate of personal consumption expenditures price index. **Unemployment** is the monthly change in the unemployment rate. **Personal_Consumption** is the monthly growth rate of real personal consumption expenditure. **EPU** is the Economic Policy Uncertainty index for the US. Table 1 provides descriptive statistics.

After establishing that consumer and influencer sentiment series are stationary (see the Augmented Dickey–Fuller tests in Panel A of Table 2), the Granger causality tests in Panels B and C of Table 2 show that influencer sentiment informs consumer sentiment (column 1), and not the opposite (column 2). This is the first indication that consumer sentiment is affected by influencer sentiment, though we acknowledge the Granger causality test may not be independently sufficient to establish a causal relationship.

3. Results

Table 3 presents the OLS-regression results. Panels A and B regress consumer sentiment on IS_Total and IS_Listed, respectively. Both panels show that consumer sentiment is significantly related to influencer sentiment. Furthermore, unreported Wald tests reveal that, across all six groups, the coefficients on IS_Total are significantly higher than those on IS_Listed. There are two possible explanations for this result. First, social media users are inclined to view non-sponsored posts as authentic content shared by influencers expressing their true feelings, views and thoughts, as opposed to posts associated with listed companies that are most likely sponsored. Consequently, users are more likely to be influenced by non-sponsored posts. Existing studies have documented that social media users tend to perceive non-sponsored posts as more credible than sponsored ones (Stubb, 2018), and they also exhibit greater engagement with non-sponsored content compared to sponsored content (De Veirman and Hudders, 2020). Second, influencer sentiment linked to all posts is likely to capture a broader range of economic and

Table 4
The effect of US-based influencer sentiment on consumer sentiment.
This table shows OLS-estimation results for Eq. (3). IS_Total_US is the influencer sentiment computed on all US-based influencers' posts. IS_Listed_US is the influencer sentiment computed on a subset of posts, from US-based influencers, exclusively linked to listed companies. All specifications include month fixed-effects. Heteroscedasticity-robust standard errors are clustered at the month level. *t*-statistics in parentheses. Intercepts included but not reported. Number of monthly observations: 96. *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively.

	(1) Young_Age	(2) Middle_Age	(3) Low_Income	(4) High_Income	(5) No_Degree	(6) Degree
Panel A						
IS_Total_US	**0.746*** **	**1.405*** **	**1.429*** **	**1.344*** **	**1.986*** **	**0.912*** **
	(6.37)	**(13.19)**	**(15.30)**	**(11.11)**	**(17.85)**	**(13.10)**
Dispostable_Income	0.661	0.580	0.605	1.143	0.172	0.695
	(1.35)	(0.86)	(1.04)	(1.34)	(0.36)	(1.12)
Interest_Rate	1.546	−2.887***	−2.075**	−2.268**	−5.021***	−0.460
	(1.30)	(−3.71)	(−2.71)	(−2.82)	(−5.39)	(−0.53)
Inflation	−8.617	−0.130	−2.232	1.612	−1.761	−0.492
	(−1.76)	(−0.03)	(−0.44)	(0.34)	(−0.63)	(−0.11)
Unemployment	−2.061	4.297	−0.361	0.608	4.530	−1.580
	(−0.43)	(0.98)	(−0.08)	(0.17)	(0.82)	(−0.88)
Personal_Consumption	1.405	−1.952	−1.865	0.236	−0.352	−1.002
	(0.71)	(−0.95)	(−0.86)	(0.18)	(−0.20)	(−0.65)
EPU	−0.041**	−0.038	−0.001	−0.060*	−0.003	−0.060**
	(−2.49)	(−1.67)	(−0.04)	(−2.17)	(−0.16)	(−2.79)
Adjusted-R^2	0.517	0.605	0.527	0.619	0.634	0.608
Panel B						
IS_Listed_US	**0.507*** **	**1.028*** **	**1.051*** **	**0.949*** **	**1.433*** **	**0.636*** **
	(5.47)	**(12.92)**	**(11.95)**	**(9.97)**	**(15.59)**	**(12.99)**
Dispostable_Income	0.869	0.990	1.023	1.526	0.746	0.953
	(1.67)	(1.19)	(1.41)	(1.56)	(1.14)	(1.34)
Interest_Rate	1.752	−2.610***	−1.801**	−1.952**	−4.600***	−0.233
	(1.49)	(−3.37)	(−2.28)	(−2.27)	(−5.13)	(−0.27)
Inflation	−9.077*	−1.405	−3.557	0.582	−3.454	−1.146
	(−1.85)	(−0.31)	(−0.72)	(0.12)	(−1.12)	(−0.26)
Unemployment	−1.920	4.112	−0.580	0.640	4.388	−1.508
	(−0.44)	(1.08)	(−0.16)	(0.19)	(0.94)	(−0.79)
Personal_Consumption	1.348	−2.195	−2.122	0.066	−0.659	−1.102
	(0.78)	(−1.23)	(−1.12)	(0.05)	(−0.42)	(−0.74)
EPU	−0.062***	−0.075***	−0.038*	−0.096***	−0.055**	−0.086***
	(−3.79)	(−3.21)	(−1.83)	(−3.33)	(−3.07)	(−3.96)
Adjusted-R^2	0.473	0.566	0.490	0.554	0.569	0.552

social factors than the influencer sentiment captured by posts exclusively linked to listed firms. In terms of control variables, when statistically significant, they show the expected signs: the higher the interest rate, inflation, and EPU, the lower the likelihood that the economy will be strong, which in turn makes consumers less confident.

Additionally, the results consistently (i.e., across both panels of Table 3) show that the consumer sentiment of middle-aged and lower educated individuals is more affected by social media influencers than that of younger age and higher education individuals, respectively.[7] The results concerning age, albeit surprising at first glance, are likely to reflect the emergence of TikTok, which prompted many younger individuals to switch away from Instagram. It is estimated that young audiences in the US spend twice as much time on TikTok as they do on Instagram.[8] Consistent with this conjecture, when we restrict the end of our sample period to 2016 (TikTok became available in 2017 in the US), the difference between young and middle-aged adults disappears, while the difference between higher and lower educated people persists. The results concerning educational levels are consistent with prior evidence indicating that education improves rationality in economic decision-making (Kim et al., 2018) and, therefore, makes consumers less susceptible to influencer marketing and communication strategies.

Table 4 presents the OLS-regression results obtained from the subsample of US-based influencers. Panels A and B regress consumer sentiment on IS_Total_US and IS_Listed_US, respectively. The results in Table 4 mirror those in Table 3. Specifically, the coefficients on IS_Total_US and IS_Listed_US are consistently positive and statistically significant across all six demographic groups. Furthermore, unreported Wald tests reveal that, for all six groups, the coefficients on IS_Total_US are significantly higher than those on IS_Listed_US, and that, across both panels, the consumer sentiment of middle-aged and lower educated individuals is more affected by social media influencers than that of younger age and higher education individuals, respectively.

A novel result to emerge from the analysis of US-based influencers' posts is that the coefficients on IS_Total_US are significantly higher than those on IS_Total across all six demographic groups, as per unreported Wald tests. These findings suggest that US-based influencers have a more pronounced impact on consumer sentiment in the US compared to non-US-based influencers. Interestingly, this pattern does not hold for posts linked to listed companies where, for 5 out of 6 demographic groups, the coefficients on IS_Listed and IS_Listed_US are not statistically different. This finding can be interpreted as another indication that, in terms of affecting consumer sentiment, non-sponsored posts tend to be more influential than sponsored posts.

4. Conclusions

We show that consumer sentiment is significantly and robustly related to the sentiment associated with the posts issued by social media influencers. The relationship is seen for influencer sentiment computed on posts exclusively linked to listed companies as well as on all

[7] IS coefficients are statistically different for age and education, as per unreported Wald tests.

[8] https://www.economist.com/business/2023/03/21/how-tiktok-broke-social-media

influencers' posts, and across age, income, and educational groupings. In short, consumer sentiment is affected by social media influencers and is not just a reflection of economic variables. Finally, similarly to Arteaga-Garavito et al. (2024), our methodology may have broader implications for future research, with possible applications in economics and finance.

Data availability

Data will be made available upon reasonable request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.econlet.2024.111638.

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