Working Papers in Economics & Finance
No. 2023-09

Do Social Media Science Stars Get Citation Premium?

Christian Lessmann, Dresden University of Technology, Ifo Institute, CESifo

Ali Sina Önder, University of Portsmouth

Portsmouth Business School
https://www.port.ac.uk/about-us/structure-and-governance/organisational-structure/our-academic-structure/faculty-of-business-and-law/portsmouth-business-school

Do Social Media Science Stars Get Citation Premium?*

Christian Lessmann
Dresden University of Technology
Ifo Institute & CESifo

Ali Sina Önder†
University of Portsmouth

November 30, 2023

Abstract

We analyze whether the social media popularity of scientists affects the number of academic citations. We use the COVID-19 global pandemic as a quasi-natural experiment exogenously increasing public attention and the demand for expertise. Using social media stars' and their coauthors' publications on COVID-related topics prior to the break out of the pandemic, we find that the social media star status added 1.10 citations following the breakout of COVID-19 per year per article, corresponding to 80% of the pre-COVID citation gap between stars and their coauthors. We find no significant treatment effect based on scientists' Kardashian indexes.

JEL Classification: J24, O33

Key Words: Social Media; Expertise; Kardashian index; Citations; Covid

---

*We are grateful to Scott Mahadeo and Sascha Schweitzer for their insightful comments and discussions. We thank Aslak Butler for research assistance. We are especially grateful to Sahar Abuelbashar and Katie Osgood for their help with SciVal and Scopus. The usual disclaimer applies.

†Contact author: ali.onder@port.ac.uk

1 Introduction

Social media is an important showcase for scientists and their research. In the age of minimum attention span and information bombardment, who does the public take as an expert in an urgent matter? Probably those who have not only some competence in the field but also enjoy high visibility. Hence, by sustaining a strong online media presence, scientists may sustain or even create their perception by the public as an expert.

Chan et al. (2023) establish a causal relationship between social media activity on a research paper and the number of citations received by that paper: Twitter engagement with an economics working paper leads up to 25% more citations when the paper is published. This is, however, a limited way to think about the impact of social media. Hall (2014) introduced the concept of Kardashian index (K-index), which captures the idea that there is a level of social media followers that is justified by the scientific prominence of a scientist. If the number of followers exceeds this justified level, this contributes to the researcher's *Kardashian*ness. "In the age of social media there are people who have high-profile scientific blogs or Twitter feeds but have not actually published many peer-reviewed papers of significance; in essence, scientists who are seen as leaders in their field simply because of their notoriety." Hall (2014, p.1)

We investigate whether social media visibility is turned into real academic currency, namely citations. In 2014, *Science* released a list of top 50 resp. 100 'Twitter science stars' (Travis, 2014, You, 2014) ranking scientists from different disciplines according to their number of followers on Twitter/X in an attempt to shed light on the newly introduced Kardashian index. Using the Travis (2014) list, we analyze whether the social media popularity of social media[1] science stars pays off in terms of an increased number of citations. To establish a causal relationship, we use the COVID-19 global pandemic as a quasi-natural experiment exogenously increasing public attention and the demand for expertise. In our empirical analysis, we concentrate on biology and virology (esp. immunology, pharmacology, biochemistry

[1] In our data's context, social media refers to Twitter/X because the list of Travis (2014) is based on follower numbers of scientists on Twitter. We refer to those scientists in the list as social media science stars, or social media stars, or very briefly as stars throughout this paper.

as explained in Section 2) among social media stars who published on COVID-related topics prior to the break out of the pandemic.

We research their relevant publications and corresponding incoming citations and compare citations to those of their co-authors on similar topics. Papers by social media stars are in the treatment group (treatment activates in 2019) while papers of coauthors form the control group, whereby we exclude joint work with the stars. We find that social media stardom added about 1.10 extra citations per year per article to the citation gap between a star and his/her coauthors in favor of the star following the breakout of COVID-19. The average annual citation difference between a star and their coauthors was in favor of coauthors between 2015 and 2019, and 1.10 citations correspond to about 80% of this difference. When we use the K-index as a treatment instead of the binary stardom treatment, we find qualitatively comparable results. When scientists with zero K-index are dropped, we find no significant difference in differences for citation inflows.

Our findings suggest that social media stardom pays off in terms of academic citations, and a plausible mechanism to explain this is that these stars benefit from visibility among their peers. Intensity of stardom, however, as captured by the non-zero K-index does not lead to differences in citations. Hence, our study adds to the literature on the rewards of social media activity for scientists (Anderson et al., 2020, Sugimoto et al., 2017). Furthermore, it provides causal results on the effects of social media on scientific productivity in a complementary manner to Chan et al. (2023).

Our paper is organized as follows. Section 2 introduces data and our identification strategy, Section 3 discusses the results, and Section 4 concludes.

2 Data and Identification

We gather annual inflow of citations to journal articles of social media stars and their coauthors using the Scopus database. We identify social media stars using the list of *Twitter's science stars* presented in Travis (2014) and we concentrate on those who have peer-reviewed journal publications in Scopus's subject areas of *immunology and microbiology* or *pharmacology, toxicology, and pharmaceutics* or *biochemistry, genetics, and molecular biology* between

2001 and 2016.[2] Ideally, we need to identify those who published in closely related areas to virology, infectious diseases, esp. SARS, MERS, or H1N1 (swine flu), which we refer to as *COVID-related research* throughout this paper. Scopus's above-mentioned three subject areas may contain publications that cannot be labeled as COVID-related research; thus, we checked publications manually to make sure that we include only those stars who have COVID-related research in our analysis. Next, we identified social media stars' coauthors as follows: Any researcher whose name appears as a coauthor on at least one of the peer-reviewed COVID-related publications of a social media star and has at least another peer-reviewed journal publication in COVID-related research that is *not* coauthored with the respective star between 2009 and 2016. This leaves us with 12 stars and their 19 coauthors. Names of stars and their respective coauthors are listed in Table 1.

Table 1: List of Twitter science stars and their coauthors with individual K-index in parantheses

Twitter science star	Coauthor
Ben Goldacre (646)	Lahiru Handunnetthi (0.1)
Daniel MacArthur (29)	David V. Erbe (0)
	Monkol Lek (2)
David Eagleman (102)	Ramiro Salas (0.1)
	Vani Pariyadath (0)
Eric Topol (352)	Nicholas J. Schork (0)
	Rachel E Meyers (0)
J. Craig Venter (32)	Amalio Telenti (0.8)
	Jonathan H. Badger (0.03)
Jonathan Eisen (46)	David A. Coil (4.3)
Matt Lieberman (28)	Elizabeth Crabb Breen (0)
	Naomi I. Eisenberger (0)
Michael Eisen (40)	Jacqueline E. Villalta (0)
	Xiaoyong Li (0)
Pascal Wallisch (59)	Frédéric Chavane (0)
Robert Winston (51)	Nicholas John Dibb (0)
Simon Baron-Cohen (32)	Barbara Jacquelyn Sahakian (0)
	Bhismadev Chakrabarti (4)
Ves Dimov (43)	Frank J. Eidelman (0)

[2]Incoming citations usually peak around two to three years after publications, which is the reason we use 2016 as the cut-off year for articles so that our analysis does not get blurred by citation inflow of too recent articles.

Our dataset contains a total of 1,276 journal articles of 31 scientists: 758 articles of 12 social media stars and 518 articles of their 19 coauthors. We construct our data set such that stars' articles contain all of their coauthors but their coauthors' articles are restricted to those that are not coauthored with the respective star.[3] We collected annual citation inflow data from Scopus for each article in our data set. We use the academic age of scientists (calculated as years from their first ever publication), annual number of articles for each year, and the total number of articles in their career up to any given year as controls in our analysis.

COVID-19 was a worldwide pandemic that caught unprecedented attention from the media and public as it was a world-wide emergency situation, and expert opinion was highly valued at that time (Lavezzolo et al., 2022). Our identification strategy is based on the exogenous attention shock caused by COVID-19: Social media stars and their coauthors may have different amounts of annual citation inflow to their journal articles over the years but if their annual citation inflows have parallel trends before 2019 and we observe a significant change in the difference of annual citations for their COVID-related research that was published between 2001 and 2016 from the treatment in 2019 on, then we show that social media stars enjoy a premium of visibility. There is no obvious reason why stars' COVID-related research from 2016 and earlier should attract disproportionately more attention after 2019 than that of their coauthors' research from the same period. Any significant change in their citation differences in favor of stars can be attributed to stars' high visibility.[4]

Figure 1 shows the means of annual citations of stars' and their coauthors' COVID-related research that was published between 2001 and 2016. We observe a boost in annual citations of stars' COVID-related research after 2019 compared to their coauthors' annual citations to papers published in the same time window. There is a reversal of the difference between stars' and their coauthors' annual citations in 2020. There is no other plausible reason as to why social media stars should get such a citation boost, especially given the existing citation gap in favor of their coauthors, except that they were perceived as experts in COVID-related

[3]Stars have many coauthors, but many of these coauthors either did not publish in the subject areas of our interest during 2009-2016 or their articles always contain the respective star as coauthor.

[4]Social media is obviously not the only medium through which stars may gain visibility. There may be positive correlations in stars' visibility on social media and other media channels. Our main claim is that visibility matters in public perception of expertise. If a star is visible via various media channels, this does not go against our claim. A social media star who is not visible in any other medium is probably not really a star.

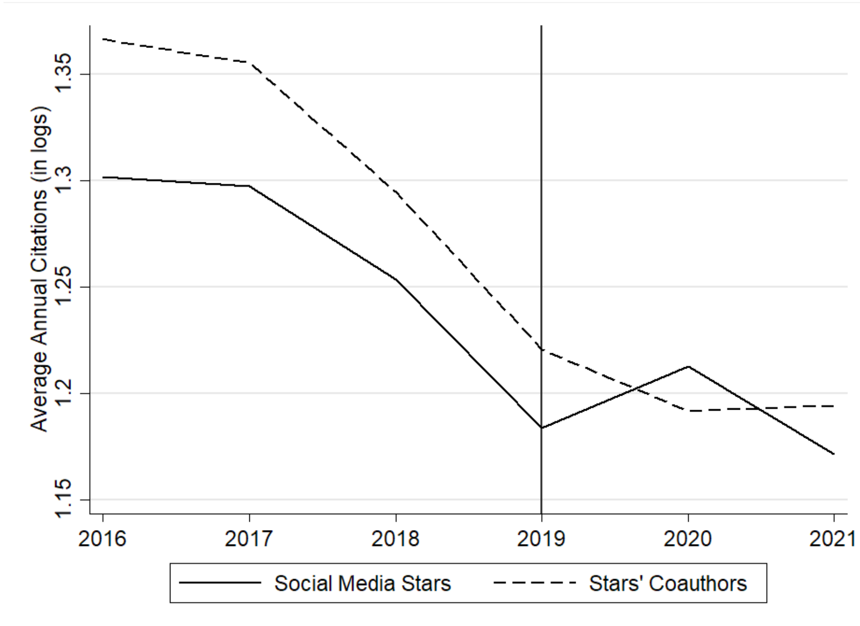

Figure 1: Means of annual citation inflow to journal articles (published from 2001 to 2016) of social media stars and their coauthors.

research to a higher degree than their coauthors due to their visibility during the COVID era.

3 Results

We estimate the following difference-in-differences (DiD) model:

$$Citations_{pst} = \alpha_1 Time + \alpha_2 Treated_s + \alpha_3 Time \times Treated_s + \beta_1 X_p + \beta_2 X_{st} + \phi_t + \phi_t p + \phi_j + \phi_s + \epsilon_{pst} \tag{1}$$

The number of incoming citations (in logs) to paper p of scientist s in year t is regressed on time, treatment, their interaction, publication characteristics (X_p), and time-variant scientist characteristics (X_{st}). We use year of citation, year of publication, journal, and individual scientist fixed effects ($\phi_t, \phi_t p, \phi_j, \phi_s$). α_3 is the main coefficient of interest.

As an alternative specification, we use the Kardashian index (K-index) of stars and their coauthors as the treatment instead of the binary variable of stardom. The main argument put forward by Hall (2014) is that a researcher with a high K-index in social media may get disproportionately more public attention that is not necessarily justified by their scientific

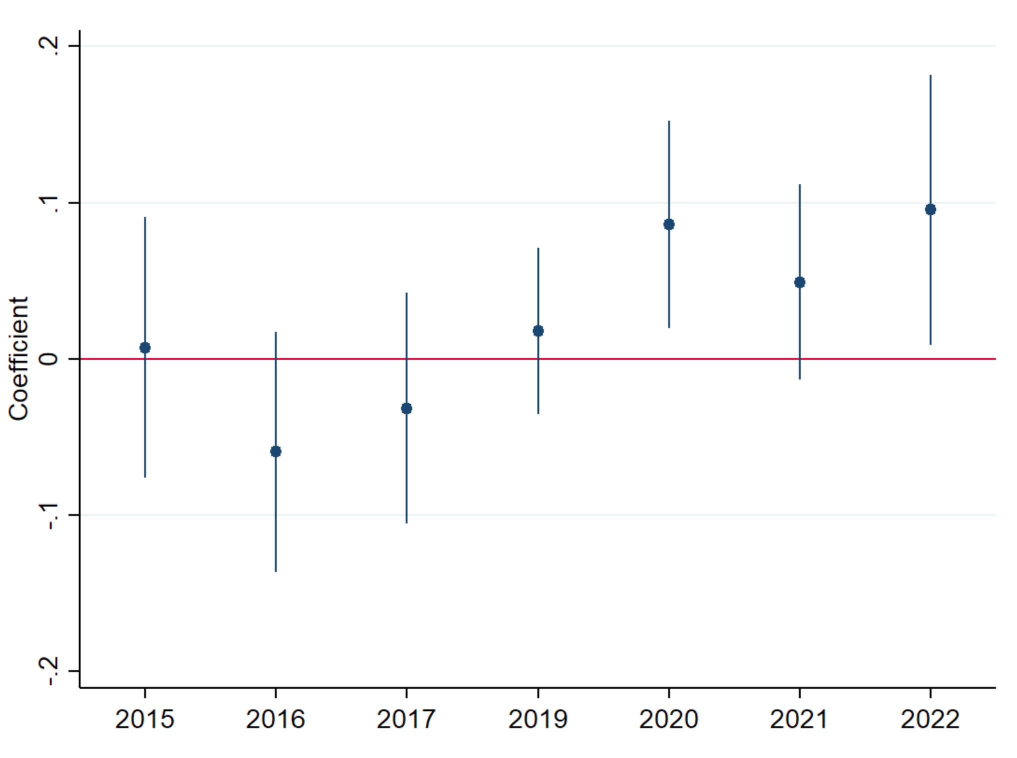

Figure 2: Mean and 90% confidence intervals for year interactions with treatment (being a social media star)

competence. K-index is a continuous variable, and although it has low values for coauthors of Twitter science stars, it is non-zero for some of the coauthors. Moreover, there is a wider variation among stars as well, as shown in Table 1.

Figure 2 shows treatment and year interactions from 2015 to 2022 where the reference year is 2018. Although we find no significantly different treatment and year interaction before 2018, we obtain significant interaction effects during the treatment period in 2020 and 2022. Hence, annual citation trends are shown to be parallel before treatment was active. The regression model that underlies Figure 2 contains article controls, age polynomials and life-cycle productivity controls for researchers, citation time lag polynomials, fixed effects for individual, journal, publication year, and citation year.

We run DiD models using the specification shown by equation 1 where the treatment is first a binary variable capturing the social media stardom of the respective scientist, which is defined as being listed as one of the scientists in Travis (2014), and then the continuous K-index variable. We show DiD coefficients for the two treatments in Tables 2 and 3, respec-

Table 2: Differences in annual citations of social media stars and their coauthors before and after COVID-19

	(1)	(2)	(3)	(4)	(5)
Post2018XTreatment	0.105^b	0.106^b	0.0884^b	0.0878^b	0.0900^b
	[0.0465]	[0.0461]	[0.0379]	[0.0378]	[0.0367]
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Pub.Year FE	No	No	No	Yes	Yes
Journal FE	No	No	Yes	Yes	Yes
Indiv.FE	No	No	No	No	Yes
Observations	8016	8016	8016	8016	8016
F	73.52	56.84	73.52	69.31	78.53
R^2	0.112	0.120	0.444	0.448	0.481

Standard errors in brackets. ^{c} $p < 0.10$, ^{b} $p < 0.05$, ^{a} $p < 0.01$ Dependent variable is the logarithm of annual citation inflow for each scientist's publication. Treatment is a binary variable capturing whether a scientists is listed in Travis (2014) or is a coauthor of a listed scientists. We consider annual citation inflow to articles published from 2001 to 2018.

Table 3: Differences in annual citations of *academic Kardashians* before and after COVID-19

	All Researchers		Only non-zero K-index	
	(1)	(2)	(3)	(4)
Post2018XTreatment	0.0206^c	0.0199^b	0.0138	0.00571
	[0.0109]	[0.00872]	[0.0175]	[0.0140]
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pub.Year FE	No	Yes	No	Yes
Journal FE	No	Yes	No	Yes
Indiv.FE	No	Yes	No	Yes
Obervations	8016	8016	5584	5584
F	56.24	78.86	31.34	75.33
R^2	0.121	0.481	0.0966	0.500

Standard errors in brackets. ^{c} $p < 0.10$, ^{b} $p < 0.05$, ^{a} $p < 0.01$ Dependent variable is the logarithm of annual citation inflow for each scientist's publication. Treatment is the Kardashian index (K-index) for each of the 31 scientists in our sample. Columns (3) and (4) present DiD coefficients where scientists with zero K-index are excluded, as they are scientists without an active Twitter/X account. We consider annual citation inflow to articles published from 2001 to 2018.

tively. Five specifications shown in Table 2 vary in their fixed effects. All five specifications yield statistically significant coefficients for the DiD interaction. The coefficient estimate in column (2) of Table 2 reveals that social media star status added about 1.10 extra citations per year per article to the citation gap between a social media star and their coauthors in favor of the star following the breakout of COVID-19. Considering that the average annual citation difference between a star and their coauthors was about 1.4 in favor of coauthors before 2019 according to Figure 1, the treatment effect corresponds to about 80% of the pre-treatment difference.

When treatment is the K-index, we find statistically significant difference-in-differences for the COVID-19 period, as can be seen in Table 3. However, statistical significance is lost when we drop those scientists who have a zero K-index (columns (3) and (4) in Table 3), meaning that they have no social media presence.[5] Hence, although the K-index when used as treatment yields similar results to those obtained when the binary stardom treatment is used, this is mainly because the K-index captures a similar but less pronounced tendency as that captured by stardom. When scientists with zero K-index are dropped, we obtain no statistical significance for the DiD interaction. Hence the magnitude of the K-index does not seem to make an incremental difference. It is probably important whether the K-index is below or above some threshold but there is no cardinal impact beyond it. Hence, the intensity of social media popularity does not affect citations once a popularity threshold is passed.

4 Conclusion

Comparing social media science stars' annual incoming citations to those of their coauthors in COVID-related research after December 2019, we find significant differences in differences between stars and their coauthors. We find that social media star status added about 1.10 extra citations following the breakout of the COVID-19 per year per article so that stars reach higher annual citations than their coauthors thanks to this effect. This effect corresponds to about 80% of the pre-treatment difference between stars and their coauthors which was in

[5] In this specific context, we restrict social media presence to having a Twitter/X account.

favor of coauthors. Our finding shows a causal link between high visibility in social media and how this translates to actual academic merit on its own. We also find that academic Kardashians, i.e. scientists with an unjustified high social media attention measured by the ratio of Twitter followers to citations, do not necessarily gain from additional social media attention caused by the pandemic. We do not find an incremental effect of the K-index when we restrict it to non-zero values.

Social media is a showcase not only for individual research papers but also for scientists, in such a way that a scientist can actively affect his or her own perception by the public as an expert by sustaining an image of being scientifically more proficient than other peers. It is important to note that some social media stars get consistently more citations than their peers which implies their celebrity status is rather well-earned. Thus one can talk about a Matthew effect in the sense that those experts who enjoy higher visibility in social media are further rewarded with more citations because of their visibility although their peers may have as much, if not more, expertise in the field. Scientists, research institutes, and research admins need to take their social media visibility very seriously as invisibility in social media can eventually hurt scientists or institutions in real terms.

References

Anderson, P. S., A. R. Odom, H. M. Gray, J. B. Jones, W. F. Christensen, T. Hollingshead, J. G. Hadfield, A. Evans-Pickett, M. Frost, C. Wilson, L. E. Davidson, and M. K. Seeley (2020): "A case study exploring associations between popular media attention of scientific research and scientific citations," *Plos One*, 15, e0234912.

Chan, H. F., A. S. Önder, S. Schweitzer, and B. Torgler (2023): "Twitter and citations," *Economics Letters*, 231, 111270.

Hall, N. (2014): "The Kardashian index: a measure of discrepant social media profile for scientists," *Genome Biology*, 15, 1–3.

Lavezzolo, S., L. Ramiro, and P. Fernandez-Vazquez (2022): "Technocratic attitudes in COVID-19 times: Change and preference over types of experts," *European Journal of Political Research*, 61, 1123–1142.

Sugimoto, C. R., S. Work, V. Larivière, and S. Haustein (2017): "Scholarly use of social media and altmetrics: a review of the literature," *Journal of the Association for Information Science and Technology*, 68, 2037–2062.

Travis, J. (2014): "Twitter's science stars, the sequel," *Science*, 6.

You, J. (2014): "Who are the science stars of Twitter?" *Science*, 345, 1440–1441.