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Education matters: the emergence of social media and scepticism towards science

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Abstract

This paper analyses General Social Survey (United States) data and provides evidence that the advent of Facebook and other social media platforms has widened the gap in scepticism towards science between low-educated Americans and their more highly educated counterparts. The same trend holds true when considering distrust in medicine, the press and television. Overall, the results suggest that education may serve as a protective factor against the influence of fake news, disinformation and misinformation. Additionally, a heterogeneity analysis shows that the increase in distrust is particularly pronounced among young people. Further analyses reveal that political affiliation plays a role in shaping attitudes towards science and that the likelihood of voting for the Republican Party has increased among low-educated individuals. A comprehensive set of robustness and placebo tests supports the reliability of these findings.

KEYWORDS

difference-in-differences, education, Facebook, general social survey, knowledge diffusion, social media, trust in science, USA

JEL CLASSIFICATION

A12, O33, D83, I21

1 INTRODUCTION

In February 2004, Mark Zuckerberg and Dustin Moskovitz founded Facebook as an 'interaction network' specifically designed for US university students. Within an exceptionally short time, its outstanding success propelled it to become the predominant social media platform on the internet, leading to a stock market listing in 2012 and boasting approximately 3 billion active monthly users globally by 2023.[1]

This pivotal event was profoundly disruptive: Facebook emerged as a significant game-changer in the realm of communication and information dissemination. It swiftly reshaped global communication patterns and significantly transformed how people worldwide interact and stay informed. In the preceding 70 years, mainstream news outlets had encompassed newspapers, radio and television. The persona of the professional journalist and the significant credibility it was associated with were seen as a safeguard for the public, serving as a bulwark constructed by traditional media against lies and falsehoods.[2] In the late 1990s, the initial effects of the internet's influence on the information sphere began to surface. However, in its nascent stages, individuals predominantly assumed a passive role online. Despite subsequent evolution, many underlying assumptions and habits from the conventional information realm remained largely unchanged.

As social media platforms emerged and proliferated, users transitioned from a passive role to an active one. Social media platforms have garnered a strategic centrality in the democratic process, significantly influencing public opinion, albeit not without challenges.[3] They have gradually evolved into a primary source of information for many individuals, supplanting traditional newspapers or other conventional information sources (see Figure A1).

In recent years, and particularly over the past decade, online channels have become the primary means through which individuals access scientific information, notably via social media platforms such as Facebook, Twitter and YouTube (Brossard, 2013). According to the National Science Board, as early as 2016 a significant majority of American citizens identified the internet as their main source of scientific information (Khan et al., 2016). A recent report from the Pew Research Center shows that 86% of Americans obtain their news from digital devices, including smartphones, tablets and computers. Today, 58% of Americans prefer to access news through digital devices, whereas 27% still rely on television, 6% on radio and 5% on print publications. Notably, of the 11 social media sites surveyed as regular news sources, Facebook emerged as the leading platform, with approximately 36% of Americans reporting that they regularly obtain news through the platform (Shearer & Mitchell, 2021). Furthermore, the Pew Research Center indicates that Facebook remains the dominant social media platform for engaging with science-related content. A larger proportion of US adults use Facebook for news (including scientific news) than any other social media platform (Hitlin & Olmstead, 2018).

[1] To describe the exponential growth of users on Facebook, Montgomery (2015) referred to a 'meteoric rise'. As of October 2023, Facebook boasts a global monthly active user (MAU) base of 3.03 billion, as reported in the 2023 Global Digital Report.

[2] This does not imply that the world of information was perfect or devoid of issues. However, the architecture of rules established over time served as a reliable safeguard against information-related risks. To further explore the issue of trust in science concerning traditional media, see Gerbner (1987), Nisbet and Goidel (2007) and Dudo et al. (2011), among others.

[3] Consumption of news and information is essential to a well-functioning democracy, and today, social media plays a significant role in this context (Napoli, 2015). To delve deeper into the issues surrounding interactions among social media governance, public perception and public discourse, refer to Obar and Wildman (2015) and Mueller (2015).

Among social media platforms, Facebook was also the first to gain popularity. According to Pew Research Center data from 2024 (Gottfried, 2024), 68% of US adults report using Facebook, whereas only 47% use Instagram, 35% use Pinterest, 33% use TikTok, 30% use LinkedIn, 27% use Snapchat and 22% use Twitter. Facebook has maintained a usage rate exceeding 57% among adults over the past decade, a figure unmatched by other social media platforms. Additionally, Facebook exhibits more uniform usage across various age cohorts (67% among 18- to 29-year-olds and 58% among those aged 65 and over). In contrast, other platforms reveal significant demographic disparities. For instance, Twitter is used by 42% of individuals aged 18–29 but only 6% of those aged 65 and older, whereas TikTok has a 62% usage rate among 18- to 29-year-olds that drops to just 10% among those aged 65 and over. It is worth noting that compared to traditional media, social media are characterized by low reputation costs, reduced production costs and a low incidence of fixed costs.[4] Moreover, the appearance and rapid spread of the smartphone, which allows people to stay connected on social media anywhere, have further accelerated the aforementioned processes.[5]

In this paper, I investigate whether this transformative shift in the communication and information landscape has influenced Americans' trust in science by examining the complex relationship between science and the public. As highlighted by Durant et al. (1989), understanding the link between science and trust is crucial for several reasons: science significantly affects everyone's lives, many public policy decisions involve science and science is publicly supported. In recent decades, various historical movements have documented a decline in public trust in scientific research, particularly following major events such as the Chernobyl disaster in 1986, the mad cow disease crisis in the United Kingdom in the early 1990s and debates over genetically modified organisms from the late 1990s to the 2000s.

In recent decades, many scholars have examined the relationship between science and the public. From the 1960s to the 1980s, discussions focused on the concept of public deficit knowledge, with Durant's (1989) research revealing that individuals in the United States and United Kingdom exhibited limited scientific understanding despite relatively high levels of interest in science, technology and medicine. The Public Understanding of Science (PUS) movement framed this issue as stemming from public deficit attitudes, referring to the notion that the public has a 'lack' or 'deficit' in understanding science and its implications. The PUS movement advocated for enhanced access to information and understanding of probabilities to foster support for scientific endeavours.

In the 1990s, the 'Science in Society' movement sought to embed science more deeply within societal contexts, promoting a responsible and inclusive approach that resonates with public needs and values. This movement aimed to facilitate broader dialogues among scientists, policymakers and citizens, ensuring that scientific initiatives were closely aligned with societal, ethical and environmental concerns (Bauer, 2009; Short, 2013). By the 2000s, the 'Public Engagement with Science and Technology (PEST)' initiative emphasized the need for inclusive and participatory discussions about science and technology. This movement advocated for a transition from a unidirectional model of public understanding to one that actively engages the public in scientific discourse and policy decisions (Leshner, 2003). This trend is further reflected in contemporary approaches such as Responsible Research and Innovation (RRI) and citizen science.

[4] In traditional media, high production and fixed costs represent an entry barrier for potential competitors.

[5] In 2007, Apple launched the first iPhone, a product that paved the way for the smartphone business and encouraged the emergence of competition. The widespread adoption of smartphones, which became an integral part of daily life, greatly facilitated the increased use of social media platforms such as Facebook. This, in turn, created a new avenue for information consumption.

These movements emphasized the significance of fostering dialogue and equitable discourse between scientists and the public, enabling non-experts to actively participate in scientific decision-making (Holden, 2002). Nonetheless, it is evident that laypeople possess only a limited understanding of science, and to effectively process scientific information, it is crucial for them to have trust in scientists and their findings. Hmielowski et al. (2014) have shown that trust in scientists is the most important heuristic that people use when expressing their opinions about scientific issues.[6] Social media has fundamentally transformed the relationship between science and the public, serving as a powerful tool for both disseminating information and, at times, perpetuating misinformation. The well-documented issues of misinformation, disinformation and fake news (Varazzani et al., 2022) are compounded by the effects of algorithms that aggregate news, creating filter bubbles, echo chambers and spirals of silence (Höttecke & Allchin, 2020). Research has explored the implications of scientific misinformation spread on social media (Liang et al., 2014)[7] and how various stakeholders leverage these platforms to influence public opinion on science-related topics, such as vaccination and climate change (Dunn et al., 2015; Jang & Hart, 2015). It is worth noting that fake news spreads six times faster than factual news and is 70% more likely to be shared (Vosoughi et al., 2018).

Furthermore, research indicates that online information-seeking can inflate self-perceived knowledge, leading individuals to believe they possess a greater understanding than they actually do (Fisher et al., 2015). This phenomenon, combined with insufficient quality control and moderation on social media, poses a significant threat to public trust in science (Weingart & Guenther, 2016). Heuristics such as confirmation bias, the bandwagon effect and availability heuristics thrive in these environments (Kahneman et al., 1982). Social network theory illustrates how users are often hesitant to shift their viewpoints due to the influence of their social circles, leading to a radicalization of initial positions and reduced openness to diverse perspectives (Sunstein, 1999).[8] Algorithms that prioritize sensational or controversial content further complicate the public's ability to discern credible scientific communication.

Conversely, some researchers argue that social media can positively impact trust in science (Huber et al., 2019). This perspective is plausible, as platforms like Facebook, Twitter, YouTube and Instagram provide scientists and institutions with direct access to a vast and diverse audience. This accessibility enhances public engagement, making scientific knowledge more widely available and comprehensible. Researchers can communicate their findings in real time, share updates on discoveries and foster discussions with both the public and fellow scientists globally. Additionally, social media has proven effective in mobilizing public support for scientific initiatives and raising awareness of critical issues such as climate change and public health. Overall, the impact of social media on the relationship between science and the public warrants further investigation. This topic remains of paramount importance in understanding contemporary science communication.

The recent COVID-19 pandemic has once again highlighted the critical importance of this issue and, of course, of individuals' trust in science. Sturgis et al. (2021) discovered that in nations characterized by substantial overall trust in science, individuals tend to exhibit higher confidence levels regarding vaccination, and many economists have questioned the impact of the

[6] To delve deeper into the topic of trust and mistrust in American views of scientific experts, see Funk et al. (2019).

[7] In a similar vein, Nicholls et al. (2024) find that dependence on social media as a primary source of news is associated with increased vaccine hesitancy, whereas Karlsen and Aalberg (2023), through an experiment on Facebook, show that the sharing of news on social media can contribute to the long-term decline in trust in news.

[8] To further explore how the structure of social media and the prevalence of fake news influence the level of misinformation and polarization within a society, refer to Azzimonti and Fernandes (2023).

COVID-19 pandemic on trust in science and scientists (Agley, 2020; Algan et al., 2021; Eichengreen et al., 2021). The COVID-19 pandemic has also highlighted the polarization surrounding scientific understanding among individuals (Rekker, 2021). This divide is particularly pronounced between those who maintain trust in scientific research, even without complete comprehension, and those who openly adopt anti-science beliefs and behaviours (Owen et al., 2013), often due to ideological reasons or because scientific facts conflict with their political identity. In this context, Rekker (2021) distinguishes between 'ideological rejection' and 'political rejection' of science. Importantly, this phenomenon of polarization regarding science is not limited to the United States; research by Tranter (2011) and Whitmarsh (2011) has demonstrated its prevalence in other countries as well.

Using American survey data covering the last 50 years, I investigate whether the emergence and establishment of social media as the main communication and information vehicle has had an impact on trust in scientists. Specifically, employing a difference-in-differences (DiD) research design, I assess the role played by education as an exposure variable.[9] Indeed, Preston et al. (2021) have pointed out that education is one of the most important tools to combat misinformation on social media, and they found that university-educated participants score significantly better on Facebook fake news detection tasks than the less educated.[10] In this context, the results of the DiD model indicate that the proliferation of social media has widened the gap in scientific distrust between these groups.

A parallel trends analysis and an event study provide both a clear visualization and a formal check of the pre-treatment trends, confirming that the parallel trends assumption holds. A placebo DiD analysis and a random allocation of the dependent variable further confirm the robustness of the findings. Overall, the main results are supported by a comprehensive set of robustness checks, which include adjustments to the period considered, alternative regression models (logit and ordered logit), a robustness test related to the emergence of the internet and different constructions of both the dependent and key independent variables.

Additional analyses confirm the widening gap in the distrust of science between low- and high-educated individuals following the proliferation of social media, which also extends to distrust in medicine, the press, and television. A further analysis reveals an increased probability of Republican affiliation among individuals with lower education levels following the emergence of Facebook; similarly, Republican affiliation plays a role in shaping attitudes towards science. A heterogeneity analysis indicates a stronger impact on younger cohorts compared to their older counterparts. Overall, this growing gap in distrust of science between the high- and low-educated is detrimental not only to science but, more importantly, to society as a whole. As has been previously established, trust in scientists is crucial for several reasons, such as its effect of reducing social complexity (Luhmann, 2018) and supporting policy decisions.

The general public's role in this process is vital. If individuals who feel disillusioned refrain from participating in research initiatives and reduce their support for science funding, the repercussions could be severe. Furthermore, this widening gap in trust in science between individuals with low and high levels of education is a challenge to the diffusion of knowledge, which is a fundamental driver of economic growth.[11] This phenomenon likely played a negative role

[9] According to Giffoni and Florio (2023) and Delugas et al. (2024), education is one potential determinant of distrust, although it is not the only one.

[10] Another highly studied topic is the relationship between social capital and education. To delve deeper into this relationship, please refer to Huang et al. (2009).

[11] To delve deeper into the topics of knowledge creation and diffusion, see Florio (2021).

in efforts to address the COVID-19 pandemic, as diminished trust in science among low-educated individuals may have resulted in lower compliance with health regulations, contributing to higher mortality rates.

The remainder of the paper is organized as follows. Section 2 describes the data, Section 3 explains the empirical strategy and Section 4 presents the results. Section 5 offers some concluding remarks, and the Appendix section presents some robustness and placebo checks, as well as an overview of trust in science across various geographical areas.

2 | DATA

The primary data source utilized is the General Social Survey (GSS), a dataset containing a series of nationally representative cross-sectional interviews conducted in the United States. Initiated in the 1970s, this biennial survey enables the monitoring and analysis of American attitudes and behaviours over nearly 50 years. The GSS is a comprehensive data source encompassing various data types, including sociological and attitudinal information, from across the United States.[12] In particular, the GSS includes diverse individual-level demographic details, which are employed as personal control variables in the analysis. These variables encompass the age, gender, marital status, employment status, homemaker status and retirement status of the respondents, as well as their real household income, parental education and political affiliation. Age is represented in the model using categorical variables grouping respondents into intervals of 10 years. Gender, marital status, retirement, and homemaking are captured by dummy variables. Employment status is depicted by a dummy variable taking a value of 0 for unemployed individuals and 1 for the employed. Household real income is represented by a categorical variable consisting of four brackets, aligning with the quartiles of the distribution. Parent's low education is captured through a dummy variable identifying whether the respondent has at least one parent with low educational qualifications (primary school or lower). Furthermore, the variable 'party' is categorical, indicating whether the respondent identifies as Republican, Democrat or Independent.

The level of confidence in scientists is gauged through the question 'What is your level of confidence in the scientific community'? Respondents could select one of the following options: (A) a great deal, (B) only some or (C) hardly any. I constructed a binary variable assigning a value of 1 if the response was (B) or (C) and 0 if the response was (A). Thus, I obtained a variable that measures distrust in scientists.[13] Additionally, the survey includes information regarding educational attainment, which I used to create a dummy that takes a value of 1 if the respondents have at most attended high school ('low-educated') and 0 if they have obtained or are currently pursuing a tertiary education degree ('high-educated').[14] Furthermore, the questionnaire collects

[12] Although the focus of this paper is on the United States, the Appendix section includes descriptive statistics on trust in science across different geographical regions (see Section A2).

[13] The rationale behind the choice of creating and using this binary dependent variable throughout the analysis stems from the aim of capturing broader trends in confidence shifts rather than subtle fluctuations. Specifically, the analysis seeks to detect whether individuals transition from a high level of confidence ('a great deal') to a reduced or minimal confidence level ('only some' or 'hardly any'). However, to ensure that this binary classification does not overly influence the results, the main analysis is also repeated using an ordered logit model with all three distinct categories. For more details, see Section 4 and the Appendix section.

[14] To account for the increase in average educational attainment over time, I implemented different education thresholds according to the historical period (pre- and post-1990). Specifically, I created a dummy variable for the pre-1990 period that, out of a maximum of 20 years of education, assigns a value of 1 to individuals with fewer than 8 years of schooling

TABLE 1 Descriptive statistics.

Variables	Mean	Std. Dev.	Min.	Max.	Obs.
1975–2021					
Years of education	13.12	3.09	0	20	40,698
LOWEDU (Education dummy)	0.30	0.46	0	1	40,698
LOWEDU2 (Education dummy 2)	0.60	0.49	0	1	40,698
Age ranges	4.16	1.77	1	8	40,698
Woman	0.44	0.50	0	1	40,698
Marital status	0.52	0.50	0	1	40,698
Status of respondent: employed	0.60	0.49	0	1	40,698
Status of respondent: retired	0.14	0.35	0	1	40,698
Status of respondent: homemaker	0.15	0.35	0	1	40,698
Real household income (in ranges)	2.65	1.14	1	4	40,698
Parent's low education	0.47	0.50	0	1	40,698
Political party: Republican	0.25	0.43	0	1	40,698
Political party: Democratic	0.36	0.48	0	1	40,698
Political party: Independent/other	0.39	0.49	0	1	40,698
Science distrust	0.57	0.50	0	1	40,698
Medicine distrust	0.56	0.50	0	1	40,527
Press distrust	0.86	0.35	0	1	40,386
TV distrust	0.88	0.32	0	1	40,389
1995–2021					
Years of education	13.73	2.98	0	20	20,329
LOWEDU (Education dummy)	0.41	0.49	0	1	20,329
LOWEDU2 (Education dummy 2)	0.50	0.50	0	1	20,329
Age ranges	4.34	1.78	1	8	20,329
Woman	0.45	0.50	0	1	20,329
Marital status	0.47	0.50	0	1	20,329
Status of respondent: employed	0.61	0.49	0	1	20,329
Status of respondent: retired	0.17	0.37	0	1	20,329
Status of respondent: homemaker	0.10	0.30	0	1	20,329
Real household income (in ranges)	2.68	1.16	1	4	20,329
Parent's low education	0.36	0.48	0	1	20,329
Political party: Republican	0.24	0.43	0	1	20,329
Political party: Democratic	0.33	0.47	0	1	20,329
Political party: Independent/other	0.43	0.49	0	1	20,329
Science distrust	0.56	0.50	0	1	20,329
Medicine distrust	0.60	0.49	0	1	20,318
Press distrust	0.90	0.30	0	1	20,258
TV distrust	0.90	0.30	0	1	20,239

Note: The data source is the General Social Survey (GSS). The descriptive statistics reported in the first panel are based on the full sample (1975–2021), whereas those in the second panel pertain to the main analysis period (1995–2021). The sample is representative of the US population, and sample weights are applied throughout all analyses. *Years of education* is a variable indicating the total number of years of education for each respondent. *LOWEDU* and *LOWEDU2* are two dummy variables indicating low education (for more details, see Section 2 and Footnote 14 in the main text). *Age ranges* is a variable that groups respondents into 10-year intervals. *Woman* is a binary variable coded as 0 if the individual is male and 1 if female. *Marital status* is a dummy variable equal to 1 if the individual is married and 0 if not married. *Employed*, *retired* and *homemaker* are dummy variables that equal 1 if the respondent holds the respective status and 0 otherwise. The household's real income is represented by a categorical variable consisting of four brackets aligned with the quartiles of the distribution. Parent's low education is captured through a dummy variable that identifies whether the respondent has at least one parent with low educational qualifications (primary school or lower). *Republican*, *Democratic* and *Independent/other* are dummy variables identifying respondents who identify as Republican, Democrat or Independent/other, respectively. A further analysis explores more detailed sub-categories, such as 'close to Republicans' and 'close to Democrats'. For more information on the science distrust, medicine distrust, press distrust and TV distrust variables, please refer to Section 2.

information on other trust-related variables, including trust in medicine, the press and television. Confidence in medicine is assessed through the question 'What is your level of confidence in medicine'? Confidence in the press is evaluated by asking, 'What is your degree of confidence in the press'? Similarly, confidence in television is measured by enquiring, 'What is your degree of confidence in TV?'. For each of these variables, the responses follow the same scale as described above, and I applied the same recoding method. The full sample from 1975 to 2021 includes 40,698 individuals, whereas the sample related to the main analysis period, 1995–2021, consists of 20,329 individuals. Table 1 presents the key descriptive statistics for both samples.

3 | EMPIRICAL STRATEGY

The analysis is based on a DiD model of the following form:

$$Y_{irt} = \alpha + \beta LOWEDU_i + \gamma Post_t + \lambda\left(LOWEDU_i \times Post_t\right) + \delta X_{irt} + \mu_r + \tau_t + \varepsilon_{irt} \quad (1)$$

where Y_{irt} is the level of distrust of scientists held by individual i born in region r[15] and interviewed at time t (1 refers to distrust in scientists and 0 to trust in scientists). $LOWEDU_i$ is a dummy variable relating to the education level of interviewees (0 indicates highly educated and 1 indicates a low level of education), whereas $Post_t$ takes a value of 1 if the interview took place in the period following Facebook's onset and 0 otherwise. The model is valid under the assumption that education is exogenous to the emergence of fake news and distrust in science. Hypothetically, if a general climate of distrust towards science were to emerge, one potential consequence might be a reduction in the demand for higher education. To confirm that this is not the case, Figure A2 presents an analysis of compositional changes over time, using the post-2008 (Facebook) dummy as the main independent variable and various controls from the analysis as dependent variables. This approach makes it possible to examine shifts in individual characteristics following 2008 that may correlate with the rise of fake news and distrust in science. Reassuringly, Figure A2 does not indicate any such occurrence.[16] The coefficient of interest is λ, which is the coefficient of the interaction of the $LOWEDU_i$ and $Post_t$ variables. This coefficient represents the average differential in the distrust of scientists between low-educated and high-educated individuals in the period following the advent of social media platforms.[17] As far as the 'post' period is concerned, based on Google Trends data, I consider a watershed in the year 2008, which is the year in which Facebook started to become popular. Although it was born in 2004, it became more broadly accessible from September 2006 (i.e., open to all those aged 13 and above with an e-mail address), and in

(middle school) and 0 otherwise. For the post-1990 period, the dummy is equal to 1 for those with fewer than 12 years of education (high school) and 0 otherwise. It is important to note that given the main analysis spans 1995–2021, in the main analysis the education variable is time-invariant (all respondents are surveyed post-1990), whereas in Table A1, it is not. As additional robustness checks, I adjusted the thresholds for defining low/high educational status and employed a rule based on the respondents' birth years rather than survey years, thus generating a time-varying education variable for the primary sample (1990–2021). For further details, please refer to Section 4 and Table A4.

[15] Because the period considered is very long, the most granular place-of-residence information is related to the macro-region (i.e., an aggregation of states). Specifically, nine areas are considered: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Atlantic, West South Central, Mountain and Pacific.

[16] For further details, please see Section 4 and Figure A2.

[17] Or rather, following the birth of the first (widespread) social media network, Facebook.

2008, it reached a very high number of active users.[18] However, as a robustness exercise, I repeat the analysis also considering 2010 and 2012 as benchmarks.[19] X_{irt} controls for observable individual characteristics (age, gender, marital status, employment status, whether the respondent is a homemaker, whether the respondent is retired, the real income of the household, parental education and declared political party). In this way, individual demographic and socio-economic characteristics that may impact trust in scientists are captured. μ_r and τ_t control for region and time fixed effects, respectively.[20]

4 | EMPIRICAL RESULTS

Table 2 presents the main results related to the 1995–2021 period. Because this setup does not reflect a 'reform' implemented on a specific date but rather the spread of the first social media platform (Facebook), I consider several post-treatment periods. As explained in Section 3 and shown in Figure A1, the most feasible time period to consider the post-treatment period is post-2008 (Columns (1)–(3) in Table 2). Later periods are also considered robustness checks. Specifically, I consider 2010 (Columns (4)–(6) in Table 2) and 2012 (Columns (7)–(9) in Table 2). In this period, Facebook emerged as the most popular social network in the United States. The simultaneous introduction of smartphones and the rise of other social media platforms played a pivotal role in accelerating the shift in communication and how information is consumed, as outlined in Section 1. In particular, the widespread adoption of smartphones, which became an integral part of daily life, greatly facilitated the increased use of social media platforms such as Facebook. This, in turn, created a new avenue for information consumption, as previously discussed.[21]

Table 2 shows that the results are stable for the different sets of controls and the different columns (post-2008, post-2010 and post-2012). The coefficient reported in Column (1) is positive, statistically significant at the conventional level (5%) and stable across the different specifications in which personal and socio-economic controls are progressively included (Columns (2) and (3), respectively).[22]

[18] According to Associated Press data, in December 2004 Facebook had 1 million active users worldwide and by December 2005 it had reached 5.5 million. By December 2006, it had reached 12 million; by April 2007, 20 million; by August 2008, 100 million; by April 2009, 200 million; and by September 2009, 300 million. According to the 2023 Global Digital Report, Facebook has over 3 billion MAUs worldwide.

[19] For more information about Facebook's takeoff, see Figure A3.

[20] For more information on the control variables, please refer to Section 2 and Table 1. For an introduction to the methods, refer to Angrist and Pischke (2009).

[21] According to a paper published on the World Economic Forum Blog in 2021, media consumption increased significantly over the decade of 2011–2021, with mobile usage being the primary driver of this growth. Mobile media consumption has surged by 460% over the past 10 years, rising from an average of 45 min per day to an astounding 252 min per day (https://www.weforum.org/stories/2021/05/rise-of-media-on-mobile-phone-chart/).

[22] Among the controls, I did not include the variable indicating whether respondents live in a rural or urban area. This is because approximately 2600 individuals out of the 20,329 who responded to the survey between 1995 and 2021 did not answer the question regarding the population size of their city of residence. Including this variable in the model would have led to the exclusion of 13%–14% of the sample, raising concerns about sample representativeness. However, as an additional robustness check, I replicated the main analysis including the rural/urban dummy among the controls. The $LOWEDU \times Post$ interaction remains significant in all cases, regardless of the population threshold used to classify municipalities as urban or rural. Results are available upon request.

TABLE 2 Main results.

Dependent variable (Y): distrust in scientists	Post-2008			Post-2010			Post-2012		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Period: 1995–2021									
LOWEDU × Post	0.035**	0.037**	0.032**	0.041**	0.043**	0.038**	0.036*	0.036**	0.032*
	(0.012)	(0.012)	(0.011)	(0.015)	(0.014)	(0.014)	(0.017)	(0.017)	(0.016)
Observations	20,329	20,329	20,329	20,329	20,329	20,329	20,329	20,329	20,329
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Personal controls		Yes	Yes		Yes	Yes		Yes	Yes
Socio-economic controls			Yes			Yes			Yes

Note: The dependent variable is the dummy related to distrust in science and is fixed in all specifications. The variable *LOWEDU* × *Post* is the DiD interaction term between the education dummy (*Low-educated*) and the *Post* dummy. All columns account for regional fixed effects (FE), as well as year FE. Personal controls include age, gender and marital status. Socio-economic controls include employment status, whether the respondent is a homemaker, whether the respondent is retired, real household income, parent's low education and political party affiliation (declared). For more information on the variables, please refer to Section 2 and specifically to the note in Table 1. The three groups of columns, respectively, consider the *Post* period to be post-2008, post-2010 and post-2012. Standard errors are clustered at the regional level. The statistical significance of the test that the underlying coefficient is equal to zero is denoted by ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

The coefficient of the main specification that accounts for the full set of controls, reported in Column (3), implies that following the advent of social media, individuals with a lower level of education had a higher probability of distrusting science compared to those with higher educational attainment. Specifically, the increase in probability is approximately 3 percentage points. This indicates that 6.12% of the increase in scepticism is mitigated by education, highlighting its critical role in curbing the rise in the distrust of science. Although education may not entirely eliminate scepticism, it seems that it may significantly contribute to its reduction.[23] So it seems that education may serve as a protective factor against the influence of fake news, disinformation and misinformation, phenomena that have always existed but are much more easily conveyed by social media.

In order to further assess the validity of the analysis, I developed a comprehensive set of robustness checks. First, I replicated the main model for several samples accounting for different periods, as presented in Table A1. This approach allows for verification that the results remain consistent regardless of the period considered. Specifically, panel A covers the years from 1975 to 2021, panel B from 1985 to 2021, panel C from 1995 to 2021 (the main sample) and panel D from 2000 to 2021. As indicated in Table A1, the results are robust across the various analysis periods[24] and remain consistent regardless of the estimation method employed (logit, Table A5; ordered logit, Table A6). Moreover, the results remain robust when replicating the analysis using a time-varying definition of highly educated individuals rather than a time-invariant one.[25] In Table A4, instead of defining individuals as highly educated if they held at least an associate degree (or bachelor degree

[23] To calculate this value, I divided the coefficient of *LOWEDU* × *Post* from the main specification (column (3), Table 2, equal to 0.0315) by the average level of distrust in scientists among highly educated individuals in the 1995–2007 period (0.5145) and multiplied the result by 100.

[24] For further details, please see the Appendix section.

[25] For additional details, see Section 2.

or higher) throughout the entire period, I replicated the analysis by incorporating the increase in average educational attainment over time into the definition.[26] This table shows that even when adding an additional year of schooling to define an individual as educated (time-invariant definition), the results remain robust and consistent. Overall, the findings are confirmed: the direction of the relationship is consistent, and the coefficients remain statistically significant in all specifications.[27]

These findings highlight that although descriptive statistics from the GSS indicate a general decline in distrust of science over the past 20 years, this trend is likely driven by consistently high levels of trust among educated individuals, who actually show increasing trust over time. In contrast, distrust in science among less educated individuals has remained stable, which has led to a widening gap in distrust between low- and high-educated individuals.

The validity of the DiD research design is based on the fact that distrust in science by the high- and low-educated was following parallel trends prior to 2008, that is, before the advent of Facebook and other social media platforms. Figure A4 provides a comprehensive visual inspection of the parallel trends, showing the full time series of distrust in science, including both the pre- and post-treatment periods (clearly separated by a vertical black line). The fitted lines reported in the figure clearly demonstrate parallel trends before 2008 and a divergent dynamic after 2008. Specifically, the graph shows that after the vertical line (2008), the gap in the distrust of science between low- and high-educated individuals widens. By the end of the period considered (2021), the two lines are further apart than at any point in the previous 30 years. Although distrust in science decreased among the highly educated, it remained stable among the less educated.

To further support the validity of the analysis, I also estimated an event-study analysis that provides a formal check of the pre-treatment trends, ensuring that the parallel trends assumption holds. The results are shown in Figure A5, where the first 'pre-' period is set as (−2)—as the survey is biennial—and is used as the reference point. As can be seen from the graph, all pre-treatment estimates and their confidence intervals overlap with zero, indicating that they are statistically insignificant. The absence of significant effects before the treatment period strengthens the case for the DiD model's appropriateness in this context. Moreover, Figure A6 shows the coefficients from a placebo DiD analysis where the treatment start date is shifted in 2-year intervals from 2006 ($LOWEDU \times Post2006$) back to 1996 ($LOWEDU \times Post1996$). In all periods considered here, Facebook was not yet publicly available (it opened to the public only in September 2006 and initially had only a few million users). The fact that all coefficients overlap with zero suggests that when periods prior to 2008 (the actual treatment date) are used as the treatment period, any effect dissipates. This finding further reinforces the robustness of the analysis.

To further validate the research design, I performed additional robustness and placebo checks.[28] In particular, in the spirit of Pei et al. (2019), Figure A7 shows the coefficients of a set of regressions from which I progressively removed a control variable from those reported in Equation (1) and used it as a placebo outcome. This test aims to check for the existence of some unobservable bias. The estimated coefficients indicate that almost all variables demonstrate no

[26] Specifically, I created a dummy variable for individuals born before 1990 that assigns a value of 1 to those with fewer than 8 years of schooling (middle school) and 0 otherwise (out of a maximum of 20 years of education). For individuals born after 1990, the dummy takes a value of 1 for those with fewer than 12 years of education (high school) and 0 otherwise. The results are presented in Table A4 and are robust to using the same rule but with thresholds set at 1980 or 1975, highlighting that regardless of how the variable is constructed, the main findings hold.

[27] For additional details, see Table A4.

[28] As already reported in Table 2 and Table A1, as robustness checks I also perturbed both the control sample and the treatment period.

significant relationship with *LOWEDU* × *Post*, with *Republican* being the only exception to show significance.[29] This highlights that the effect of education level on trust in science may be partially explained by political affiliation. In other words, assuming various factors have contributed to differing trends in trust in science among individuals with higher and lower education levels, political affiliation is likely to be one of these channels. Facebook has likely intensified polarization, especially among less educated individuals, leading them to accept information from their political parties via social media and distrusting science. In Table 4, I investigate this aspect further.

A further robustness check is again aimed at the validation of the identification strategy. The identification strategy is based on the fact that social media has increased the gap in scientific distrust between low- and high-educated individuals. To check that the education dummy is not spuriously correlated with distrust in science, I created a fake education dummy and distributed it randomly to individuals in the same proportion of 0s and 1s as the true education dummy variable. I interacted the fake education dummy variable with the actual *Post* dummy variable and replicated this model 1000 times. The results are shown in Figure A8, where *LOWEDU* × *Post* is the placebo variable of interaction between the fake educational attainment dummy and the *Post* variable. The mean of the estimated coefficient is close to 0, showing that no relationship is present. This test checks for the possibility that the correlation could result from chance. Furthermore, to ensure that the analysis is not merely capturing time-varying effects of the independent variables (*X*s) on distrust of science, I repeated the DiD analysis with distrust of science as the dependent variable. In this analysis, I included various control variables for which I did not expect any significant effects on distrust in science interacted individually with the *Post* dummy (considering each as *main X* × *Post*). Specifically, I included the following variables: *Woman* × *Post*, *Retired* × *Post*, *Homemaker* × *Post* and *Income* × *Post* (each separately, in different regressions). The results of this analysis, presented in Table A3, demonstrate the absence of differentiated effects on distrust of science: All coefficients across the various specifications examined (baseline, which includes only a subset of controls, as well as the full set of controls) are not statistically significant.

In Table 3, I test whether the rise of social media impacted not only trust in scientists but also other trust-related outcomes. The descriptive statistics from the GSS presented in Table 1 show that from 1995 to 2021, 56% of individuals reported a distrust in science, 60% in medicine and 90% in the media (including both the press and television).[30] The low levels of trust in the media in the United States are corroborated by various Gallup surveys (Swift, 2016; Brenan, 2022). Additionally, data from the Pew Research Center highlights that trust in science in the United States is generally higher than trust in the media; specifically, between 2016 and 2021, the proportion of US adults expressing a high level of trust in scientists was more than three times that of those reporting trust in journalists (Kennedy et al., 2022). It is reasonable to expect that distrust of traditional media (TV and press) is greater than that towards science and medicine. The primary reason is that traditional media has often been at the centre of political controversies and scandals, potentially fuelling scepticism, whereas scientific institutions are generally perceived as more neutral and less politically driven. The analysis shows that in the period following the emergence of social media, in addition to the aforementioned increasing gap in the distrust of science between low- and high-educated individuals, there was also an increase in distrust of medicine, the press and television. The coefficients are statistically significant across the various specifications (see Table 3).

[29] The variable *Age* is only weakly significant. Table 5 further explores the role of age in the analysis.

[30] It is worth noting that the variables were constructed by categorizing individuals as distrustful if they reported having only 'some' or 'hardly any' trust. For further details, please refer to Section 2.

TABLE 3 Other dependent variables.

Dependent variable (Y):	Post-2008			Post-2010			Post-2012		
	Medicine distrust	Press distrust	TV distrust	Medicine distrust	Press distrust	TV distrust	Medicine distrust	Press distrust	TV distrust
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Period: 1995–2021									
LOWEDU × Post	0.057***	0.022**	0.019**	0.054***	0.032***	0.019**	0.057***	0.041***	0.022***
	(0.010)	(0.007)	(0.007)	(0.010)	(0.006)	(0.006)	(0.012)	(0.010)	(0.006)
Observations	20,256	20,197	20,176	20,256	20,197	20,176	20,256	20,197	20,176
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Personal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable in Columns (1), (4) and (7) is the dummy related to distrust of medicine. The dependent variable in Columns (2), (5) and (8) is the dummy related to distrust of the press. The dependent variable in Columns (3), (6) and (9) is the dummy related to distrust of television. The variable *LOWEDU* × *Post* is the DiD interaction term between the education dummy (*Low-educated*) and the *Post* dummy. All columns account for regional FE, as well as year FE and a full set of controls. Personal controls include age, gender and marital status. Socio-economic controls include employment status, whether the respondent is a homemaker, whether the respondent is retired, real household income, parent's low education and political party affiliation (declared). For more information on the variables, please refer to Section 2 and specifically to the note in Table 1. The three groups of columns, respectively, consider the *Post* period to be post-2008, post-2010 and post-2012. Standard errors are clustered at the regional level. The statistical significance of the test that the underlying coefficient is equal to zero is denoted by $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

TABLE 4 Analysis of mediating factors: political affiliation.

	Party affiliation (1)	Science distrust (2)	Science distrust (3)	Science distrust (4)
$EDU \times Post$	0.063*** (0.016)	0.040** (0.013)	0.037** (0.012)	0.032** (0.011)
$EDU \times Post \times Rep$				0.016 (0.018)
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Personal controls	Yes	Yes	Yes	Yes
Socio-economic controls	Yes	Yes	Yes	Yes
Observations	18,444	18,444	18,444	18,444

Note: In Column (1), the dependent variable is party affiliation (Democrats/Republican); in Columns (2)–(4), it is science distrust. The variable $LOWEDU \times Post$ is the DiD interaction term between the education dummy (*Low-Educated*) and the *Post* dummy. In Column (4), this variable is additionally interacted with Republican dummy (*Rep*). In Columns (3) and (4), Republican Party affiliation is also included among the controls. All columns account for regional FE as well as year FE. Personal controls include age, gender and marital status. Socio-economic controls include employment status, whether the respondent is a homemaker, whether the respondent is retired, real household income and parent's low education. For more information on the variables, please refer to Section 2 and specifically to Note 1 in Table 1. 'Post' refers specifically to the period after 2008. Standard errors are clustered at the regional level. The statistical significance of the test that the underlying coefficient is equal to zero is denoted by ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

More specifically, the coefficients of the preferred specifications reported in the post-2008 columns imply that the low-educated have increased their distrust in medicine compared to the high-educated by 5.7 percentage points, distrust in the press by 2.2 percentage points and distrust in television by 1.9 percentage points. The increase in distrust in medicine among individuals with lower levels of education aligns with the growing trend of patients increasingly seeking information (including medical data) from electronic platforms that often fail to differentiate effectively among information sources. This shift has sparked a reassessment of the doctor–patient relationship (Baron & Berinsky, 2019) and can be considered an additional factor contributing to the erosion of trust in science. In contrast, the increase in distrust in the press and television highlights another phenomenon: the decline in trust in traditional media among low-educated individuals. The fact that the coefficients for distrust of the press and TV are lower than those for medicine and science may relate to the greater distrust of traditional media mentioned previously. These results add to previous evidence indicating that the most significant challenge facing journalism today is the public's lack of trust (Fink, 2019).

Table A2 shows the results of replicating these results across several samples representing different time windows. This approach enables verification of the consistency of the results, irrespective of the period considered. Specifically, panel A covers the years from 1975 to 2021, panel B from 1985 to 2021, panel C from 1995 to 2021 (the main sample) and panel D from 2000 to 2021. As can be seen from Table A2, the results remain robust across the various periods.[31]

In Table 4, I further investigate the potential role of political affiliation, as highlighted by the Pei test (Figure A7). Specifically, Table 4 presents additional analyses focusing on individuals affiliated with one of the two major US political parties—Democratic and Republican—and

[31] For further details, please see Table A2.

TABLE 5 Analysis of heterogeneous effects: age.

Dependent variable (*Y*): distrust in scientists		
	Post-2008	
	(1) Age <Median age	(2) Age >Median age
Period: 1995–2021		
LOWEDU × Post	0.031**	0.016
	(0.013)	(0.016)
Region FE	Yes	Yes
Year FE	Yes	Yes
Personal controls	Yes	Yes
Socio-economic controls	Yes	Yes
Observations	10,310	10,019

Note: The dependent variable is the dummy related to distrust in science, and it is fixed in all specifications. The variable *LOWEDU × Post* is the DiD interaction term between the education dummy (*Low-educated*) and the *Post* dummy. All columns account for regional FE, as well as year FE. Personal controls include age, gender and marital status. Socio-economic controls include employment status, whether the respondent is a homemaker, whether the respondent is retired, real household income, parent's low education and political party affiliation (declared). For more information on the variables, please refer to Section 2 and specifically to the note in Table 1. Standard errors are clustered at the regional level. The statistical significance of the test that the underlying coefficient is equal to zero is denoted by ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

excluding those without a political affiliation.[32] Column (1) illustrates how the interaction term *LOWEDU × Post* influences political affiliation, confirming the results from the previous test while considering only those with political affiliations, which vary by education level and the post-2008 period. Notably, the results indicate an increased probability of Republican affiliation among individuals with lower education levels post-2008, aligning with descriptive evidence from our GSS sample that shows a rise in strong Republican affiliation from 9% in 2008 to 18% in 2021. Additionally, political affiliation impacts distrust in science: the coefficient in Column (2), where the political party variable is excluded from the controls, is higher than in Column (3), where it is included. Specifically, the coefficient in Column (3) is approximately 8% lower than that in Column (2), suggesting that part of the effect of Facebook on low-educated individuals' distrust in science is mediated by political affiliation. To explore this further, Column (4) presents estimates from a specification that includes both *LOWEDU × Post* and *LOWEDU × Post × Republican*. The coefficient of the *LOWEDU × Post × Republican* interaction is not statistically significant, whereas both the *LOWEDU × Post* interaction and the Republican dummy are highly significant (*Republican* = 0.050***, SE = 0.001). These results confirm that Republican affiliation plays a role and that Republicans—regardless of education level—are more likely to distrust science compared to Democrats.

In Table 5, I examine the presence of heterogeneous effects based on the age of individuals. Notably, in the early years, social media usage was predominantly associated with younger demographics. Furthermore, the shift towards using social media for everyday information, as well

[32] That is, individuals who identified as Independent did not respond or declared support for another party. Individuals who identify as 'close to Republicans' are classified as Republican and those 'close to Democrats' as Democrat. The results remain unchanged when considering only strong Republicans, Republicans, strong Democrats and Democrats. Results are available upon request.

TABLE 6 Robustness test related to the emergence of the internet.

Dependent variable (*Y*): distrust in scientists						
	Post-1996		*Post-1998*		*Post-2000*	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel B: 1985–2007						
LOWEDU × Post	−0.011	−0.000	−0.013	−0.006	−0.005	−0.001
	(0.013)	(0.013)	(0.015)	(0.013)	(0.018)	(0.018)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Personal controls		Yes		Yes		Yes
Socio-economic controls		Yes		Yes		Yes
Observations	18,379	18,379	18,379	18,379	18,379	18,379

Note: The dependent variable is the dummy related to distrust in science, and it is fixed in all specifications. The variable *LOWEDU* × *Post* is the DiD interaction term between the education dummy (*Low-educated*) and the *Post* dummy. All columns account for regional FE, as well as year FE. Personal controls include age, gender and marital status. Socio-economic controls include employment status, whether the respondent is a homemaker, whether the respondent is retired, real household income, parent's low education and political party affiliation (declared). For more information on the variables, please refer to Section 2 and specifically to the note in Table 1. The three groups of columns respectively consider the *Post* period to be post-1996, post-1998 and post-2000. Standard errors are clustered at the regional level. The statistical significance of the test that the underlying coefficient is equal to zero is denoted by ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

as its emergence as a primary source of information, primarily affects younger individuals, and specifically millennials and Generation Z, with individuals in the latter being referred to as 'digital natives'. The coefficients presented in Table 5 corroborate this, revealing a greater impact on the younger cohort (those below the median age) compared to their older counterparts (those above the median age).[33]

Finally, as some might argue that a comparable trend in trust in scientists took place among low-educated individuals following the introduction of the internet, in Table 6, I replicate the main analysis, instead considering the widespread access to the internet for the vast majority of the American population as the turning point. For this particular scenario, I investigated the timeframe from 1985 to 2007, excluding the period following 2007, as this was the year just prior to the rise of Facebook.[34] As the choice remains arbitrary in this case as well, I considered three scenarios with three different turning points: 1996, 1998 and 2000.[35] As indicated by the coefficients reported in Table 6, the introduction of the internet itself did not differentially impact distrust in science among low- and high-educated Americans.

[33] I split the sample based on the median age, which is 46 years. This median is very close to the mean age of the sample, which is 47.4 years. The results remain consistent even when the threshold for the split sample is reduced to 40 years and below. The results are available upon request. An additional theme discussed in the literature concerning social media, with a primary focus on young individuals, is the matter of policy interventions and social implications related to surveillance on Facebook. For a more in-depth exploration, see Montgomery (2015).

[34] This analysis period covers comparable timeframes both before and after the introduction of the internet. Notably, the results remain statistically insignificant even when the analysis is extended to include the years preceding 1985. Results are available upon request.

[35] It is important to note that there is no specific date pinpointing the exact moment when the majority of Americans gained access to the internet. Although this was gradual over the years, the data highlight that most of the American population gained access to the internet in the late 1990s and early 2000s.

Annals of Public and Cooperative Economics
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5 | CONCLUSION

This paper contributes to the literature on the relationship between science and the public by testing whether social media played a role in shaping the dynamics of scepticism towards science and, if so, in what ways. In particular, comparing trust in scientists among low- and high-educated Americans before and after the advent of the first major social media network, Facebook, I find that the gap between the two has increased.

A parallel trends analysis and an event study offer a clear visualization and a formal test of pre-treatment trends, validating the parallel trends assumption. Additionally, a placebo DiD analysis and random allocation of the dependent variable provide further evidence of the robustness of the findings. Overall, the main results are corroborated by a set of robustness checks encompassing modification to the time period considered, alternative regression models (logit and ordered logit), a robustness test regarding the emergence of the internet, and different constructions of both the dependent and key independent variables.

Further analyses provide additional support for the growing divide in distrust of science between low- and high-educated individuals as social media proliferated, with similar patterns observed in terms of distrust of medicine, the press and television. In addition, the results show a higher likelihood of Republican affiliation among individuals with lower education levels following the rise of Facebook. Additionally, a heterogeneity analysis reveals a more pronounced impact on younger cohorts (below the median age) relative to older individuals (above the median age). Overall, it appears that education provides the antibodies to avoid succumbing to fake news, disinformation and misinformation. Facebook first, and then social media as a whole, have been gamechangers in the world of communication and information, and the widespread adoption of smartphones, which have become an integral part of daily life, greatly facilitated the increased use of social media platforms. This, in turn, created a new avenue for information consumption.

However, the growing gap in trust in science among individuals with different levels of education represents a problem for knowledge diffusion. By way of example, it is very plausible that this dynamic played a negative role in efforts to combat the COVID-19 pandemic: lower trust in science among the low-educated may have led to lower compliance with rules among these groups and, therefore, to more deaths.

This study has some limitations. First, although it specifically focuses on the role of Facebook, it is likely that other social media platforms have also contributed to the patterns observed (and the fact that the results remain robust even when considering periods post-2010 and post-2012 is indicative of this). However, the analysis does not allow for a clear identification of the role played by other social media platforms or for disentangling the specific contributions of each platform in this relationship.

Furthermore, distrust in science is a complex and multifaceted phenomenon shaped by a range of factors beyond social media, such as misinformation, inconsistent messaging, perceived conflicts of interest, historical unethical practices, cultural and ideological conflicts and systemic inequalities. Naturally, these factors cannot be fully captured by the analysis, which is focused solely on examining the role of Facebook in exacerbating distrust in science between low- and high-educated individuals, rather than offering a comprehensive analysis of all potential contributing factors.

Nevertheless, what emerges from this empirical study is a result that can greatly impact a community's quality of life and has many negative spillover effects, contributing to the increased division and polarization of society. It is thus crucial for policymakers at all levels to address this issue. Although there is no single solution to reduce the gap in trust in science between more and less educated groups, several actions are clearly desirable. Investing in educational programs that enhance scientific understanding from primary school through to university, strengthening the teaching of critical thinking, improving the regulation of content on social media (e.g., guidelines to reduce the spread of scientific misinformation, promoting verified content, penalizing false information) and reinforcing the connection between science and society could all contribute to narrowing the trust gap and fostering greater confidence in science among less educated populations. An important avenue for future research is to assess whether the trend of increasing distrust in science in the low-educated population has also occurred in European, Asian, African and South American countries.[36]

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[36] The Appendix section provides an overview of trust and distrust in science across different geographical regions.

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APPENDIX
ADDITIONAL ROBUSTNESS CHECKS

Figure A2 presents an analysis of compositional changes over time, displaying the coefficients from a set of regressions in which the post-2008 (Facebook) dummy serves as the main independent variable and various control variables from the analysis are used as dependent variables. This approach assesses shifts in population characteristics following 2008 that may correlate with the emergence of fake news and increasing distrust in science. The coefficients in Figure A2 indicate trends that align with long-term secular patterns.

First, the coefficient for education (where 0 denotes the highly educated and 1 denotes less educated individuals) is negative, reflecting a continued increase in the proportion of educated individuals rather than any decline in demand for tertiary education. Similarly, the increase in parental education levels indicates that younger cohorts of parents have generally achieved higher education levels than previous generations.

Other significant coefficients in Figure A2 are likewise in line with secular trends. The coefficient for age shows an increase in average population age, consistent with factors such as improved socio-economic conditions, longer life expectancy, and declining birth rates. This demographic shift, common in advanced economies such as the United States, has substantial

TABLE A1 Main results—different time periods

Dependent variable (Y): distrust in scientists	*Post-2008*			*Post-2010*			*Post-2012*		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Panel A: 1975–2021									
LOWEDU × Post	0.033*	0.040**	0.037**	0.038*	0.046**	0.043**	0.035	0.042*	0.040*
	(0.015)	(0.014)	(0.014)	(0.017)	(0.016)	(0.016)	(0.019)	(0.018)	(0.018)
Observations	40,698	40,698	40,698	40,698	40,698	40,698	40,698	40,698	40,698
Panel B: 1985–2021									
LOWEDU × Post	0.032*	0.037**	0.033*	0.037*	0.043**	0.0397*	0.033	0.038*	0.036
	(0.017)	(0.016)	(0.015)	(0.018)	(0.018)	(0.017)	(0.020)	(0.020)	(0.019)
Observations	29,854	29,854	29,854	29,854	29,854	29,854	29,854	29,854	29,854
Panel C: 1995–2021									
LOWEDU × Post	0.035**	0.037**	0.032**	0.041**	0.043**	0.038**	0.036*	0.036*	0.032*
	(0.012)	(0.012)	(0.011)	(0.015)	(0.014)	(0.014)	(0.017)	(0.017)	(0.016)
Observations	20,329	20,329	20,329	20,329	20,329	20,329	20,329	20,329	20,329
Panel D: 2000–2021									
LOWEDU × Post	0.035**	0.037**	0.031*	0.040**	0.043**	0.038**	0.032	0.034*	0.029
	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)	(0.017)	(0.017)	(0.017)
Observations	16,806	16,806	16,806	16,806	16,806	16,806	16,806	16,806	16,806
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Personal controls		Yes	Yes		Yes	Yes		Yes	Yes
Socio-economic controls			Yes			Yes			Yes

Note: The dependent variable is the dummy related to distrust in science, and it is fixed in all specifications. The variable *LOWEDU* × *Post* is the DiD interaction term between the education dummy (*Low-educated*) and the *Post* dummy. All columns account for regional FE, as well as year FE. Personal controls include age, gender and marital status. Socio-economic controls include employment status, whether the respondent is a homemaker, whether the respondent is retired, real household income, parent's low education and political party affiliation (declared). For more information on the variables, please refer to Section 2 and specifically to the note in Table 1. The three groups of columns, respectively, consider the *Post* period to be post-2008, post-2010 and post-2012. Each panel refers to a different period, as specified in the table. Standard errors are clustered at the regional level. The statistical significance of the test that the underlying coefficient is equal to zero is denoted by ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

TABLE A2 Other dependent variables—different time windows.

Dependent variable (Y):	*Post-2008*			*Post-2010*			*Post-2012*		
	Medicine distrust (1)	**Press distrust (2)**	**TV distrust (3)**	**Medicine distrust (4)**	**Press distrust (5)**	**TV distrust (6)**	**Medicine distrust (7)**	**Press distrust (8)**	**TV distrust (9)**
Panel A: 1975–2007									
LOWEDU × Post	0.057***	0.026**	0.028***	0.057***	0.034***	0.028***	0.061***	0.043***	0.030***
	(0.009)	(0.009)	(0.005)	(0.011)	(0.008)	(0.005)	(0.011)	(0.009)	(0.006)
Observations	40,527	40,386	40,389	40,527	40,386	40,389	40,527	40,386	40,389
Panel B: 1985–2021									
LOWEDU × Post	0.058***	0.026**	0.017**	0.057***	0.034***	0.017***	0.061***	0.043***	0.020***
	(0.009)	(0.009)	(0.005)	(0.010)	(0.009)	(0.003)	(0.011)	(0.010)	(0.0042)
Observations	29,741	29,647	29,639	29,741	29,647	29,639	29,741	29,647	29,639
Panel C: 1995–2021									
LOWEDU × Post	0.057***	0.022**	0.019**	0.054***	0.032***	0.019**	0.057***	0.041***	0.022***
	(0.010)	(0.007)	(0.007)	(0.010)	(0.006)	(0.006)	(0.012)	(0.010)	(0.006)
Observations	20,256	20,197	20,176	20,256	20,197	20,176	20,256	20,197	20,176
Panel D: 2000–2021									
LOWEDU × Post	0.042***	0.017	0.015**	0.039***	0.029***	0.016*	0.043**	0.039**	0.019**
	(0.009)	(0.010)	(0.006)	(0.011)	(0.008)	(0.007)	(0.013)	(0.012)	(0.008)
Observations	16,752	16,711	16,690	16,752	16,711	16,690	16,752	16,711	16,690
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Personal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable in Columns (1), (4) and (7) is the dummy related to distrust in medicine. The dependent variable in Columns (2), (5) and (8) is the dummy related to distrust of the press. The dependent variable in Columns (3), (6) and (9) is the dummy related to distrust of television. The variable *LOWEDU × Post* is the DiD interaction term between the education dummy (*Low-educated*) and the *Post* dummy. All columns account for regional FE, as well as year FE and a full set of controls. Personal controls include age, gender and marital status. Socio-economic controls include employment status, whether the respondent is a homemaker, whether the respondent is retired, real household income, parent's low education and political party affiliation (declared). For more information on the variables, please refer to Section 2 and specifically to the note in Table 1. The three groups of columns, respectively, consider the *Post* period to be post-2008, post-2010 and post-2012. Each panel refers to a different period, as specified in the table. Standard errors are clustered at the regional level. The statistical significance of the test that the underlying coefficient is equal to zero is denoted by ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

TABLE A3 Other main independent variables.

Dependent variable (Y): distrust in scientists			
		Post-2008	
	(1)	**(2)**	**(3)**
Panel A Period: 1995–2021			
Woman × Post	−0.001	−0.003	−0.002
	(0.012)	(0.013)	(0.013)
Observations	20,329	20,329	20,329
Panel B Period: 1995–2021			
Retired × Post	0.003	0.021	0.022
	(0.019)	(0.020)	(0.020)
Observations	20,329	20,329	20,329
Panel C Period: 1995–2021			
Homemaker × Post	−0.015	−0.006	−0.007
	(0.030)	(0.028)	(0.028)
Observations	20,329	20,329	20,329
Panel D: 1995–2021			
Income × Post	−0.010	−0.008	−0.007
	(0.008)	(0.007)	(0.007)
Observations	20,329	20,329	20,329
Region FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Personal controls		Yes	Yes
Socio-economic controls			Yes

Note: The dependent variable is the dummy related to distrust in science and is fixed in all specifications. Each panel presents the coefficient of a different interaction variable. All columns account for regional FE, as well as year FE. Personal controls include age, gender, and marital status. Socio-economic controls include employment status, whether the respondent is a homemaker, whether the respondent is retired, real household income, parent's low education and political party affiliation (declared). For more information on the variables, please refer to Section 2 and specifically to the note in Table 1. *Post* refers to the period after 2008. Standard errors are clustered at the regional level. The statistical significance of the test that the underlying coefficient is equal to zero is denoted by ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

implications for pensions, healthcare and labour markets. The *Retired* variable also shows an increase in the number of retirees over time, whereas the employment variable reflects a decrease in employment levels, likely influenced by periods of economic and financial instability.

Lastly, the variable for party affiliation is particularly noteworthy. In Section 4 of the main text, I further explore the role of party affiliation, suggesting that alignment with the Republican Party has played a role in driving distrust in science during the Facebook era. Over the past decade, it appears plausible that the Republican Party has increasingly attracted voters by leveraging fake news and echo chambers as tools of political strategy.

A separate compositional change analysis for high- and low-educated subsamples generally aligns with the findings from the full sample, indicating that both groups have followed similar secular trends over time.

TABLE A4 Robustness check: time-variant/invariant education dummy.

Dependent variable (Y): distrust in scientists			
		Post-2008	
	(1)	**(2)**	**(3)**
Panel A: 1995–2021—time-variant education dummy 1 ($y = 1990$)			
LOWEDU × Post	0.039**	0.033**	0.028**
	(0.012)	(0.012)	(0.011)
Observations	20,329	20,329	20,329
Panel B: 1995–2021—time-variant education dummy 2 ($y = 1980$)			
LOWEDU × Post	0.038***	0.034**	0.029**
	(0.011)	(0.012)	(0.011)
Observations	20,329	20,329	20,329
Panel C: 1995–2021—time-variant education dummy 3 ($y = 1975$)			
LOWEDU × Post	0.031**	0.035**	0.032**
	(0.010)	(0.011)	(0.011)
Observations	20,329	20,329	20,329
Panel D: 1995–2021—time-invariant education dummy 2			
LOWEDU × Post	0.024*	0.027**	0.023*
	(0.012)	(0.011)	(0.011)
Observations	20,329	20,329	20,329
Region FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Personal controls		Yes	Yes
Socio-economic controls			Yes

Note: The dependent variable is the dummy related to distrust in science and is fixed in all specifications. The variable *LOWEDU* × *Post* is the DiD interaction term between the education dummy (*Low-educated*) and the *Post* dummy. The education variable differs across the various panels. Specifically, I created a dummy variable based on a maximum of 20 years of schooling. In panel A, for individuals born before 1990, this dummy is set to 1 for those with fewer than 8 years of schooling and to 0 otherwise, whereas for individuals born after 1990, it takes a value of 1 for those with fewer than 12 years of schooling. In panel B, the threshold year is set to 1980, and in panel C, to 1975. In panel D, using a time-invariant definition of the education dummy, I add an extra year of schooling to classify an individual as educated, relative to the definition used in the main analysis. All columns account for regional FE, as well as year FE. Personal controls include age, gender and marital status. Socio-economic controls include employment status, whether the respondent is a homemaker, whether the respondent is retired, real household income, parent's low education and political party affiliation (declared). For more information on the variables, please refer to Section 2 and specifically to the note in Table 1. *Post* refers to the period after 2008. Standard errors are clustered at the regional level. The statistical significance of the test that the underlying coefficient is equal to zero is denoted by ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

TABLE A5 Main results: logit estimations.

Dependent variable (Y): distrust in scientists			
	Post-2008		
	(1)	**(2)**	**(3)**
Period: 1995–2021			
LOWEDU × Post	0.036***	0.038***	0.032***
	(0.012)	(0.012)	(0.011)
Observations	20,329	20,329	20,329
Region FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Personal controls		Yes	Yes
Socio-economic controls			Yes

Note: The dependent variable is the dummy related to distrust in science and is fixed in all specifications. The variable *LOWEDU* × *Post* is the DiD interaction term between the education dummy (*Low-educated*) and the *Post* dummy. All columns account for regional FE, as well as year FE. Personal controls include age, gender and marital status. Socio-economic controls include employment status, whether the respondent is a homemaker, whether the respondent is retired, real household income, parent's low education and political party affiliation (declared). For more information on the variables, please refer to Section 2, and specifically to the note in Table 1. Standard errors are clustered at the regional level. The statistical significance of the test that the underlying coefficient is equal to zero is denoted by ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

TABLE A6 Main results: ordered logit estimations.

Dependent variable (Y): distrust in scientists			
	Post-2008		
	(1)	**(2)**	**(3)**
Period: 1995–2021			
LOWEDU × Post	1.099**	1.106***	1.079**
	(0.042)	(0.042)	(0.035)
cut1	0.206	1.041	0.947
	(0.030)	(0.126)	(0.156)
cut2	3.086	3.945	3.873
	(0.038)	(0.143)	(0.172)
Observations	20,329	20,329	20,329
Region FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Personal controls		Yes	Yes
Socio-economic controls			Yes

Note: The dependent variable is the dummy related to distrust in science and is fixed in all specifications. The variable *LOWEDU* × *Post* is the DiD interaction term between the education dummy (*Low-educated*) and the *Post* dummy. All columns account for regional FE, as well as year FE. Personal controls include age, gender and marital status. Socio-economic controls include employment status, whether the respondent is a homemaker, whether the respondent is retired, real household income, parent's low education and political party affiliation (declared). For more information on the variables, please refer to Section 2 and specifically to the note in Table 1. The cut-off points represent the thresholds that separate the ordered categories in the model. Standard errors are clustered at the regional level. The statistical significance of the test that the underlying coefficient is equal to zero is denoted by ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

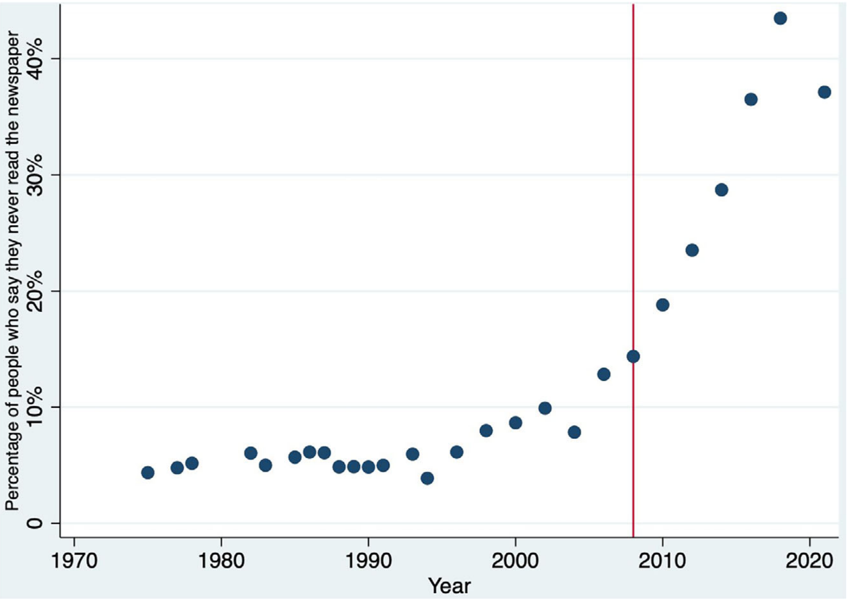

FIGURE A1 Newspaper-reading trend. The graph is an elaboration by the author on data from the General Social Survey (GSS). [Colour figure can be viewed at wileyonlinelibrary.com]

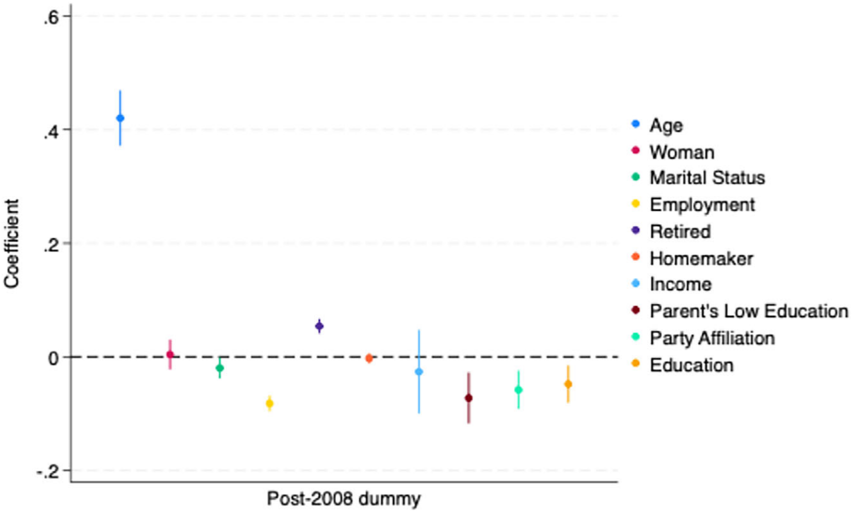

FIGURE A2 Compositional change over time: pre-Facebook and Facebook era. The graph displays the estimated coefficients from the compositional change analysis. Specifically, the coefficients refer to the *Post-2008* dummy. The dependent variables are listed in the legend. Each point represents the estimated value, with the associated 95% confidence interval indicated by the vertical line. For more information on the variables, please refer to Section 2 and specifically to the note in Table 1. [Colour figure can be viewed at wileyonlinelibrary.com]

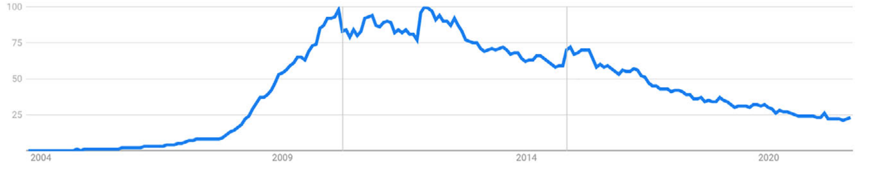

FIGURE A3 Google Trends. The graph is based on US aggregate data sourced from Google Trends for the period from 2004 to 2022 (word searched: 'Facebook'). [Colour figure can be viewed at wileyonlinelibrary.com]

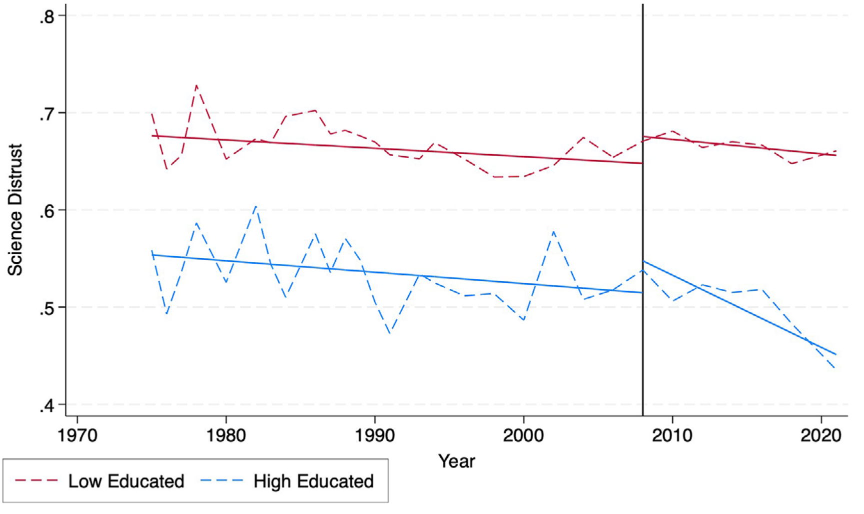

FIGURE A4 Parallel trends. The graph is constructed using data from the General Social Survey (GSS) and shows, for each year, the average distrust of science for the low-educated and the high-educated, respectively. For further details, refer to Section 4. [Colour figure can be viewed at wileyonlinelibrary.com]

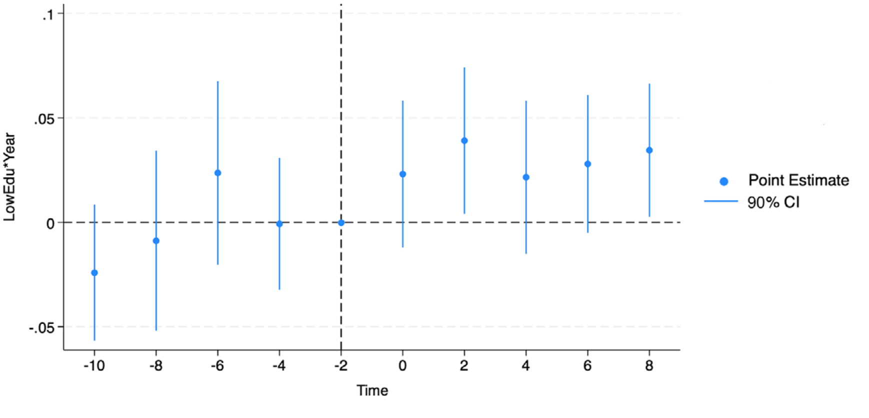

FIGURE A5 Event study. The graph presents a formal test of the pre-treatment trends. The first pre-treatment period is set as (−2) and serves as the reference point (because the survey is biennial, −2 corresponds to the last 'pre-' period, i.e., 2006). For more information on the variables, please refer to Section 2 and specifically to the note in Table 1. [Colour figure can be viewed at wileyonlinelibrary.com]

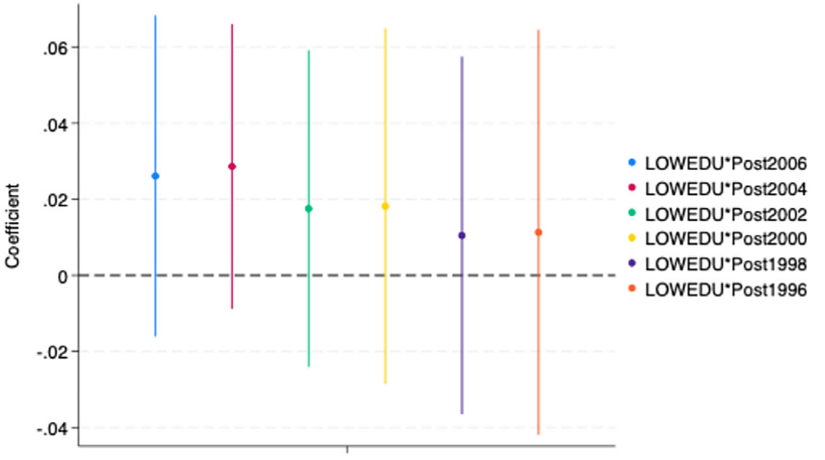

FIGURE A6 Placebo difference-in-differences (DiD) analysis. The graph displays the estimated coefficients from the placebo DiD analysis. Specifically, the coefficients correspond to the main independent variable, as detailed in the legend. The dependent variable is distrust in science. Each point represents the estimated coefficient, with the associated 95% confidence interval indicated by the vertical line. [Colour figure can be viewed at wileyonlinelibrary.com]

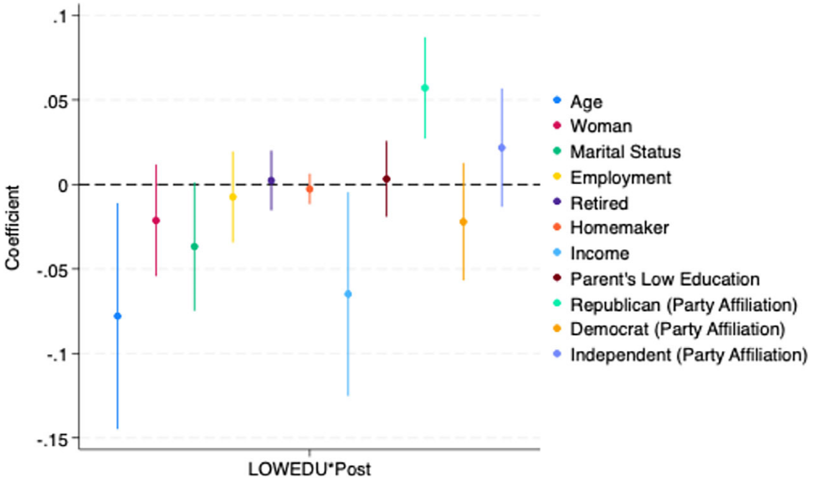

FIGURE A7 Test of covariate balance. The figure shows the coefficient estimates for the variable *LOWEDU* × *Post* (see Equation 1). Each regression is estimated by removing one covariate at a time and using it as the dependent variable. The dots correspond to the point estimates, whereas the vertical lines represent the 95% confidence intervals. *LOWEDU* is a dummy variable indicating low education (for more details, see Section 2 and Footnote 14 in the main text). Age is a variable that groups respondents into 10-year intervals. *Woman* is a binary variable coded as 0 for males and 1 for females. *Marital status* is a dummy variable equal to 1 if the respondent is married and 0 otherwise. *Employed*, *retired* and *homemaker* are dummy variables that equal 1 if the respondent belongs to the respective category and 0 otherwise. Household income is represented by a categorical ordinal variable with four brackets, corresponding to the quartiles of the income distribution. *Parent's low education* is a dummy variable indicating whether the respondent has at least one parent with low educational attainment (primary school or lower). *Republican*, *Democrat* and *Independent* are dummy variables identifying respondents' political affiliation. For more information on the variables, please refer to Section 2 and specifically to the note in Table 1. [Colour figure can be viewed at wileyonlinelibrary.com]

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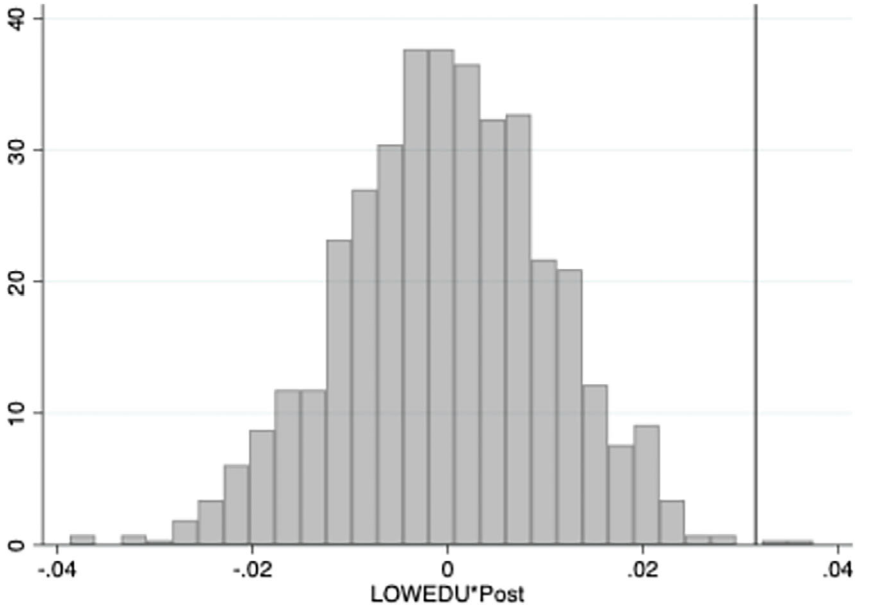

FIGURE A8 Random assignment of the education dummy. To check that the education dummy is not spuriously correlated with distrust in science, I created a low-education dummy containing the same percentage of 0s and 1s as the true variable and distributed it randomly to individuals. I replicated this placebo 1000 times. *LOWEDU* × *Post* is the placebo variable of interaction between the fake dummy of educational attainment and the *Post* variable. The vertical black line is placed in correspondence with the true estimated coefficient, reported in Column (3) of Table 2 (0.032**). [Colour figure can be viewed at wileyonlinelibrary.com]

EXPLORING TRUST IN SCIENCE ACROSS DIFFERENT GEOGRAPHICAL AREAS: INSIGHTS FROM GLOBAL, EUROPEAN AND AFRICAN REPORTS

Although the focus of this paper is on the US context, this section presents qualitative evidence regarding trust in science from other geographical regions. Specifically, after providing global summary data obtained from a survey conducted in over 140 countries (Wellcome Global Monitor, 2018) and a Eurobarometer report, regions of particular interest—Europe and Africa—are discussed in more detail. This section offers only a general overview, and future research should assess the trends and determinants of trust in science across these and other geographical areas more comprehensively, examining both similarities and differences.

Of course, it is not easy to obtain data that provide a comprehensive overview of the dynamics of trust in science across different geographical regions. Gallup, in collaboration with the Wellcome Global Monitor (2018), investigated trust in science and scientists across major global regions through a survey of 140,000 people in more than 140 countries. The data presented in Figure A9 illustrate that countries with the highest levels of trust in scientists include Northern Europe, Central Asia, Western Europe and the United States, whereas those with the lowest levels of trust are found in South America and Central Africa. These broad global data highlight the significant heterogeneity in trust in scientists across different countries and continents.

To explore the topic in greater depth, it is necessary to zoom in at the macro-regional level, which requires additional data. Regarding the European case, the Eurobarometer (2021) survey focusing on 'European citizens' knowledge and attitudes towards science and technology' is of particular interest. Summary data from this report are useful for providing an overview of the relationships of citizens of the 27 European countries with science. On the one hand, 33% of citizens express a strong interest, and 49% show a moderate interest, in new scientific discoveries and technological developments, resulting in a combined total of 82%. These statistics indicate a higher level of interest in these topics compared to non-scientific areas such as culture and art, politics and sports. However, the figures are lower when looking at actual knowledge of these issues: Only 13% report being well-informed, whereas 53% consider themselves moderately informed about new scientific discoveries and technological developments. This aligns with the large proportion of Europeans who feel that science is so complex that they struggle to understand it—almost half, or 46%.

As for the preferred sources of information, television stands out as the most popular medium, with 63% of Europeans indicating it as their preferred choice. This is followed by social networks and blogs (29%) and online and printed newspapers (24%). Although these numbers differ from those observed in the United States, they still point to a significant shift towards social media, which did not exist 15 years ago but is now regarded as a key source of scientific information by a substantial portion of the European population.

The European data also show a positive trend: Almost 9 out of 10 Europeans believe that the overall influence of science and technology on society is positive (86%, specifically), with only a minority (25%) believing that science and technology do not truly benefit people like them.

Regarding trust in scientists, respondents generally view scientists positively, with 89% stating that 'intelligent' is an accurate descriptor of scientists. However, half of respondents (50%) agree that we can no longer trust scientists to tell the truth about controversial scientific and technological issues.

Regarding the African continent, data are considerably more limited compared to Europe and other regions. However, the Wellcome Global Monitor (2018) provides valuable insights into African citizens' attitudes towards science. According to this source, trust in science is mixed:

On the one hand, a large majority of the African population strongly agrees that vaccines are safe (75%) and effective (74%), and that it is important for children to be vaccinated (88%). On the other hand, when asked about general trust in scientists, only 17% report a high level of trust in scientists, 45% report a medium level of trust and 20% report low trust, with 18% either unsure or unwilling to comment. In Southern and Central Africa, high levels of trust are even less common (13% and 12%, respectively). These data must be considered in conjunction with the fact that 55% of African citizens claim to know little or nothing about science.

Two other noteworthy figures are the percentage of Africans who believe that scientists' work benefits people like them (64%) and the just 33% who think scientists' work benefits most people in the country. These statistics highlight considerable differences between the European, American and African contexts. Although the European and American situations are distinct from each other, the African situation is undoubtedly very different from both. This warrants further examination through more specific analyses that are outside the scope of this paper.

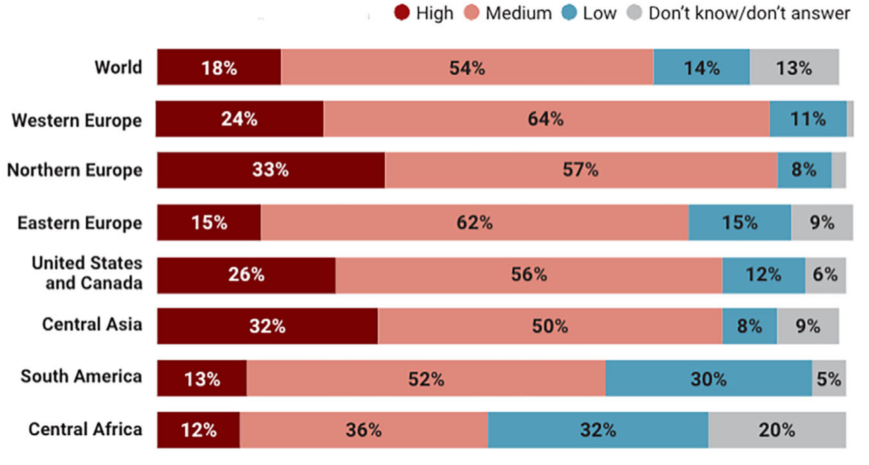

FIGURE A9 Level of trust in scientists in selected regions. *Source*: Wellcome Global Monitor (2018). [Colour figure can be viewed at wileyonlinelibrary.com]