Ctrl-Shift: How Privacy Sentiment Changed from 2019 to 2021

Angelica Goetzen
Max Planck Institute for Software Systems
agoetzen@mpi-sws.org

Samuel Dooley
University of Maryland
Max Planck Institute for Software Systems
sdooley1@cs.umd.edu

Elissa M. Redmiles
Max Planck Institute for Software Systems
eredmiles@mpi-sws.org

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Abstract

People's privacy sentiments drive changes in legislation and may influence their willingness to use a variety of technologies. While single-point-in-time investigations of privacy sentiment offer useful insight, longitudinal study of people's privacy sentiments is necessary to better understand and anticipate evolving privacy attitudes. In this work, we use longitudinal survey data (n=6,676) to model Americans' sentiments toward collection and use of data for government- and health-related purposes in 2019, 2020 and 2021. After the onset of COVID-19, we observe significant changes in Americans' privacy sentiments toward government- and health-related data uses and find that Americans' privacy attitudes largely converged on these topics. We observe additional changes in the context of other national events such as the U.S. presidential elections and Black Lives Matter protests. Our results offer insight into how privacy attitudes may have been impacted by recent events, and these results allow us to identify potential predictors of changes in privacy attitudes during times of geopolitical (e.g., global pandemic) or national (e.g., political elections, the rise of the Black Lives Matter movement) change.

1 Introduction

Privacy, as defined by Westin [137], is an individual's right to determine what personal information should be known or used by others. While the meaning and importance of privacy can vary by context [137, 34], national polls taken across 15 years show that a majority of Americans view privacy as an important right [15]. In recent years, Americans have expressed concern over the way their information has been used by private companies and the government [10].

People's privacy concerns and opinions influence digital privacy-related legislation, as well as their adoption of technologies and willingness to share their personal information [11, 25] – albeit with known biases [4]. Thus, it is critical for technologists to understand people's sentiments toward various uses of their personal data to ensure that technology is built in ethical alignment with the broader population, and that these technologies will ultimately be used [110].

Most studies examine privacy sentiment at a single point in time, however longitudinal study of privacy sentiment is necessary to gain a deeper, anticipatory understanding of how and why sentiment changes and evolves, which can in turn allow us to *design for* rather than *react to* people's privacy preferences. Prior work has longitudinally tracked privacy sentiment from the 1970s through the 2000s [137, 15, 68, 9]. More recently, however, only a few studies have investigated privacy with a longitudinal approach – several relevant works have examined changes in people's willingness to share personal information and use privacy settings in digital and online contexts over time, but do not explore changes in broader privacy sentiment [127, 44, 70, 131].

In this work, we take a longitudinal view toward privacy sentiment, seeking to understand how Americans have changed their views on privacy throughout the COVID-19 pandemic. Our work focuses on key interest areas we feel are increasingly relevant both in the context of the COVID-19 pandemic and in the area of data privacy at large: the use and sharing of health-related data, and the collection and use of data by government entities. We seek to answer the following research questions:

(**RQ1**): Did people's attitudes toward health-related and/or government data uses change after the onset of the COVID-19 pandemic, from 2019 to 2020?

(**RQ2**): Did any changes observed in RQ1 sustain or subside after the onset of the pandemic, between 2020 and 2021?

(**RQ3**): Do changes observed in RQ1 and RQ2 differ across sociodemographics, particularly gender, age, race, ethnicity, education level, and/or political leaning?

To answer these questions, we statistically analyze survey data collected in June 2019, May through June 2020, and June 2021 (total $n = 6,676$).

After the onset of the COVID-19 pandemic (**RQ1**), from 2019 to 2020, we observe a significant decrease in people's odds of accepting the use of their data for government assessment of terrorism threats, and significant increases in both the acceptance of fitness tracker data for medical research and the acceptance in use of social media data for detecting and intervening in mental health. A year later (**RQ2**), in 2021, these changes were sustained, and additionally, Americans were less accepting of law enforcement use of genetic data for crime solving when compared to their 2019 acceptance levels, which we hypothesize was triggered by the growth in visibility of the Black Lives Matter movement [95, 16, 63, 61, 94].

We find also that sentiment changed within demographic groups – men vs. women, those over 50 vs. those younger, Republicans vs. Democrats, and college educated respondents vs. high-school educated respondents – primarily between 2019 and 2020 (**RQ3**). The observed socio-demographic changes largely led to increased consensus within different socio-demographic groups who previously had divergent attitudes regarding privacy. A notable exception is in the attitudes of Republicans vs. Democrats, which remained divergent but changed in direction in 2021 following the November 2020 presidential election.

Overall, our results suggest privacy sentiments may shift substantially and in distinct ways when following major geopolitical events, such as the COVID-19 pandemic, and national events, like the 2020 presidential election or rise in visibility of the Black Lives Matter movement. In this work, we discuss potential predictors of future privacy sentiment shifts and contextualize the changes we observe in the context of prior shifts.

2 Related Work

Here, we review prior work on changes in American privacy sentiments over time and on privacy sentiment in the context of the COVID-19 pandemic with which our research is concerned, as well as prior work on key areas of interest in our research: health data privacy and government data privacy.

2.1 Longitudinal Studies of Privacy

Americans' views towards privacy have shifted over time. In the first nationally representative survey on different dimensions of privacy in the United States, Westin [137] reported that in 1978 most Americans never felt like their privacy had been invaded, though 64% also said that they were "concerned" over privacy threats. The proportion of Americans with privacy concerns grew to 84% by 1995 [137]. Katz and Tassone [68] also found that privacy concern rose in the 1980s through the 90s, and that Americans speculated that privacy would become a larger problem in the future. Best et al. [15] identified further growth in privacy concern from the 1990s to 2000.

Making sense of these changes over time can be aided by viewing public opinion in the context of important social or political changes [137]. While they may not fully explain changes in public sentiment around privacy, impactful events, especially those with privacy implications, provide possible rationale for large scale public opinion shifts. One salient example is the terrorist attacks in New York City on September 11, 2001. Prior to September 11, polling data showed an increasing percentage of Americans who viewed government data gathering as a serious threat to privacy between 1985 through 1996 [9], as well as an increasing percentage who were concerned about threats to their personal privacy in general between 1990 and 2000 [15]. Surveys taken after September 11 show a sharp increase in public support for giving up civil liberties and privacy protections for security against terrorism, with support for different types of government surveillance varying but always garnering majority approval [15]. A substantial increase in trust in government was also seen [23]. Following the immediate aftermath of September 11, a "rebound" effect was observed as support for giving up civil liberties and concern over government surveillance returned to similar levels as before the terrorist attacks [15]. However, while support for surveillance measures steadily declined, the percentage of Americans who viewed government data gathering as a threat to their privacy also declined between 1996 and 2006 [9].

Understanding the ongoing changes in Americans' views on privacy, in an era defined by an explosion of information technologies, is challenging; relatively few studies take a longitudinal view toward digital privacy, and those that do find conflicting results. Some research finds that over time, people are less willing to share their personal information on social media [127] and with online marketers [44], and that they use increasingly more privacy protections on social media [127], including when considering the data shared with brands [70]. However, other research observes social media users increasing their online self-disclosures and relaxing their privacy attitudes with time [131].

Our work builds on existing longitudinal research examining privacy, particularly in the context of significant events. We explore how American data privacy sentiments have changed during the COVID-19 pandemic, from 2019 to 2021. Unlike prior longitudinal work, we focus on privacy sentiment rather than privacy behaviors. This is critical due to both the role of such sentiment in influencing privacy policy and legislation, as well as concerns regarding the privacy paradox and the validity of people's reported privacy behaviors [4, 11, 25]; see further discussion in Section 3.3.

2.2 Privacy and COVID-19

The COVID-19 pandemic is not only a major medical event, but also a technological, privacy-relevant one. Measures to control the spread of the COVID-19 virus across the globe were implemented quickly, and for many of these implemented solutions, the use and sharing of personal data was central. For example, location and/or Bluetooth data was utilized for digital contact tracing, which helped health authorities trace the spread of COVID-19 and notify participating users when they came into contact with an infected person [6, 109], and in some cases for mapping risk areas [33, 19]. Health data like body temperatures and negative COVID-19 test results were provided in exchange for the permission to enter buildings or travel [114, 120, 12]. Some countries even deployed public surveillance measures to enforce stay-at-home policies via location-tracking wearables and drones [27].

Research has found that these data uses have varying levels of public approval, with participants voicing privacy concerns across studies (e.g., [142, 123, 66, 141, 74, 109]). But, have these new and expanded uses of personal data in the COVID-19 context altered Americans' views on data privacy more broadly? In this work we seek to answer this question and provide insight into the ever-changing context in which people engage in privacy-sensitive data disclosures and technology behaviors.

2.3 Health Data Privacy

As mentioned, Americans have been asked to consider several novel and expanded uses for data relating to their personal health during the COVID-19 pandemic. The importance of health-related data to COVID-19 relief efforts, and the increased digitization of healthcare during the pandemic [78], lead us to ask whether the onset of the pandemic had lasting effects on Americans' views on health data privacy in particular.

Prior to the pandemic, researchers investigated attitudes towards health data privacy. Broadly, personal health information has been found to be "very sensitive" for most Americans [82]. When asked about concerns towards health data sharing, people from the United States and beyond bring up concerns around a lack of control over their data, such as misuse or overuse of their data beyond the use to which they consented, and concerns related to a lack of anonymity [58, 56, 7, 24, 65, 126, 115]. Yet, despite these concerns, Howe et al. [58] find that across health-data-sharing research studies, participants are willing to share their data for medical benefits at the individual and societal level. For instance, Americans are accepting of online or electronic health systems that improve the patient care experience [104, 41]. Additionally, the concept of "the greater good," referring to advances in the medical field that would benefit the general public, motivates people to allow use and sharing of their data [7, 126, 125].

People generally approve of sharing their data with healthcare professionals [28, 49, 138], university researchers within their home countries [83, 45], and relevant non-profit organizations [53, 45]. Those with chronic health conditions or diseases report being especially willing to consent to sharing their health data with other parties [79, 28, 138]. For example, Goodman et al. [45] find that patients with a history of cancer are more likely to want their health data to be made available to "as many research studies as possible" compared to those without cancer. However, prior work finds that people are least willing to share their health data with private companies or other profit-seeking ventures [56, 7, 45]. Among those who are willing to consider sharing their data with for-profit entities, Trinidad, Platt and Kardia [130] find that people are more comfortable with companies accessing their health data for purposes related to their care as a patient, compared to business purposes. Other favorable conditions for health data sharing include when consent for data collection is obtained for each specific research study as opposed to blanket consent [85, 75], assurance of de-identification and other anonymity safeguards [55, 7, 136, 53], and continuous information on the research process [28, 13].

In sum, prior work finds that Americans feel protective of their personal health data in general, but are willing to allow wider access to it under adequate privacy protections and with a fair tradeoff of benefits. This nuanced perspective leads us to investigate how Americans feel about sharing different types of health-related data with various stakeholders and how those sentiments may have changed in the context of the pandemic. Specifically, our study investigates views on the use and sharing of genetic data, data from fitness trackers, and mental health disclosures on social media. We review prior work in these three areas below.

Genetic Data Privacy. Recent advances in genetic science have unlocked many uses for DNA data in fields like ancestry tracing, disease research, and criminal justice [46, 134]. These uses have inspired conversations around the ethics of collecting and sharing genetic data. Like health data broadly, people perceive risks to sharing their genetic data – such as privacy breaches and unauthorized uses – along with benefits, like aiding research and societal welfare [121, 80]. Prior work shows that people are generally willing to share genetic data with researchers or with research databases and biobanks [118, 69, 116, 62]. Notably, Sanderson et al. find that participants' overall willingness to share genetic data did not change based on whether they were asked to give broad consent to sharing, or more controlled consent [118]. Kaufman et al. find differences in acceptability of various stakeholders accessing personal genetic data, with academic researchers being most acceptable [69].

Genetic data is increasingly being used by law enforcement as genealogy companies become more popular with consumers and accessible online genetic databases grow [124]. For example, in 2018 police used the genealogy website GEDMatch to identify and arrest a 72 year-old man on suspicion of being the "Golden State Killer," a criminal accused of committing high-profile murders throughout the 1970s and 80s, due to his matching DNA [77]. Since then law enforcement have been able to revisit over 50 cold cases with new leads acquired from genealogy databases [72]. This method of crime solving is new, leaving it largely unregulated [54]. One study suggests that a majority of Americans support law enforcement use of genealogy websites [47]. Our work hopes to gauge current public opinion on the practice, particularly in the wake of the growing discourse surrounding the role of police and law enforcement in communities during the COVID-19 pandemic and the growth in visibility of the Black Lives Matter movement [95, 16, 63, 61, 94].

Fitness Tracking Data. Along with genetic data, our study seeks to understand the sentiments on use and sharing of data from wearable fitness tracking technology [129, 102]. Data generated by these technologies can include anything from users' heart rates, to sleep patterns, to number of steps [36]. A number of privacy-related factors including trust in the device [101] and the reputation of the company producing it [5], as well as perceived privacy risks [40, 81] are all highly influential in user adoption. Marakhimov and Joo [84] also find that privacy concerns impact current users' views on the threats that wearable technology pose, which impacts whether they will continue to use the devices.

Relevant to our study, Wiesner et al. [139] find that while most users of fitness trackers they surveyed were unconcerned with their data being shared without their consent, only one in seven were willing to actively share their data for research purposes. In light of the COVID-19 pandemic, when the use and sharing of health-related data for research has become increasingly necessary and urgent, we investigate whether views on sharing fitness data for research have shifted.

Mental Health Monitoring Using Social Media Data. We also explore sentiments towards the use and sharing of mental health data derived from social media. Increasingly, technologies that can recognize emotions and moods using various data like biometrics and online behavior are being developed and deployed [8]. In the context of social media, researchers have analyzed data from users' posts, online activities, and profile characteristics on platforms like Twitter, Facebook, and Reddit to predict mental health issues in users with reasonable accuracy [132, 122, 60, 67, 128, 31, 30, 113]. Insights can be derived at the population level — as shown by e.g., Choudhury et al. [29] and Schwartz et al. [119] who examined seasonal, geographic and demographic trends in depression — or at the individual level, e.g., O'Dea et al. [92] and Coppersmith et al. [26] detail techniques to identify specific users at risk for self harm based on their social media activity. Social media platform Facebook has disclosed their active use of both human and artificial intelligence to identify users who may be in mental health crises based on their posts, in order to get first responders and resources to them [117, 88].

Analyzing social media content for mental health information has benefits, the most prominent being the opportunity to provide mental health care to at-risk individuals. But prior work has also noted concerns related to privacy and ethics. Nicholas et al. [91] detail the difficulties of gaining fully informed consent from users whose social media data are monitored for mental health purposes, and the importance of data protections not just during collection, but also during data analysis and sharing. McKee [86] explains that guidelines surrounding the practice are not clear-cut, and that issues such as whether social media posts are public or private, or whether users have a right to anonymity for things they post online, are unresolved. Chancellor et al. [22], in their taxonomy of existing methods for deriving mental health information from users' social media posts, acknowledges the benefits of early detection of mental disorders, while also noting the risks to users such as inaccurate mental health predictions and a lack of proper data protections when analyzing and sharing social media data, especially when third parties or bad actors are involved.

The limited body of research on how users feel about this practice has produced, like other studies relating to opinions on health data uses, complex results. Andalibi and Buss find that the concept of emotion detection and prediction on social media evoked feelings of discomfort in social media users [8]. One UK survey finds that most social media users supported data analysis on Facebook content for the purpose of targeting mental health resources, but less than half were willing to give consent for their own Facebook data to be analyzed this way; the study also found that users did not feel that the benefits of the practice outweighed the privacy risks [37]. Meanwhile, a US focus group study revealed that despite a few members who called the practice "creepy," there were mostly favorable views towards using Twitter data to monitor mental health at a population level, and a shared perspective that Twitter data was public domain [87]. Our research hopes to clarify current public sentiment surrounding the monitoring of mental health data on social media and pays particular attention to changes in sentiment during the COVID-19 pandemic, a period where mental health challenges have been an increasingly important public health topic [93, 20].

2.4 Data Privacy and the Government

In addition to sharing health-related data, we also investigate attitudes towards sharing personal data with the government. Government surveillance involves federal entities collecting data on civilians, often to exert social control [38]. In recent decades, Western societies have increasingly used and relied on "surveillance-oriented security technologies" to proactively combat terrorism and other crimes [96]. We seek to examine how public opinion on surveillance by the government has changed across time in tangent with social and political circumstance.

The terrorist attacks of September 11, 2001 mark a moment in recent history where attitudes towards government use and collection of personal data shifted in the United States. In determining where Americans now stand on sharing personal data with the government, studies from the last decade paint a conflicting picture. On the one hand, some research indicates that the decreasing approval of sharing data with the government has continued post-September 11. Possibly exacerbated by Edward Snowden's leaking of classified National Security Agency information in 2013, over half of Americans disapproved of the US government's collection of phone and internet data for anti-terrorism purposes in the months following the leaks [42]. During this time most Americans also reported believing that the government was using their data for uses beyond combating terrorism, with more people expressing concern over protecting civil liberties than national security [97]. Americans continued to disapprove of the monitoring of average American citizens in the years that followed [105], and in 2017, 76% of Americans were unwilling to share personal communications like emails, texts or calls with law enforcement, "even to help foil terror plots" [135]. Most recently, Pew Research [10] finds that most Americans in 2019 felt that the risks of government data collection outweighed the benefits.

On the other hand, other work suggests that the government's use of big data and digital surveillance technologies is becoming more normalized in modern society, largely through its necessity for various administrative functions and perceived benefits like crime control [59]. Literature on privacy has identified a "privacy paradox," in which people express concern over their privacy yet continue to engage in online behaviors that may undermine their privacy, like disclosing personal information on social media [140, 4]. The paradox may be due to a number of factors such as insufficient knowledge of risks, acceptance of the limited control one has over their data, or a willingness to trade privacy for rewards [140, 52, 107, 76, 50]. If this paradox extends to cover behavior and attitudes towards different forms of government surveillance – and data from one focus group study suggests that it might [32] – we may expect a higher tolerance of data sharing with the government in situations where individuals can assess risks, agency, rewards, and other relevant factors. One recent show of acceptance happened in 2016, when the FBI ordered technology company Apple to unlock the iPhone of a mass shooter, a request the company did not comply with in order to preserve their encryption systems [48]; Pew Research [98] found that just over half of Americans sided with the FBI in this case.

Broadly, opinions on government surveillance are nuanced. Outside of social or political circumstance, research also finds that personal factors like confidence in the current president, attitudes towards the economy, and concern with crime or political corruption have been linked to individuals' levels of trust in the government [23]; correspondingly, prior work finds that trust is related to how much an individual views the government or security technologies as threatening [9, 96]. Turow et al. [133] captures the complexity in Americans' attitudes towards "everyday surveillance practices," finding that government and law enforcement surveillance practices evoked the most emotional division in participants, with similar percentages of Americans saying they feel happy vs. sad, and pleased vs. angry, that they take place.

Our research builds on the current body of work documenting shifts in public opinion on government surveillance over time, with a focus on how attitudes may have changed throughout the COVID-19 pandemic. Related to the pandemic context in which our work takes place, Zhang et al. [142] find modest to low levels of support for government surveillance measures to combat the spread of COVID-19 in the US, like encouraging use of contact tracing apps or implementing immunity pass systems. Additionally, Simko et al. [123] find that while participants acknowledge that the benefits of data sharing with the government during the pandemic outweigh the risks, a majority of participants doubted that the government would delete their data or use it solely for COVID-19 related purposes. Our research investigates views on government uses of data that are not directly related to COVID-19 relief efforts to gain a holistic view of how data privacy attitudes may have changed during the pandemic.

3 Methodology

In this work we compare privacy sentiment across three years: 2019, 2020, and 2021. In this section, we describe the survey data we collected, our statistical analyses, and the limitations of our work.

3.1 Survey Data

The 2019 privacy sentiment dataset that we use in our analysis was collected by Pew Research Center (Pew) in June 2019 via their nationally-representative American Trends Panel [10].[1] We chose the following four items administered in their survey on online privacy that asked participants to consider whether different uses of data or information were acceptable or unacceptable:

1. The government collecting data about all Americans to assess who might be a potential terrorist threat

2. DNA testing companies sharing their customers' genetic data with law enforcement agencies in order to help solve crimes

3. Makers of a fitness tracking app sharing their users' data with medical researchers seeking to better understand the link between exercise and heart disease

4. A social media company monitoring its users' posts for signs of depression, so they can identify people who are at risk of self-harm and connect them to counseling services

[1]For full detail on the panel methodology, see `https://www.pewresearch.org/our-methods/u-s-surveys/the-american-trends-panel/`.

Pew showed items 1 and 2 to a subset of their panelists ($n = 2,012$) and showed items 3 and 4 to a different subset of their panelists ($n = 1,989$).

In May through June 2020, and in June 2021, we administered the same four items using the exact same phrasing, as well as a series of demographic questions assessing the respondents' age, gender identity, race, ethnicity, level of educational attainment, and political leaning. We administered both surveys online, as was done in the original Pew survey. Cint (`www.cint.com`) recruited both our 2020 ($n = 1,138$) and 2021 ($n = 1,537$) panels for these surveys and ensured that the demographics of our respondents covered a wide demographic range.

Ethics. The methods for our data collection (2020 and 2021 datasets) were approved by our institution's review board. The 2019 data were collected by Pew. We use only the de-identified data that Pew publicly released on their website in our analysis. The full Pew data report can be found in [10] and an overview of their ethical principals can be found at: `https://www.pewresearch.org/about/our-mission/`.

3.2 Analysis

Our primary outcome of interest (dependent variable) was whether a respondent found the data use presented in each of the four items acceptable. We built three sets of logistic regression models to understand sentiment toward these data uses and particularly changes in that sentiment.

To address RQ1 and RQ2, we report on overall changes between each pair of years (2019-2020, 2020-2021, and 2019-2021) by using regressions which include the year as a linear predictor and control for demographic effects; these results can be found in Table 2. In these regressions, an odds ratio below 1 would indicate a *decrease* of acceptability in the second year compared to the first, and an odds ratio above 1 would indicate an *increase*.

In addressing RQ3, we first report on baseline effects using our regression data rather than using raw numbers in order to control for demographic variance between our various samples. As such, our second set of regression models is a separate logistic regression model for each item and for each year that predicts the dependent variable from the demographic information collected in the surveys: gender, age (as a categorical variable), race, whether the participant was Hispanic, education, and political party. These regressions can be found in Tables 3-6. Further information on the categories for each variable can be found in Table 1. This second set of regressions tells us which sociodemographics were significant for a

	Metric (%)	2019 [Q1,Q2]	2019 [Q3,Q4]	2020	2021	2020 U.S. Census
Sex	Male	44	45	56	47	50
	Female	56	55	44	53	50
Race/Ethn.	White	78	78	48	65	62
	Hispanic	14	13	19	10	19
	Black/African American	12	11	22	16	14
	Asian/Asian American	3	3	12	10	7
	Other	8	8	19	10	10
Educat.	H.S. or Less	34	34	30	25	38
	Some college	28	28	30	35	26
	B.S. or above	39	38	40	40	35
Age	18-29 years	15	15	21	24	16
	30-49 years	31	30	39	40	26
	50-64 years	30	31	23	18	19
	65+ years	23	23	17	18	16
Pol	Dem/Lean Dem	56	55	64	63	–
	Rep/Lean Rep	45	45	36	37	–

Table 1: Demographics for our four samples as compared to the demographics of the U.S. [1, 64, 2].

given question in a given year, but do not allow us to reason about changes in sociodemographics between years. Therefore, we construct a third set of regression models to answer the core of RQ3: whether changes observed in RQ1 and RQ2 differ across demographic groups. Specifically, we construct models for each pair of years (2019-2020, 2020-2021, and 2019-2021) to evaluate whether the demographic changes are sustained. In these models, we treat the year as an interaction term with the demographic variables, which allows us to statistically test whether an observed demographic change from one year to another was significant or just occurred by chance. These regressions can be found in Tables 7-9.

The regression models provide significance values for odds ratios found from the regression's fitted values. Significance values for our conclusions were set with $\alpha = 0.05$. See [17] for a deeper explanation of odds ratios and logistic regressions.

Finally, we note that, consistent with the literature [43], because our data are organized longitudinally from three similar, non-identical populations and the comparisons we make are purely complementary, we do not make any multiple comparison corrections in our regressions.

3.3 Limitations

It is important to note that nationally-representative samples such as those used by Pew (our 2019 data) consist of respondents who were originally recruited via randomized sampling and consist of respondents who would not otherwise have access to the internet who are provided with mechanisms (i.e., a tablet provided by Pew) to access the internet. On the other hand, quota samples such as those used by Cint (our 2020 and 2021 data) aim to recruit respondents with reasonably representative demographics through a variety of methods such as mailers, airline frequent flyer programs, print, TV, digital advertisements, etc.[2] Without homegrown infrastructure such as Pew's American Trends Panel, nationally-representative panel surveys can be cost prohibitive and as such we use Cint's online survey panel as an alternative [111, 112]. We acknowledge that this difference in Pew's sampling methodology vs. our own may be confounding when determining attitude changes across time. As described in Section 3.2, to mitigate the effects of demographic variance between our samples we report all baseline and change effects in the context of logistic regression models that control for demographics.

Additionally, while our interest is in how privacy sentiment changed over the course of the COVID-19 pandemic, our analysis is not causal. We report on changes observed between 2019, 2020, and 2021 but cannot definitively conclude that particular events (the onset of the pandemic) caused these changes.

Finally, our work is subject to limitations typical to most survey work: respondents may have been vulnerable to social-desirability bias or the privacy-specific "privacy paradox," and as a result may have reported stronger or different opinions than those they actually held. To mitigate the former, Pew engages in extensive pre-testing and multiple rounds of question draft-

[2]For more detail on Cint's methodology for panel respondents please see `https://www.cint.com/quality`.

Table 2: Overall changes between in perceived acceptability between each pair of years with odds ratios, confidence intervals, and p-values even when controlling for demographic effects (demographics odds ratios omitted for brevity, see Tables 3-9 for demographic information).

	Question 1 Government/Terrorism	Question 2 Law Enforcement/Genetic	Question 3 Medical Research / Fitness	Question 4 Corporate/Mental Health
2019-2020	0.782 (0.668, 0.915) p = 0.003**	0.942 (0.805, 1.102) p = 0.456	1.264 (1.080, 1.479) p = 0.004**	2.180 (1.846, 2.574) p < 0.001**
2020-2021	0.908 (0.773, 1.066) p = 0.239	0.897 (0.765, 1.052) p = 0.183	0.987 (0.841, 1.159) p = 0.874	0.948 (0.806, 1.114) p = 0.514
2019-2021	0.680 (0.591, 0.782) p < 0.001**	0.814 (0.709, 0.936) p = 0.004**	1.246 (1.083, 1.434) p = 0.003**	2.039 (1.757, 2.365) p < 0.001**

Note: *p < 0.05; **p < 0.01

ing, editing, and piloting as described in more depth at `https://www.pewresearch.org/our-methods/u-s-surveys/writing-survey-questions/`. Regarding the latter, we note that we study privacy sentiments rather than privacy behavior; the latter is the chiefly effected variable of the privacy paradox. Further, while privacy sentiment does not always accurately predict digital behavior, these sentiments still influence policy makers and have been shown to be among multiple behavioral factors related to people's digital privacy-related choices; thus, they are still an important area to study, especially in the longitudinal approach used in this work [4, 11, 25].

4 Results

We analyze the results from each item individually. Results are shown in Figure 1. We report regression results in Table 2 and Appendix[3] Tables 3 - 9.

4.1 Government Data Collection to Assess Terrorism Threats

Overall, we see that respondents found the acceptability of the government collecting data to assess a terrorism threat waned from 2019 into 2020 and stayed at a lower level in 2021 compared to 2019, even when controlling for demographic changes (O.R.= 0.782, $p = 0.003$ for 2020 compared to 2019; O.R. = 0.908, $p = 0.239$ for 2021 compared to 2020; O.R. = 0.680, $p < 0.001$ for 2021 compared to 2019; Table 2).

Considering 2019 as our baseline, we observe the following statistically significant effects. Males have significantly lower odds[4] than females of finding terrorist assessments by the government acceptable (O.R. = 0.72, $p < 0.001$, Table 3). We also observe an increasing trend in acceptability by age (O.R.s = 1.05, 1.35, and 1.44 for the age groups 30-49, 50-64, and 65+ compared to age group 18-29), with the oldest two age groups rising to the level of statistical significance (p = 0.034 and p = 0.018 respectively, Table 3). We see that those who have a Bachelor's degree or higher have significantly lower odds of finding terrorist assessments by the government acceptable when compared to those with a high school degree or less (O.R. = 0.74, p = 0.005, Table 3). Finally, Republican or Republican-leaning individuals have significantly higher odds of accepting government terrorist assessments compared to their Democratic counterparts (O.R. = 1.52, $p < 0.001$, Table 3).

In 2020, however, we observe only one demographic variable that has significant differences when compared to its reference group, political party: Republicans have higher odds of finding government data use for terrorist assessment acceptable than Democrats (O.R. = 1.43; p = 0.007; Table 3).

The lack of other demographic differences in 2020 is due in part to increases in acceptability for the demographic groups: those with a Bachelor's degree or more and males (Table 7). The increase for those with a Bachelor's degree from 2019 to 2020 is significant at $p = 0.014$ and males' increase is significant at $p = 0.05$.

[3]In the remainder of the paper, when we reference a Table other than Table 2, it can be found in the Appendix.

[4]In all cases where we describe a change throughout the paper, we refer to a change in the odds of acceptability, even if, for brevity, this phrase is not specifically used.

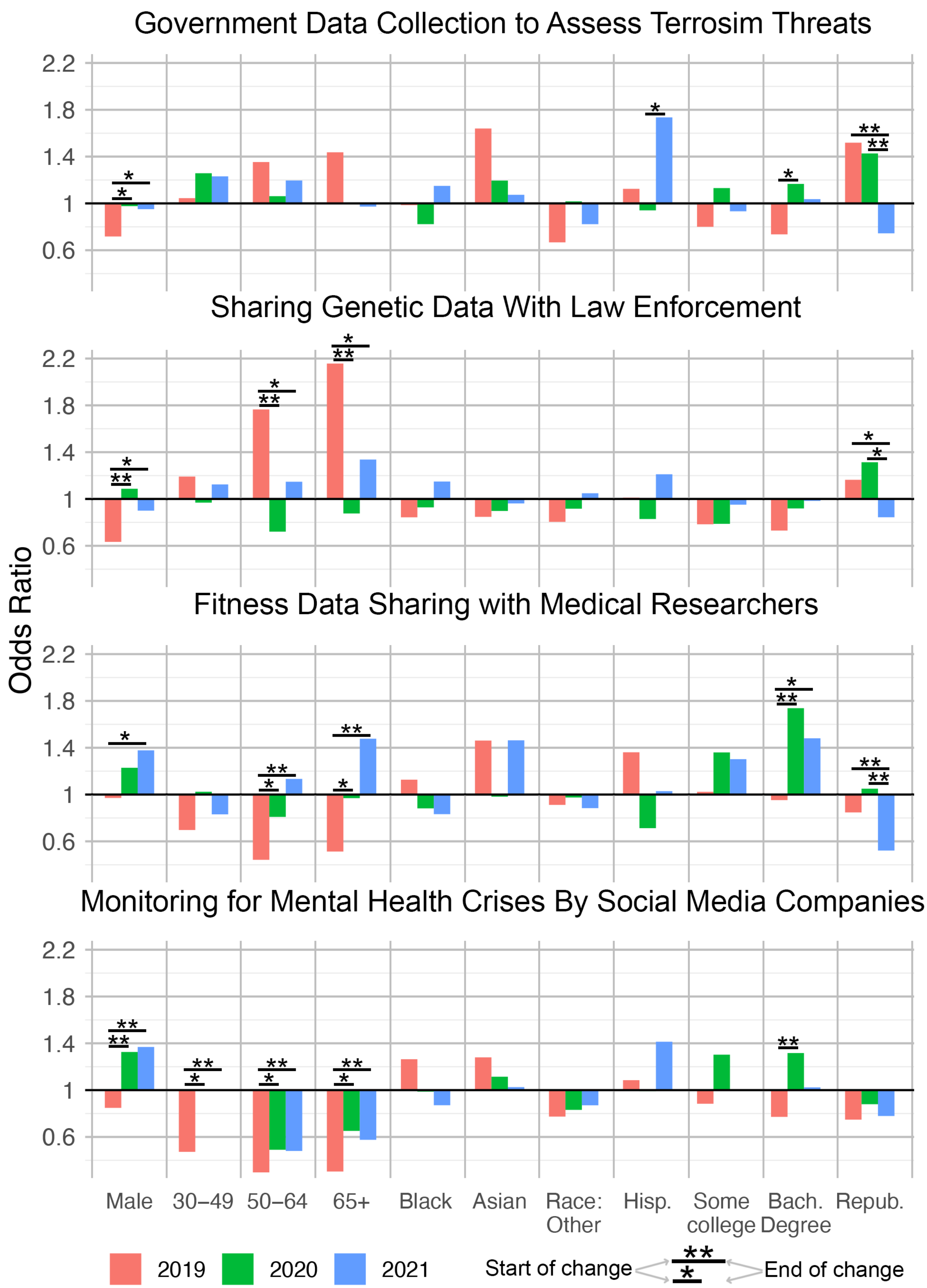

Figure 1: Summary figure reporting odds ratios from regressions for each survey item and each year. Odds ratios are reported for regressions from each individual year and stars report significant differences between 2019 and 2020 and 2019 and 2021 for the different demographic groups. Full regression tables are in Tables 3- 9

When we examine whether these changes persisted into 2021, we see that males' decreased acceptance of this data use held in 2021 ($p = 0.049$; Table 9). The Bachelors degree difference between 2019 and 2021 is just barely no longer significant at $p = 0.051$ (Table 9), although the 2021 level is also not significantly different from the decreased 2020 level ($p = 0.561$, Table 8).

As for changes that were brought about in 2021, we see two significant differences: Hispanic ethnicity and political party. We observe in Table 8 that Hispanics became significantly more likely to find terrorist assessments by the government acceptable (O.R. = 1.84; $p = 0.043$). Acceptability of terrorist assessments by the government is significantly moderated by a participant's political party affiliation both between 2019 and 2021 and between 2020 and 2021; specifically, Republicans, who were *more* likely than Democrats to find terrorist assessments by the government acceptable in 2019 and 2020 became *less* likely to find it acceptable in 2021 (O.Rs = 0.52 and 0.49 for 2019-2021 and 2020-2021 respectively; $p<0.001$ for both; Tables 9 and 8).

4.2 Sharing Genetic Data with Law Enforcement

When controlling for demographic changes, we see that acceptability of genetic data sharing with law enforcement did not change significantly from 2019 to 2020 or 2020 to 2021. However the overall effect was a steady decline from 2019 to 2021 such that the difference between these two years shows a significant decrease (O.R.= 0.814, $p = 0.004$ for 2021 compared to 2019; O.R. = 0.942, $p = 0.456$ for 2020 compared to 2019; O.R. = 0.897, $p = 1.83$ for 2021 compared to 2020; Table 2).

Before the onset of the pandemic, we observe the following demographic effects, seen in Table 4: males are significantly less likely to find sharing genetic data with law enforcement acceptable (O.R. = 0.63, $p < 0.001$); age positively correlates with acceptance — O.R. for 50-64 is 1.77 and O.R. for 65+ is 2.16 (both with $p < 0.001$); and education negatively correlates with acceptance — O.R. for some college is 0.78 ($p = 0.038$) and O.R. for a Bachelor's degree or more is 0.73 ($p = 0.005$).

After the pandemic's onset in 2020, we see significant demographic shifts in responses, again leading to fewer within-group differences. Specifically, older individuals, who were generally more likely to agree with the statement became just as likely as younger individuals to find it acceptable to share genetic data with law enforcement (O.R.s = 0.408 and 0.406 for 50-64 and 65+ respectively; $p < 0.001$; Table 7). Further, males, who in 2019 were less likely than females to think genetic data sharing with law enforcement was acceptable, became just as likely as females in 2020 (O.R. = 1.717; $p < 0.001$; Table 7). The two demographic shifts that occurred in 2020, age and gender, both held firm into 2021 when compared to their 2019 levels (O.R. = 0.62-0.65 for 50-65+ year olds and O.R. = 1.422 for males; Table 9).

Finally, we again observe a change between respondents with differing political affiliations. In 2020, all demographics do not show disparities between their different levels, except for political party – Republican-leaning individuals were more likely to find sharing genetic data with law enforcement acceptable (O.R. = 1.134; $p = 0.039$; Table 4. However, in 2021, this trend reversed and Republican-leaning individuals were no longer more likely than Democratic-leaning individuals to find it acceptable to share genetic data with law enforcement.

4.3 Fitness Data Sharing with Medical Researchers

Overall, we see that the acceptability of sharing fitness data with medical researchers increased from 2019 into 2020 and remained at a higher level in 2021. (O.R.= 1.264, $p = 0.004$ for 2020 compared to 2019; O.R. = 0.987, $p = 0.874$ for 2021 compared to 2020; O.R. = 0.814, $p = 0.003$ for 2021 compared to 2019; Table 2).

In 2019 (Table 5), age negatively correlated with acceptance of data sharing with medical researchers (O.R.s = 0.697, 0.442, 0.513 for 30-49, 50-64, and 65+ respectively, $p < 0.01$). Further, Hispanic individuals were slightly more likely to find this practice acceptable (O.R. = 1.361; $p = 0.046$). No other demographic groups exhibited internal disparities in acceptance for this item in 2019.

However, after the onset of the pandemic, we saw significant changes in acceptability between different demographic groups, again leading to fewer overall within-group differences. First, we see that older individuals became as accepting as younger individuals (O.R. = 1.829 and 1.890 for 50-64 and 65+ respectively; $p = 0.012$ and $p = 0.015$). An increase also occurred for those who have a Bachelor's degree (O.R. = 1.824; $p = 0.002$). Acceptability for those who identify as Hispanic (O.R. = 0.524; $p = 0.012$) decreased to the level of non-Hispanics.

The demographic changes brought on by the pandemic lasted into 2021 for both age and education. Being over 65, which in 2019 *negatively* correlated with acceptability, in 2021 was *positively* correlated with acceptability of sharing data with medical researchers (O.R = 1.477; $p = 0.026$). We hypothesize this change is due to sustained higher COVID-19 risk and concern – even with vaccines that came out in 2021 – among those 65+. Concerns about the pandemic may have generalized to general increases in acceptability of medical research for other conditions at which they are high risk (i.e., heart disease) among older Americans [21, 90]. The change in sentiment among Bachelor's degree holders also holds in 2021: there was no education effect in 2019, but those a Bachelor's degree viewed this data use as more acceptable in 2021 as well as 2020 than their less-educated peers (O.R. = 1.554; $p = 0.013$; Table 9), who may have become more informed about the role of medical research in fighting various conditions as a result of the pandemic [106].

Gender, which saw no difference in acceptability in 2019, saw increases for males in 2020, and in 2021 that increase rose to the level of statistically significant from 2019 (O.R. = 1.418; $p = 0.016$; Table 9.

Like the previous two items, we also saw a marked change in the political party disparity in 2021. Whereas there was no significant difference in acceptability views for 2019 and 2020, Republican-leaning identified individuals became significantly less likely to accept sharing fitness data than Democratic-leaning individuals in 2021 both when compared to 2019 (O.R. = 0.615, $p = 0.002$, Table 9) and 2020 (O.R. = 0.497, $p < 0.001$, Table 8).

4.4 Monitoring for Mental Health Crises by Social Media Companies

Finally, we see that, overall, the acceptability of a social media company monitoring posts for mental health crises increased significantly and with large magnitude between 2019 and 2020 (O.R.= 2.180, $p < 0.001$) and remained at a higher level in 2021 (O.R. = 0.948, $p = 0.514$ for 2021 compared to 2020, Table 8; O.R. = 2.039, $p < 0.001$ for 2021 compared to 2019, Table 9).

In 2019 (Table 6), we found all individuals over 30 were less accepting of the idea of social media companies monitoring data for mental health crises compared to the youngest group (O.R. = 0.297-0.473; $p < 0.001$). Additionally, we see that Bachelor's degree holders and Republican-leaning individuals are less likely to find this behavior acceptable in 2019 (O.R. = 0.772, $p = 0.043$ for Bachelor's degree holders; O.R. = 0.7498, $p = 0.013$ for Republican-leaning respondents).

After the onset of the pandemic, we see meaningful changes amongst demographic groups. First, those in the 30-49 group became as likely as the youngest group to find this acceptable, a statistically significant change (O.R. = 2.119, $p = 0.008$, Table 7). Older individuals in the 50-64 and 65+ groups also saw a relative increase in their thoughts on acceptability, though older people still found social media monitoring for mental health crises to be less acceptable than younger people; this difference between years was significant (O.R.s = 1.650 and 2.141, $p = 0.044$ and $= 0.005$ for 50-65 and 65+ respectively; Table 7). Further, males, who in 2019 had similar levels of acceptance of this data use to females, became more likely than females in 2020 to find this practice acceptable, another significant change in sentiment (O.R. = 1.563; $p = 0.008$; Table 7). This is also the case for those with a Bachelor's degree, who in 2019 were less likely to find social media companies monitoring for mental health crises acceptable but in 2020 were more likely to find it acceptable (O.R. = 1.706, $p = 0.007$; Table 7).

The demographic changes for age and gender both held into 2021. When compared to 2019, older individuals became more accepting of this practice (O.R. range 1.616 - 2.131; $p < 0.040$; Table 9). Males also continued to find social media monitoring for mental health crises was acceptable at higher rates than females in 2021, a significant change from 2019 (O.R. = 1.614; $p = 0.002$; Table 9). However, the significant change from 2019 to 2020 we saw for those with a Bachelor's degree receded in 2021; in 2021, like 2019, a person with a Bachelor's degree was no more likely than those with less education to find social media monitoring for mental health crises acceptable (O.R. = 1.327; $p = 0.131$; Table 9).

5 Discussion

Our study sought to examine changes in data privacy sentiments during the COVID-19 pandemic. In this section we present our overarching takeaways from the data collected.

Data privacy sentiment changes in tandem with major events. Overall, we observe significant shifts in acceptability in all four data use items we investigated. Between the years 2019 and 2020, we observe: a *decrease* in acceptability in government collection of data on Americans to assess terrorism threats; an *increase* in acceptability of sharing user data from a fitness tracking app with medical researchers studying the link between exercise and heart disease; and an *increase* in acceptability of a social media company monitoring its users' posts for signs of depression to identify people who are at risk of self-harm and connect them to counseling services. Between the years 2020 and 2021, we observe no significant changes for any data use. Looking at changes between the whole data collection period, from 2019 to 2021, we observe all aforementioned changes that occurred in the first year of data collection, as well as one additional change: a *decrease* in acceptability of DNA testing companies sharing their customers' genetic data with law enforcement agencies in order to help solve crimes.

Our results add to the body of work exploring the influence of major events on privacy sentiments. While public opinion polls are limited in their ability to determine the cause of shifts, we note the importance of the timing of the shifts and posit several factors related to the pandemic that may have contributed to changes in data privacy sentiment.

We hypothesize that acceptance of government and law enforcement data uses likely decreased due to the salient roles these entities played throughout the pandemic. As the pandemic progressed, federal and local entities were key sources for information and guidelines regarding COVID-19 in the U.S. [73]. Recent work finds that public trust in the government is related to people's perceptions of their governments as well-organized, fair, and with clear messaging and knowledge on COVID-19 [51]. Considering the findings of a 2020 Pew Research poll that show low levels of trust in the US federal government [99], we posit that reduced perceptions of the U.S. government as organized and fair, combined with unclear messaging and perceived lack of knowledge surrounding COVID-19, may have led Americans to lower their acceptance of government use of personal data throughout the pandemic. In a similar vein, issues with law enforcement increased in salience with the rise of the Black Lives Matter, a movement that first started in 2013 in response to police brutality and other systemic issues impacting Black individuals but gained widespread visibility with international protests occurring in the summer of 2020 [57, 94]. Considering our data collection period for 2020 took place during the peak of Black Lives Matter protests in the U.S. [18], we hypothesize that Americans, while initially unchanged in their law enforcement sentiment in May and June 2020, grew less accepting of this data use in response the movement, resulting in the more substantial change we observe by 2021.

Regarding Americans' increase in approval toward fitness tracker data use for medical research, we hypothesize that Americans' focus on COVID-19 increased the apparent relevance of medical research, even on other diseases. Indeed, the "spread of infectious diseases" became the top perceived national threat by Americans in 2020 [103]. This concern regarding medical issues may have also increased Americans' acceptance of the use of their social media data for detecting and intervening in mental health issues. Further, contextual factors such as the increase in mental health issues [100] and social media use [71], respectively, as well as mental health issues caused by social media use [143] during the pandemic, may have further increased Americans' willingness to allow their social media data to be used for mental health purposes.

We also acknowledge that participants may have judged these scenarios based on the data uses or data types instead of, or in addition to, the data stakeholders. For example, when assessing the scenario regarding government data use, it is possible that respondents put more focus on the purpose of data collection – in this case, assessing terrorist threats – than on the government as a stakeholder in the data collection process. Once the spread of infectious diseases grew to be the top threat for Americans in 2020 and surpassed the concern for terrorism [103], this re-prioritization of threats may have led fewer Americans to find this data use acceptable, thus providing an alternative explanation for our results. Prior qualitative work finds the degree of perceived reward to be an important factor in the public's willingness to allow government data use [32] (see further background in Section 2.4); our findings offer quantitative support for this premise. More broadly, future work may seek to isolate participants' attitudes towards different data types vs. data uses vs. stakeholders; doing so would further our understanding of triggers associated with changes in data privacy sentiment.

Changes in data privacy sentiment made during the pandemic have sustained. Apart from the sentiment changes we observed, the lack of significant changes in our overall sample between 2020 and 2021 are also suggestive. We consider two possibilities: first, we consider that views on data privacy, in government- and health-related contexts particularly, have changed in a lasting way. Second, we consider that, as the COVID-19 pandemic has not fully ended, data privacy sentiments are different during the pandemic but are subject to change afterwards. Past longitudinal studies on privacy in the context of major events show mixed results regarding sustained changes in privacy attitudes: for instance, surveillance sentiment changed briefly after the September 11 terrorist attacks, but reverted to prior levels following the immediate aftermath [15, 23]; yet, sentiments towards government surveillance have continued to trend downwards since the National Security Agency leaks by Edwards Snowden [42, 105]. We hypothesize that our results are indicative of a longer-term shift in sentiment, given the sustained effects we observe one year later. However, we encourage future longitudinal work to continue tracking data privacy sentiment as the pandemic progresses and after its conclusion.

Sentiments became more similar across demographic groups during the pandemic. On the whole, many of the strong differences in data privacy sentiment within demographic groups that we observed in 2019 are not present in 2020 or 2021. This point is especially true for government and law enforcement data uses: when controlling for other variables, we note that females, older Americans, and less educated Americans were all more likely to find these data uses acceptable compared to their counterparts in 2019. Confirming the direction of the sentiment changes with the raw data, we see that these groups decrease their acceptance of government and law enforcement data uses, so that in 2020 differences between in-group members disappeared. Overall, there are more differences in sentiment between demographic groups at the start of our data collection in 2019 than there are now in 2021; with this, we consider the possibility of opinions becoming more unified in the face of a large-scale global crisis.

Privacy attitudes among political affiliation groups are not static. However, one notable exception to our previous point is the significant differences in Republican and Democrat sentiments throughout our data collection period. In 2019 and 2020, we find that Republicans had significantly higher acceptance of government data collection for terrorism assessment compared to Democrats; however, by 2021, their acceptance dropped to be significantly lower than Democrats. We also observe Republicans becoming less accepting of sharing their genetic data with law enforcement between 2019 and 2021.

There are few surveys that explore partisan differences in data privacy attitudes in detail; sentiment is usually assessed by capturing Democrat and Republican views on privacy-related topics at singular points in time (e.g., [10, 108, 98]). Recent work finds conservative Republicans to be associated with warmer attitudes towards surveillance, and liberalism to be associated with less acceptance of government surveillance compared to conservatism [133, 89]. However, one study finds that, rather than being static, individuals' privacy views may be influenced by political circumstance, such as presidential approval [14]. Our findings for Republicans' acceptance of government and law enforcement data uses provide further support for this argument. While our work cannot draw causal conclusions, we note the presidential election – in which Republican candidate Donald Trump finished his term and was succeeded by Democratic candidate Joe Biden [3] – that occurred before our third round of data collection as a possible reason for the stark decrease in acceptance in government and law enforcement data uses. We hypothesize that views on data uses by federal entities may follow political cycles or vary based on the political affiliation of the President and other lawmakers, and therefore may be more easily predictable.

Additionally, we also find that Republicans were significantly less accepting of sharing fitness tracking data with medical researchers in 2021 only – here, we look to the growing partisan divide in trust in scientists as a possible explanation, noting that Republicans were less trusting of scientists compared to Democrats during the pandemic [39, 35]. We hypothesize that political leaning may be an especially strong predictor of privacy attitudes moving forward, and thus should be a variable of focus in future privacy studies. Further, these shifts in privacy sentiment in the context of the 2020 U.S. presidential elections offer support for the relevance of major events to shifts in privacy attitudes.

6 Conclusion

We longitudinally examined Americans' data privacy sentiments between 2019 and 2021 by measuring their acceptance of four different data use scenarios. We find that following the onset of the COVID-19 pandemic, Americans' acceptance of government collection of data on Americans to assess terrorism threats decreased, while their acceptance of health-related data use increased for both 1) use of fitness tracker data by medical researchers studying the link between exercise and heart disease, and 2) use of social media data by a social media company to detect and intervene in mental health. In 2021, we observe that the 2020 changes in sentiment are sustained, and that Americans' acceptance of law enforcement use of genetic data for crime detection decreased when compared to 2019. Together, these results offer quantitative evidence regarding the relationship between privacy sentiment and major geopolitical (i.e., the COVID-19 pandemic) and national (e.g., the 2020 elections, the rise of in visibility of the Black Lives Matter movement) events. We also find that sentiments became more cohesive across demographic groups during the pandemic; one notable exception to this finding is sentiment within political affiliation groups, which appeared to change in tandem with the changing of U.S. presidents in the 2020 election. These results suggest that major events may bring end-users together with regard to their privacy opinions, but that politically-based opinions may be robust even to such significant change factors.

At the time of this writing the COVID-19 pandemic continues to progress. We encourage future longitudinal privacy research on data privacy sentiments as they may continue to change throughout and after the pandemic, offering insight into the changing landscape of end-user sentiment into which new privacy-sensitive technologies may be introduced.

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A Tables

Table 3: Question 1 (government data collection for terrorism threat assessment) regressions for each year separately 2019, 2020, and 2021

	2019	2020	2021
	(1)	(2)	(3)
GENDERMale	0.717	0.977	0.951
	(0.598, 0.861)	(0.762, 1.251)	(0.769, 1.177)
	p = 0.0004**	p = 0.853	p = 0.645
AGECAT30-49	1.045	1.257	1.231
	(0.793, 1.378)	(0.904, 1.749)	(0.941, 1.611)
	p = 0.755	p = 0.174	p = 0.131
AGECAT50-64	1.353	1.062	1.196
	(1.023, 1.790)	(0.733, 1.538)	(0.861, 1.661)
	p = 0.035*	p = 0.752	p = 0.287
AGECAT65+	1.437	0.998	0.973
	(1.065, 1.938)	(0.660, 1.508)	(0.688, 1.376)
	p = 0.018*	p = 0.993	p = 0.877
RACEBlack or African American	0.986	0.823	1.150
	(0.730, 1.331)	(0.592, 1.144)	(0.855, 1.546)
	p = 0.926	p = 0.246	p = 0.356
RACEAsian or Asian-American	1.640	1.195	1.073
	(0.933, 2.883)	(0.805, 1.775)	(0.747, 1.542)
	p = 0.086	p = 0.378	p = 0.702
RACEOther	0.667	1.017	0.822
	(0.465, 0.958)	(0.678, 1.527)	(0.522, 1.297)
	p = 0.029*	p = 0.934	p = 0.401
HISPANICYes	1.124	0.941	1.735
	(0.845, 1.496)	(0.633, 1.398)	(1.118, 2.691)
	p = 0.422	p = 0.763	p = 0.014*
EDUCATIONBachelor's or more	0.735	1.166	1.036
	(0.592, 0.913)	(0.869, 1.566)	(0.793, 1.353)
	p = 0.006**	p = 0.307	p = 0.795
EDUCATIONSome college	0.801	1.131	0.933
	(0.636, 1.007)	(0.830, 1.541)	(0.711, 1.223)
	p = 0.058	p = 0.437	p = 0.615
POLPARTYRep/Lean Rep	1.518	1.427	0.745
	(1.253, 1.841)	(1.101, 1.848)	(0.595, 0.932)
	p = 0.00003**	p = 0.008**	p = 0.011*
Constant	1.014	0.571	0.658
	(0.755, 1.363)	(0.380, 0.857)	(0.484, 0.895)
	p = 0.925	p = 0.007**	p = 0.008**
Observations	2,012	1,138	1,537
Log Likelihood	−1,361.237	−769.597	−1,026.828
Akaike Inf. Crit.	2,746.474	1,563.193	2,077.655
Note:			*p<0.05; **p<0.01

Table 4: Question 2 (sharing genetic data with law enforcement) regressions for each year separately 2019, 2020, and 2021

	2019	2020	2021
	(1)	(2)	(3)
GENDERMale	0.633	1.087	0.900
	(0.527, 0.761)	(0.850, 1.390)	(0.730, 1.111)
	p = 0.00001**	p = 0.505	p = 0.327
AGECAT30-49	1.191	0.969	1.124
	(0.902, 1.574)	(0.700, 1.342)	(0.862, 1.467)
	p = 0.218	p = 0.849	p = 0.389
AGECAT50-64	1.765	0.721	1.147
	(1.332, 2.340)	(0.499, 1.041)	(0.829, 1.587)
	p = 0.0001**	p = 0.081	p = 0.407
AGECAT65+	2.157	0.876	1.337
	(1.594, 2.919)	(0.584, 1.315)	(0.954, 1.874)
	p = 0.00000**	p = 0.524	p = 0.092
RACEBlack or African American	0.843	0.928	1.149
	(0.623, 1.142)	(0.672, 1.283)	(0.856, 1.542)
	p = 0.270	p = 0.653	p = 0.355
RACEAsian or Asian-American	0.847	0.897	0.962
	(0.480, 1.495)	(0.604, 1.333)	(0.671, 1.380)
	p = 0.568	p = 0.593	p = 0.834
RACEOther	0.805	0.917	1.049
	(0.562, 1.152)	(0.612, 1.374)	(0.673, 1.636)
	p = 0.236	p = 0.675	p = 0.834
HISPANICYes	1.012	0.829	1.211
	(0.760, 1.347)	(0.559, 1.230)	(0.785, 1.867)
	p = 0.938	p = 0.353	p = 0.387
EDUCATIONBachelor's or more	0.730	0.919	0.984
	(0.587, 0.908)	(0.687, 1.230)	(0.756, 1.281)
	p = 0.005**	p = 0.571	p = 0.906
EDUCATIONSome college	0.784	0.788	0.951
	(0.623, 0.987)	(0.580, 1.071)	(0.729, 1.242)
	p = 0.039*	p = 0.128	p = 0.714
POLPARTYRep/Lean Rep	1.164	1.314	0.844
	(0.959, 1.412)	(1.015, 1.700)	(0.677, 1.052)
	p = 0.124	p = 0.039*	p = 0.131
Constant	1.006	1.006	0.754
	(0.748, 1.355)	(0.674, 1.500)	(0.557, 1.022)
	p = 0.967	p = 0.978	p = 0.069
Observations	2,012	1,138	1,537
Log Likelihood	−1,352.573	−778.105	−1,049.512
Akaike Inf. Crit.	2,729.146	1,580.209	2,123.024
Note:			*p<0.05; **p<0.01

Table 5: Question 3 (fitness data sharing with medical researchers) regressions for each year separately 2019, 2020, and 2021

	2019	2020	2021
	(1)	(2)	(3)
GENDERMale	0.971	1.228	1.377
	(0.806, 1.170)	(0.960, 1.572)	(1.114, 1.704)
	p = 0.758	p = 0.102	p = 0.004**
AGECAT30-49	0.697	1.023	0.831
	(0.528, 0.922)	(0.738, 1.420)	(0.635, 1.088)
	p = 0.012*	p = 0.890	p = 0.178
AGECAT50-64	0.442	0.809	1.134
	(0.332, 0.590)	(0.560, 1.170)	(0.817, 1.573)
	p = 0.00000**	p = 0.261	p = 0.454
AGECAT65+	0.513	0.969	1.477
	(0.378, 0.696)	(0.645, 1.457)	(1.048, 2.082)
	p = 0.00002**	p = 0.881	p = 0.026*
RACEBlack or African American	1.127	0.882	0.833
	(0.824, 1.541)	(0.638, 1.220)	(0.617, 1.122)
	p = 0.454	p = 0.449	p = 0.230
RACEAsian or Asian-American	1.461	0.982	1.463
	(0.881, 2.424)	(0.661, 1.460)	(1.013, 2.113)
	p = 0.143	p = 0.930	p = 0.043*
RACEOther	0.912	0.975	0.884
	(0.631, 1.317)	(0.649, 1.465)	(0.564, 1.386)
	p = 0.623	p = 0.904	p = 0.593
HISPANICYes	1.361	0.713	1.029
	(1.007, 1.840)	(0.479, 1.061)	(0.664, 1.594)
	p = 0.046*	p = 0.096	p = 0.899
EDUCATIONBachelor's or more	0.952	1.738	1.481
	(0.764, 1.188)	(1.295, 2.331)	(1.132, 1.936)
	p = 0.666	p = 0.0003**	p = 0.005**
EDUCATIONSome college	1.023	1.360	1.302
	(0.810, 1.292)	(0.999, 1.850)	(0.993, 1.708)
	p = 0.848	p = 0.051	p = 0.057
POLPARTYRep/Lean Rep	0.848	1.050	0.522
	(0.696, 1.033)	(0.810, 1.361)	(0.417, 0.653)
	p = 0.102	p = 0.713	p = 0.000**
Constant	1.191	0.687	0.778
	(0.881, 1.610)	(0.459, 1.028)	(0.572, 1.058)
	p = 0.257	p = 0.068	p = 0.110
Observations	1,989	1,138	1,537
Log Likelihood	−1,314.534	−774.020	−1,026.291
Akaike Inf. Crit.	2,653.068	1,572.040	2,076.582
Note:			*p<0.05; **p<0.01

Table 6: Question 4 (monitoring for mental health crises by social media companies) regressions for each year separately 2019, 2020, and 2021

	2019	2020	2021
	(1)	(2)	(3)
GENDERMale	0.848	1.326	1.369
	(0.686, 1.049)	(1.034, 1.700)	(1.106, 1.694)
	p = 0.129	p = 0.027**	p = 0.004***
AGECAT30-49	0.473	1.002	1.007
	(0.353, 0.632)	(0.723, 1.387)	(0.773, 1.312)
	p = 0.00000***	p = 0.993	p = 0.958
AGECAT50-64	0.297	0.490	0.480
	(0.218, 0.405)	(0.337, 0.713)	(0.344, 0.672)
	p = 0.000***	p = 0.0002***	p = 0.00002***
AGECAT65+	0.304	0.652	0.576
	(0.218, 0.426)	(0.433, 0.982)	(0.409, 0.810)
	p = 0.000***	p = 0.041**	p = 0.002***
RACEBlack or African American	1.264	0.987	0.871
	(0.903, 1.770)	(0.712, 1.368)	(0.646, 1.173)
	p = 0.173	p = 0.938	p = 0.364
RACEAsian or Asian-American	1.280	1.114	1.026
	(0.741, 2.211)	(0.748, 1.660)	(0.716, 1.470)
	p = 0.377	p = 0.595	p = 0.890
RACEOther	0.774	0.831	0.870
	(0.511, 1.173)	(0.551, 1.255)	(0.555, 1.365)
	p = 0.228	p = 0.380	p = 0.546
HISPANICYes	1.085	0.992	1.413
	(0.776, 1.517)	(0.665, 1.478)	(0.912, 2.191)
	p = 0.634	p = 0.967	p = 0.123
EDUCATIONBachelor's or more	0.772	1.317	1.023
	(0.601, 0.991)	(0.979, 1.771)	(0.784, 1.337)
	p = 0.043**	p = 0.069*	p = 0.865
EDUCATIONSome college	0.884	1.303	1.006
	(0.680, 1.147)	(0.955, 1.778)	(0.768, 1.319)
	p = 0.354	p = 0.096*	p = 0.963
POLPARTYRep/Lean Rep	0.748	0.880	0.779
	(0.596, 0.938)	(0.677, 1.143)	(0.624, 0.973)
	p = 0.013**	p = 0.338	p = 0.028**
Constant	1.099	0.802	0.942
	(0.798, 1.513)	(0.536, 1.200)	(0.695, 1.277)
	p = 0.562	p = 0.284	p = 0.701
Observations	1,989	1,138	1,537
Log Likelihood	−1,089.413	−765.412	−1,030.537
Akaike Inf. Crit.	2,202.825	1,554.824	2,085.073
Note:			*p<0.05; **p<0.01

Table 7: Interaction between 2019 and 2020, with 2019 as reference. Fixed effects are omitted for brevity. See Table 3-6 for reference.

	Question 1 Government Terrorism	Question 2 Law Enforcement Genetic	Question 3 Medical Research Fitness	Question 4 Corporate Mental Health
	(1)	(2)	(3)	(4)
YEAR2020	0.562	0.999	0.577	0.729
	(0.340, 0.930)	(0.607, 1.645)	(0.349, 0.954)	(0.436, 1.221)
	p = 0.025*	p = 0.999	p = 0.033*	p = 0.230
GENDERMale:YEAR2020	1.362	1.717	1.265	1.563
	(1.001, 1.852)	(1.264, 2.332)	(0.929, 1.723)	(1.127, 2.167)
	p = 0.050*	p = 0.001**	p = 0.136	p = 0.008**
AGECAT30-49:YEAR2020	1.203	0.813	1.468	2.119
	(0.782, 1.851)	(0.530, 1.248)	(0.954, 2.257)	(1.369, 3.279)
	p = 0.400	p = 0.345	p = 0.081	p = 0.001**
AGECAT50-64:YEAR2020	0.785	0.408	1.829	1.650
	(0.493, 1.248)	(0.257, 0.649)	(1.146, 2.920)	(1.015, 2.683)
	p = 0.307	p = 0.0002**	p = 0.012*	p = 0.044*
AGECAT65+:YEAR2020	0.695	0.406	1.890	2.141
	(0.417, 1.157)	(0.245, 0.674)	(1.135, 3.146)	(1.261, 3.636)
	p = 0.162	p = 0.0005**	p = 0.015*	p = 0.005**
RACEBlack or African American:YEAR2020	0.835	1.101	0.783	0.781
	(0.535, 1.303)	(0.707, 1.715)	(0.499, 1.228)	(0.489, 1.248)
	p = 0.427	p = 0.671	p = 0.287	p = 0.302
RACEAsian or Asian-American:YEAR2020	0.729	1.059	0.672	0.871
	(0.366, 1.451)	(0.530, 2.116)	(0.353, 1.279)	(0.443, 1.712)
	p = 0.368	p = 0.871	p = 0.227	p = 0.689
RACEOther:YEAR2020	1.524	1.140	1.070	1.074
	(0.885, 2.624)	(0.663, 1.958)	(0.618, 1.851)	(0.598, 1.929)
	p = 0.129	p = 0.636	p = 0.811	p = 0.811
HISPANICYes:YEAR2020	0.837	0.820	0.524	0.914
	(0.513, 1.364)	(0.503, 1.335)	(0.318, 0.863)	(0.543, 1.539)
	p = 0.475	p = 0.425	p = 0.012*	p = 0.735
EDUCATIONBachelor's or more:YEAR2020	1.586	1.259	1.824	1.706
	(1.100, 2.286)	(0.875, 1.811)	(1.263, 2.635)	(1.158, 2.515)
	p = 0.014*	p = 0.215	p = 0.002**	p = 0.007**
EDUCATIONSome college:YEAR2020	1.412	1.005	1.329	1.475
	(0.961, 2.076)	(0.685, 1.475)	(0.903, 1.956)	(0.982, 2.214)
	p = 0.079	p = 0.979	p = 0.149	p = 0.062
POLPARTYRep/Lean Rep:YEAR2020	0.940	1.129	1.239	1.176
	(0.680, 1.297)	(0.818, 1.558)	(0.894, 1.716)	(0.832, 1.662)
	p = 0.706	p = 0.462	p = 0.199	p = 0.359
Observations	3,150	3,150	3,127	3,127
Log Likelihood	−2,130.834	−2,130.678	−2,088.554	−1,854.825
Akaike Inf. Crit.	4,309.667	4,309.355	4,225.108	3,757.649
Note:				*p<0.05; **p<0.01

Table 8: Interaction between 2020 and 2021, with 2020 as reference. Fixed effects are omitted for brevity. See Table 3-6 for reference.

	Question 1 Government Terrorism (1)	Question 2 Law Enforcement Genetic (2)	Question 3 Medical Research Fitness (3)	Question 4 Corporate Mental Health (4)
YEAR2021	1.153 (0.692, 1.920) p = 0.585	0.750 (0.454, 1.239) p = 0.262	1.133 (0.682, 1.881) p = 0.630	1.175 (0.709, 1.948) p = 0.532
GENDERMale:YEAR2021	0.974 (0.703, 1.350) p = 0.874	0.828 (0.600, 1.144) p = 0.253	1.121 (0.810, 1.552) p = 0.491	1.032 (0.744, 1.432) p = 0.850
AGECAT30-49:YEAR2021	0.979 (0.639, 1.499) p = 0.923	1.160 (0.762, 1.767) p = 0.488	0.812 (0.531, 1.241) p = 0.336	1.006 (0.661, 1.530) p = 0.980
AGECAT50-64:YEAR2021	1.126 (0.686, 1.848) p = 0.638	1.592 (0.975, 2.598) p = 0.064	1.401 (0.856, 2.293) p = 0.181	0.980 (0.593, 1.619) p = 0.936
AGECAT65+:YEAR2021	0.975 (0.568, 1.671) p = 0.926	1.526 (0.900, 2.588) p = 0.117	1.524 (0.894, 2.597) p = 0.122	0.883 (0.518, 1.506) p = 0.649
RACEBlack or African American:YEAR2021	1.397 (0.898, 2.176) p = 0.139	1.238 (0.799, 1.916) p = 0.339	0.944 (0.607, 1.466) p = 0.797	0.882 (0.567, 1.373) p = 0.580
RACEAsian or Asian-American:YEAR2021	0.898 (0.526, 1.535) p = 0.695	1.072 (0.627, 1.831) p = 0.800	1.490 (0.868, 2.557) p = 0.149	0.921 (0.538, 1.575) p = 0.763
RACEOther:YEAR2021	0.808 (0.439, 1.488) p = 0.495	1.144 (0.627, 2.087) p = 0.662	0.907 (0.495, 1.663) p = 0.753	1.047 (0.569, 1.926) p = 0.884
HISPANICYes:YEAR2021	1.844 (1.021, 3.331) $p = 0.043^{*}$	1.460 (0.813, 2.624) p = 0.206	1.443 (0.799, 2.606) p = 0.225	1.425 (0.788, 2.579) p = 0.242
EDUCATIONBachelor's or more:YEAR2021	0.888 (0.597, 1.322) p = 0.561	1.071 (0.723, 1.585) p = 0.734	0.852 (0.572, 1.268) p = 0.430	0.777 (0.522, 1.158) p = 0.217
EDUCATIONSome college:YEAR2021	0.825 (0.547, 1.245) p = 0.360	1.207 (0.804, 1.812) p = 0.363	0.958 (0.635, 1.444) p = 0.837	0.773 (0.512, 1.166) p = 0.220
POLPARTYRep/Lean Rep:YEAR2021	0.522 (0.371, 0.735) $p = 0.0003^{**}$	0.642 (0.458, 0.902) $p = 0.011^{*}$	0.497 (0.352, 0.700) $p = 0.0001^{**}$	0.886 (0.628, 1.249) p = 0.489
Observations	2,675	2,675	2,675	2,675
Log Likelihood	−1,796.424	−1,827.617	−1,800.311	−1,795.949
Akaike Inf. Crit.	3,640.848	3,703.234	3,648.622	3,639.897
Note:				$^{*}p<0.05$; $^{**}p<0.01$

Table 9: Interaction between 2019 and 2021, with 2019 as reference. Fixed effects are omitted for brevity. See Table 3-6 for reference.

	Question 1 Government Terrorism	Question 2 Law Enforcement Genetic	Question 3 Medical Research Fitness	Question 4 Corporate Mental Health
	(1)	(2)	(3)	(4)
YEAR2021	0.649	0.750	0.653	0.857
	(0.423, 0.994)	(0.490, 1.147)	(0.425, 1.005)	(0.551, 1.332)
	p = 0.047*	p = 0.184	p = 0.053	p = 0.494
GENDERMale:YEAR2021	1.326	1.422	1.418	1.614
	(1.002, 1.755)	(1.076, 1.879)	(1.069, 1.881)	(1.195, 2.180)
	p = 0.049*	p = 0.014*	p = 0.016*	p = 0.002**
AGECAT30-49:YEAR2021	1.178	0.944	1.191	2.131
	(0.801, 1.733)	(0.642, 1.387)	(0.808, 1.756)	(1.439, 3.156)
	p = 0.406	p = 0.768	p = 0.376	p = 0.0002**
AGECAT50-64:YEAR2021	0.884	0.650	2.562	1.616
	(0.574, 1.361)	(0.423, 0.999)	(1.657, 3.962)	(1.024, 2.551)
	p = 0.575	p = 0.050*	p = 0.00003**	p = 0.040*
AGECAT65+:YEAR2021	0.677	0.620	2.880	1.891
	(0.428, 1.070)	(0.394, 0.975)	(1.819, 4.560)	(1.171, 3.054)
	p = 0.096	p = 0.039*	p = 0.00001**	p = 0.010**
RACEBlack or African American:YEAR2021	1.166	1.363	0.739	0.689
	(0.765, 1.778)	(0.893, 2.078)	(0.479, 1.139)	(0.439, 1.080)
	p = 0.475	p = 0.151	p = 0.170	p = 0.105
RACEAsian or Asian-American:YEAR2021	0.655	1.135	1.001	0.802
	(0.335, 1.279)	(0.579, 2.225)	(0.536, 1.872)	(0.417, 1.542)
	p = 0.216	p = 0.712	p = 0.997	p = 0.508
RACEOther:YEAR2021	1.232	1.304	0.970	1.124
	(0.689, 2.203)	(0.736, 2.309)	(0.543, 1.734)	(0.609, 2.075)
	p = 0.482	p = 0.364	p = 0.919	p = 0.708
HISPANICYes:YEAR2021	1.543	1.197	0.756	1.303
	(0.914, 2.606)	(0.712, 2.012)	(0.444, 1.286)	(0.750, 2.262)
	p = 0.105	p = 0.498	p = 0.303	p = 0.348
EDUCATIONBachelor's or more:YEAR2021	1.409	1.348	1.554	1.327
	(0.999, 1.987)	(0.958, 1.897)	(1.098, 2.200)	(0.920, 1.913)
	p = 0.051	p = 0.087	p = 0.013*	p = 0.131
EDUCATIONSome college:YEAR2021	1.165	1.214	1.273	1.139
	(0.817, 1.661)	(0.854, 1.726)	(0.890, 1.820)	(0.782, 1.659)
	p = 0.399	p = 0.282	p = 0.187	p = 0.497
POLPARTYRep/Lean Rep:YEAR2021	0.490	0.725	0.615	1.041
	(0.365, 0.659)	(0.541, 0.972)	(0.456, 0.830)	(0.758, 1.431)
	p = 0.00001**	p = 0.032*	p = 0.002**	p = 0.803
Observations	3,549	3,549	3,526	3,526
Log Likelihood	−2,388.064	−2,402.085	−2,340.825	−2,119.949
Akaike Inf. Crit.	4,824.129	4,852.170	4,729.651	4,287.898
Note:				*p<0.05; **p<0.01