The Scale of COVID-19 Graphs Affects Understanding, Attitudes, and Policy Preferences

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Abstract

Mass media routinely present data on COVID-19 diffusion using either a log scale or a linear scale. We show that the scale adopted on these graphs has important consequences on how people understand and react to the information conveyed. In particular, we find that when we show the number of COVID-19 related deaths on a logarithmic scale, people have a less accurate understanding of how the pandemic has developed, make less accurate predictions on its evolution, and have different policy preferences than when they are exposed to a linear scale. Consequently, merely changing the scale the data is presented on can alter public policy preferences and the level of worry, despite the fact that people are exposed to a lot of COVID-19 related information. Reducing misinformation can help improving the response to COVID-19, thus, mass media and policymakers should always describe the evolution of the pandemic using a graph on a linear scale, or at least they should show both scales. More generally, our results confirm that policymakers should not only care about *what* information to communicate, but also about *how* to do it, as even small differences in data framing can have a significant impact.

Keywords: COVID-19, Public Understanding, Framing, Media

1. Introduction

The coronavirus disease 2019 (COVID-19) pandemic is a formidable challenge to public health [26, 12, 11] and the economy [3, 4, 31]. Absent a cure or a vaccine, it is crucial that people are adequately informed about the pandemic [17], so that they stand behind policies that aim to minimize the spread of the virus and adopt behaviors that can limit the risk of contagion like social distancing [13, 16, 37]. However, research has shown the challenges of communicating scientific facts in a way that effectively conveys essential information to the general public [39]. In this article, we highlight the importance of this problem by focusing on one of the most basic pieces of information relative to the pandemic: the number of deaths.

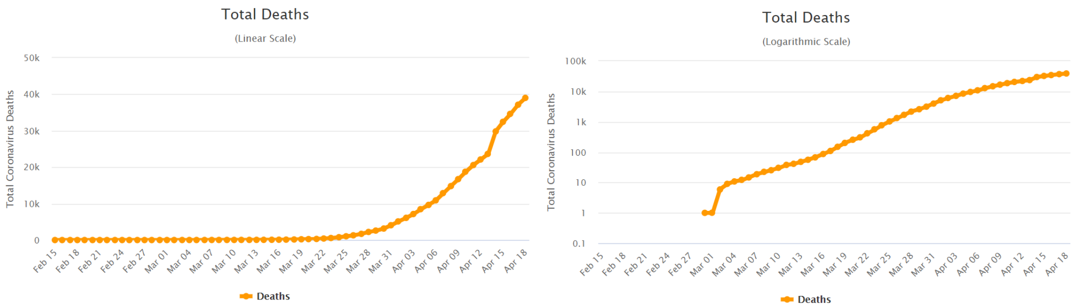
To provide information on the diffusion of the virus, mass media routinely publish graphs that depict the evolution in the number of COVID-19 related deaths in a given area. Many of these graphs present quantities on the Y-axis on either a linear scale [43, 48] or a logarithmic scale [24, 19, 34].

We show that the scale has important consequences on how people understand and react to the information conveyed. In particular, we find that when people are exposed to a logarithmic scale they have a less accurate understanding of how the pandemic unfolded until now, make less accurate predictions on its future, and have different policy preferences than when they are exposed to a linear scale. This result is consistent with existing evidence that even scientists have trouble understanding information conveyed in logarithmic scale graphs [32]. Since reducing misinformation can help improving the response to COVID-19 [45], mass media and policymakers should present data on the evolution of the pandemic using a graph in a linear scale, or at least they should show both scales. More generally, our research relates to the works that use the insights of behavioral science to mitigate the COVID-19 outbreak [8, 25], and to research on the factors that determine public compliance with Covid-19 mitigation measures [5, 29, 47].

2. Experiment

We devised a double-blind experiment to test people's graph comprehension and its effects on attitudes and policy preferences. The experiment was approved by Yale's Institutional Review Board, and we asked all participants to confirm that they were 18 years old or older at the time of taking the survey and giving their informed consent before participating. Those clicking no on any of the two statements were not allowed to answer any question. All participants were recruited through Cloud Research, while the survey was structured on and administered via Qualtrics, where we were able to download the anonymized data. We recruited a sample of approximately $n = 2000$ (after exclusion criteria, with no regression with less than 1825 observations) U.S. residents on

Figure 1: COVID-19 Related Deaths in United States Between February 15th and April 18th in a linear scale (left panel) and in a log scale (right panel). Source: www.worldometers.info



Cloud Research. Half of them were randomly assigned to linear group, in which they were shown the evolution of COVID-19 deaths in the U.S. on a linear scale. The other half were assigned to logarithmic group, in which participants saw the data on the evolution of COVID-19 deaths in U.S., but plotted on a logarithmic scale. The graphs were taken from the popular website www.worldometers.info (See Fig 1). We asked respondents three sets of questions: (i) attitudes and policy preferences, (ii) graph understanding, and (iii) standard demographic questions. In the supplementary material, we report the questions we asked and the order in which they were asked.

The analyses can be grouped into: 1) determinants of worry, 2) policy preferences and 3) differences in understanding. In all three cases our primary variable of interest is "linear", a binary taking value 1 whenever the participant was exposed to the linear scale graphs, and zero otherwise.

Health and Economic Crises

In this set of regressions we investigate whether the scale of the graph affects respondents' level of worry for the health and economic crises caused by the pandemic (Table 1).

Table 1 here

The group exposed to the linear scale graph is more worried about the health crisis, but not about the economic crisis. This result is robust to different specifications and controls. The variables go in the expected direction: men are less worried than women [22], which is consistent with the evidence that man are less risk averse [18]. Furthermore, people in states with a high number of COVID-19 deaths per 100000 inhabitants are more worried about the health crisis, while people in states with stronger restrictions are more worried about the economic crisis. Moreover, people who read more COVID-19 related news are significantly more worried about both crises [33]. The direction of causality between news and worry is unclear. However, we also observe that there is a high correlation between the level of worry for the economic and the health crisis [44].

Policy Preferences

People in linear linear groupre less in favor of closing stores, but they want to keep stores closed for longer (Tables 2). As predictable, we find that people who are more worried about the health crisis support more strongly keeping non-essential businesses closed, and want to keep them closed for longer. Instead, a higher level of economic worry is associated with less support for the policy of keeping non-essential businesses closed. Similarly, participants who are more worried about the economy want to reopen non-essential businesses earlier. We also observe that Democrats support more strongly the policy of keeping non-essential businesses closed. This finding is in line with the results of many studies showing systematic differences in responses to the COVID-19 pandemic between Democrats and Republicans [1, 6, 40, 46]. Moreover, we find that men and people who live in cities with 50000 or more inhabitants (small or big city) want to reopen later.

Table 2 here

Last we find that linear group is more willing to support a tax to provide everyone with masks, but state they would wear them less often. We also find that Democrats and people who are more worried for the health crisis are more willing to support a tax to buy protective masks. Instead, Republicans would wear the masks less often. Older people and people who live in big cities (i.e., cities with more than 500000 inhabitants) are more willing to wear masks. These results are reasonable and in line with previous findings [49], as older people are more at risk [14], and COVID-19 spread faster in densely populated cities. However, older people are less in support of a tax to buy masks.

Table 3

Understanding Questions

We tested respondents' understanding of linear and logarithmic scales by asking three questions. First, we showed them the COVID-19 graph in the scale that they had been assigned and asked them whether the number of deaths increased more between March 31st and April 6th or between April 6th and April 12th. Second, we showed them a graph describing non-COVID-19 related data on the number of deaths from an hypothetical infection Z (taken from [35]) and asked them a similar question. As for the first graph shown to participants, people in linear group saw the data plotted on a linear scale, whereas respondents in logarithmic group saw data plotted on a logarithmic one. The goal of this question was to test whether respondents' ability to answer correctly the first question depended on prior information on COVID-19, or on a correct understanding of the scale in which their graphs are plotted.

Third, we asked respondents to make a prediction on the total number of deaths on April 25th – one week after we launched the experiment – as attitudes and future behaviors are likely to be driven also by expectations on how the pandemic will evolve. Predicting the number of COVID-19 related deaths in a week is difficult, but some predictions are more reasonable than others. We forecast the number of total deaths on April 25th using ARIMA, a standard method already used to forecast the evolution of COVID-19 related deaths [2, 7]. We use a ARIMA (0,2,1), as we find after a number of simulations that it offers the best fit for the data, and forecast the number of cases and its 95% and 99% confidence intervals (CIs). On the 18th of April the number of deaths was $39,014$. The 95% CI forecasted using the ARIMA(0,2,1) ranges from $49,203.15$ to $62,559.27$, whereas the 99% CI ranges from $46,895.47$ to $64,685.95$. We remark that the number of deaths on the 25th of April were 54256, as opposed to the 55791 deaths predicted by our ARIMA model, but still in line with the 95% CI.

We use these CIs to divide predictions in three groups. In the first group, we include the predictions that fall within the 95% CI ("accurate range"). We consider these predictions "accurate". In the second group, we include the predictions that fall within the 99% CI, but outside the 95% CI ("unlikely range"). We refer to these predictions as "unlikely". Last, we consider the predictions that fall outside the 99% CI ("unreasonable range") as "unreasonable".

Additionally, for each of the understanding questions we asked how confident respondents were about their answers. The level of confidence is important as it can shed some light on how much weight people will attach to the information represented in the graph.

Table 4 here

Figure 2: The left panel reports the percentage of correct and incorrect answers provided by the members of the two groups to the understanding question related to COVID-19 real world data. The right panel reports the percentage of correct and incorrect answers provided by the members of the two groups to the understanding question related to Infection Z hypothetical data

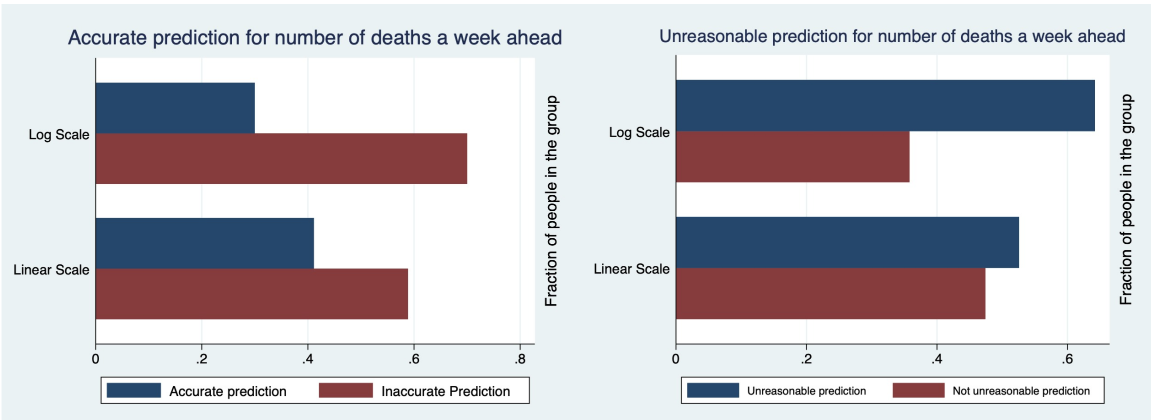


Figure 3: The left panel reports the percentage of accurate and inaccurate (i.e. not accurate) predictions provided by the members of the two groups. The right panel reports the unreasonable and reasonable (i.e. not unreasonable) predictions provided by the members of the two groups.

We observe that linear group gives the correct answer more often to all graph understanding questions (Table 4 and Figures 2 and 3). The gap is even higher for the question on the imaginary disease Z. This seems to suggest that all the information on COVID-19 to which people were exposed reduced to some extent the understanding gap between the two groups. This understanding gap, however, remains wide. Given the enormous amount of information on COVID-19 that was communicated to the public, this suggests that logarithmic scales confuse the public no matter how much additional information is provided.

Table 5 here

We find that linear linear grouplso makes more often predictions that are accurate (Table 5). As predictable, reading more COVID-19 related news increases the accuracy of predictions. We do not find significant differences among demographic group. However, Republicans are more likely to make unreasonable predictions.

3. Discussion

We find that people in linear group understand the graphs better and make better predictions. logarithmic group gives predictions that are higher and are on average unreasonable. Therefore, using linear graphs reduces the risk of misinforming the public.

People in linear group are more worried about the health crisis and prefer that non-essential businesses remain closed for longer. However, they support less strongly the idea of closing non-essential business in the first place, and would wear masks less often. These results are statistically significant and robust to a series of different controls and specifications (the regressions presented use logit, probit and OLS and the results are robust to different sets of controls). The odds ratios show that the magnitude of the effects is non-negligible. Moreover, empirical evidence suggests that self-reported measures of social distancing track actual behavior both at the individual and at the group level [23]. This finding is remarkable because the data underlying the graphs is identical. Merely changing the scale can alter public policy preferences and the level of worry, despite the endless flow on COVID-19 related information to which everyone is exposed.

A possible explanation of our finding is that the linear scale gives the impression of a growing pandemic, without any sign of improvement. At the same time, the logarithmic scale looks flatter and reassuring. However, it has a higher end-point value on the Y-axis, which might act as anchor when assessing the short-term evolution of the pandemic. Therefore, while logarithmic group predicts more deaths in the short term due to the higher anchor, linear group expects the crisis to last longer. Consequently, linear group is more worried about the health crisis, while anticipates to wear masks less often in order to ration them.

Regardless of the possible explanations, it is noteworthy that changing the scale can alter policy preferences, intentions to adopt precautionary measures, and level of worry for the health consequences of the pandemic. Combined with the fact that people have significant problems understanding the logarithmic scale, these findings suggests that representing data in a linear scale is preferable. [21] noted that during a public health crisis, the general public relies on the media to convey accurate and understandable information, so that it can take informed decisions regarding health protective behaviors. Absent information of this kind, people cannot form informed preferences or take informed decisions. Moreover, unclear information conveyed by the media could undermine how much people trust science, which is a key predictor of compliance with COVID-19 guidelines [10, 38]. In turn, this might facilitate the spread of misinformation and conspiracy theories [9, 27, 30], for instance, via social media [15, 36, 41], and increase people's reliance on social media as a source of information. Studies show that a frequent use of social media during the COVID-19 pandemic increases the risk of mental health problems [20]. More generally, our results confirm that policymakers should not only care about *what* information to communicate, but also about *how* to do it, as even small differences in data framing can have significant impact [28, 42].

While our results are robust and significant, we acknowledge that we rely on stated preferences and our sample is not demographically representative.

Tables and Questionnaire

Summary Statistics

Regression tables

Table 1: Determinants of worry about health crisis caused by Covid-19. The coefficients are estimated through ordered Logit regressions. P-values are reported in parentheses. Standard errors can be found in the Appendix. All coefficients for the control variables are reported.

	(1) Worry About Health Crisis	(2) Worry About Health Crisis	(3) Worry About Health Crisis
Worry About Health Crisis			
In Linear Group	0.141*	0.258*	0.327**
	(0.081)	(0.091)	(0.038)
COVID-19 News Checking		0.500***	0.434***
		(<0.001)	(<0.001)
Male		-0.806***	-0.654***
		(<0.001)	(<0.001)
Understanding Q.1: Real Data		-0.00425	0.00558
		(0.967)	(0.958)
Confidence in Understanding Q.1		-0.00134	-0.00152
		(0.706)	(0.674)
Understanding Q.2: Hypothetical		-0.137	-0.225
		(0.386)	(0.171)
Confidence in Understanding Q.2		-0.00374	-0.00428
		(0.302)	(0.246)
Accurate Prediction		0.156	0.218
		(0.404)	(0.255)
Unreasonable Prediction		0.225	0.325*
		(0.216)	(0.084)
Confidence in Prediction		0.00622***	0.00579***
		(0.005)	(0.009)
Democrat			0.732***
			(<0.001)
Republican			-0.282**
			(0.017)
Worry About Economic Crisis			0.707***
			(<0.001)
Live in city with <50K People			0.0156
			(0.880)
Live in city with >500K People			-0.132
			(0.280)
Education			-0.0258
			(0.473)
Age			-0.00132
			(0.694)
State of Residence			0.00777**
			(0.030)
Restrictions in the State			-0.156
			(0.160)
Observations	2074	1837	1828

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Determinants for support for keeping shops closed (Columns 1-3) and suggested reopening day (Columns 4-6). Columns 1-3 report coefficients estimated through ordered Logit regressions and Columns 4-6 report coefficients obtained through ordinary least squares regressions (OLS). P-values are reported in parentheses. The standard errors can be found in the Appendix. All coefficients for the control variables are reported

	(1)	(2)	(3)	(4)	(5)	(6)
	Support for	Support for	Support for	Days Until	Days Until	Days Until
Closing Businesses	Closing Businesses	Closing Businesses	Reopening Businesses	Reopening Businesses	Reopening Businesses	
In Linear Group	0.0406	-0.378**	-0.424**	2.295	17.38**	14.65**
	(0.621)	(0.019)	(0.012)	(0.464)	(0.014)	(0.037)
Worry About Health Crisis		0.997***	1.067***		12.45***	13.14***
		(<0.001)	(<0.001)		(<0.001)	(<0.001)
COVID-19 News Checking		0.0288	0.0748		3.071*	3.932**
		(0.531)	(0.117)		(0.056)	(0.018)
Male		-0.112	-0.0890		10.53***	9.169***
		(0.242)	(0.366)		(0.002)	(0.006)
Understanding Q.1: Real Data		0.131	0.132		-1.236	-0.517
		(0.228)	(0.236)		(0.762)	(0.900)
Confidence in Understanding Q.1		0.00955***	0.00842**		0.109	0.0996
		(0.009)	(0.023)		(0.391)	(0.440)
Understanding Q.2: Hypothetical		0.300*	0.348**		-18.05**	-15.87**
		(0.075)	(0.047)		(0.012)	(0.026)
Confidence in Understanding Q.2		-<0.001421	-<0.001228		-0.310**	-0.299**
		(0.911)	(0.952)		(0.025)	(0.032)
Accurate Prediction		0.480**	0.450**		10.58*	9.343
		(0.012)	(0.019)		(0.093)	(0.138)
Unreasonable Prediction		0.0871	0.0806		6.590	4.787
		(0.635)	(0.665)		(0.277)	(0.431)
Confidence in Prediction		-0.00451*	-0.00426*		0.216***	0.205**
		(0.054)	(0.073)		(0.007)	(0.012)
Democrat			0.545***			0.107
			(<0.001)			(0.977)
Republican			-0.491***			1.912
			(<0.001)			(0.683)
Worry About Economic Crisis			-0.494***			-3.597*
			(<0.001)			(0.069)
Live in city with <50K People			0.0314			6.259*
			(0.770)			(0.085)
Live in city with >500K People			0.0230			9.164**
			(0.858)			(0.037)
Education			-0.0258			-1.798
			(0.496)			(0.173)
Age			-0.00105			-0.151
			(0.769)			(0.192)
State of Residence			0.00274			-0.00686
			(0.456)			(0.957)
Restrictions in the State			-0.0175			-1.382
			(0.881)			(0.741)
In Linear Group						0
						(.)
Constant				65.38***	-0.312	24.09
				(<0.001)	(0.979)	(0.155)
Observations	2074	1837	1828	2061	1828	1819

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Determinants of likelihood to wear a mask when going out if provided with one (Columns 1-3) and supporting a tax to finance their distribution (Columns 4-6). The coefficients are estimated through ordered Logit regressions. P-values are reported in parentheses. The standard errors can be found in the Appendix. All coefficients for the control variables are reported.

	(1) Likelihood to Wear Masks	(2) Likelihood to Wear Masks	(3) Likelihood to Wear Masks	(4) Support for Mask-Buying Tax	(5) Support for Mask-Buying Tax	(6) Support for Mask-Buying Tax
In Linear Group	0.00311	-0.314**	-0.350**	-0.0218	0.307**	0.305**
	(0.970)	(0.045)	(0.029)	(0.780)	(0.042)	(0.046)
Worry About Health Crisis		0.907***	0.908***		0.481***	0.471***
		(<0.001)	(<0.001)		(<0.001)	(<0.001)
COVID-19 News Checking		0.138***	0.129***		0.0403	0.0682
		(0.003)	(0.006)		(0.341)	(0.116)
Male		-0.255***	-0.270***		0.0372	0.0455
		(0.007)	(0.005)		(0.673)	(0.612)
Understanding Q.1: Real Data		0.0281	0.0136		0.152	0.169*
		(0.796)	(0.902)		(0.133)	(0.097)
Confidence in Understanding Q.1		0.00571	0.00493		0.00648*	0.00602*
		(0.125)	(0.192)		(0.065)	(0.088)
Understanding Q.2: Hypothetical		0.189	0.237		-0.454***	-0.452***
		(0.249)	(0.157)		(0.004)	(0.004)
Confidence in Understanding Q.2		0.00250	0.00272		-0.0108***	-0.0112***
		(0.510)	(0.479)		(0.003)	(0.002)
Accurate Prediction		0.435**	0.431**		0.186	0.141
		(0.020)	(0.022)		(0.312)	(0.444)
Unreasonable Prediction		0.497***	0.493***		0.165	0.147
		(0.007)	(0.007)		(0.357)	(0.414)
Confidence in Prediction		0.00211	0.00276		0.00675***	0.00734***
		(0.352)	(0.231)		(0.002)	(0.001)
Democrat			0.161			0.378***
			(0.154)			(<0.001)
Republican			-0.384***			-0.261**
			(0.001)			(0.024)
Worry About Economic Crisis			-0.132**			-0.0979*
			(0.021)			(0.069)
Live in city with <50K People			0.0832			0.115
			(0.424)			(0.240)
Live in city with >500K People			0.588***			0.0488
			(<0.001)			(0.681)
Education			-0.0767**			-0.0209
			(0.040)			(0.543)
Age			0.00713**			-0.00942***
			(0.041)			(0.004)
State of Residence			0.0170***			-0.00313
			(<0.001)			(0.358)
Restrictions in the State			-0.154			-0.122
			(0.177)			(0.258)
Likelihood to Wear Masks					0.648***	0.617***
					(<0.001)	(<0.001)
Observations	2072	1835	1826	2072	1834	1825

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Understanding questions: The coefficients are estimated through a Logit regression. P-values are reported in parentheses. The standard errors can be found in the Appendix. Columns 1 and 2: Right answer to the question on the understanding question on COVID-19 data. Columns 3 and : Right answer to question on Infection Z (hypothetical data). P-values are reported in parentheses. Standard errors for the same tables can be found in the Appendix. All coefficients for the control variables are reported.

	(1)	(2)	(3)	(4)
	Understanding Q.1: Real Data	Understanding Q.1: Real Data	Understanding Q.2: Hypothetical	Understanding Q.2: Hypothetical
In Linear Group	2.021***	2.054***	4.634***	4.819***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Confidence in Understanding Q.1		0.00886***		
		(<0.001)		
Worry About Health Crisis		-0.0310		-0.0851
		(0.585)		(0.318)
COVID-19 News Checking		0.0780		0.0860
		(0.145)		(0.290)
Education		0.0213		0.152**
		(0.619)		(0.021)
Male		-0.147		0.321*
		(0.193)		(0.066)
Age		0.00445		0.0154**
		(0.268)		(0.012)
Democrat		0.00380		0.0870
		(0.977)		(0.660)
Republican		-0.0190		-0.183
		(0.895)		(0.413)
Confidence in Understanding Q.2				0.0308***
				(<0.001)
Constant	-0.378***	-1.375***	-2.164***	-6.119***
	(<0.001)	(0.001)	(<0.001)	(<0.001)
Observations	2074	1830	2074	1830

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Determinants of making an accurate prediction (Columns 1 and 2) and an unreasonable prediction (Columns 3 and 4). The coefficients are estimated through Logit regressions. P-values are reported in parentheses. The standard errors can be found in the Appendix. All coefficients for the control variables are reported.

	(1) Accurate Prediction	(2) Accurate Prediction	(3) Unreasonable Prediction	(4) Unreasonable Prediction
In Linear Group	0.489***	0.482***	-0.481***	-0.480***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Confidence in Prediction		-0.00178		0.00188
		(0.447)		(0.411)
Worry About Health Crisis		-0.0112		0.0494
		(0.830)		(0.327)
COVID-19 News Checking		0.150***		-0.175***
		(0.002)		(<0.001)
Education		0.0477		-0.0461
		(0.221)		(0.224)
Male		-0.0327		-0.0149
		(0.749)		(0.881)
Age		0.00182		-0.00480
		(0.616)		(0.175)
Democrat		0.0920		-0.106
		(0.437)		(0.360)
Republican		-0.181		0.221*
		(0.172)		(0.087)
Constant	-0.848***	-1.378***	0.585***	1.147***
	(<0.001)	(<0.001)	(<0.001)	(0.001)
Observations	2074	1832	2074	1832

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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