Journal of Experimental Political Science **5** (2018) 159–164
doi:10.1017/XPS.2017.32

Sex Trafficking, Russian Infiltration, Birth Certificates, and Pedophilia: A Survey Experiment Correcting Fake News

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Following the 2016 U.S. election, researchers and policymakers have become intensely concerned about the dissemination of "fake news," or false news stories in circulation (Lazer et al., 2017). Research indicates that fake news is shared widely and has a pro-Republican tilt (Allcott and Gentzkow, 2017). Facebook now flags dubious stories as disputed and tries to block fake news publishers (Mosseri, 2016). While the typical misstatements of politicians can be corrected (Nyhan et al., 2017), the sheer depth of fake news's conspiracizing may preclude correction. Can fake news be corrected?

To answer, we exposed subjects ($n = 2{,}742$) on Mechanical Turk to multiple examples of fake news. As far as we know, this represents one of the first experimental tests of corrections on fake news.[1] Our fake news examples came from across the political spectrum. We used six fake news examples, randomly exposing each subject to two examples. For each fake news example, subjects randomly saw either the fake news story alone, or the story and a correction. All subjects were asked to agree with the position advanced by the fake news story.

Both the fake news examples and corrections came from the real world. We utilized a wide range of sources for stories and corrections. Some came from traditional media, while others emanated from Internet message boards. For one of the fake stories, we varied the media type, showing subjects a video. For another fake story, we presented subjects with one of two real-world corrections. The full text of each fake story and correction appear in the appendix.

As the top row of Figure 1 shows, on every issue, corrected subjects on average became significantly less convinced by the fake news story. Corrections improved

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[1]While Pennycook and Rand (2017) evaluated Facebook's corrective efforts, they neither provide corrections, nor do they test complete articles.

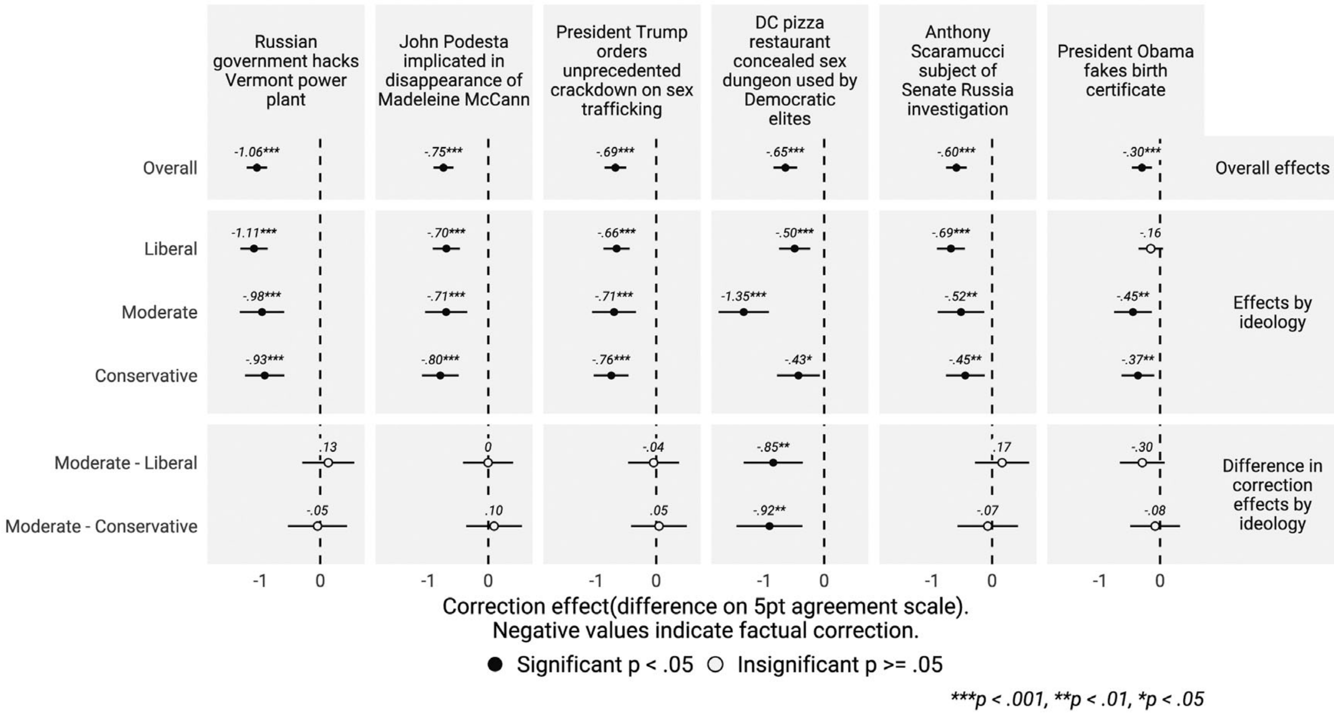

Figure 1

Correction effects by fake story, overall, and by ideology. Text labels report beta coefficients and *p*-values adjusted via Bonferroni method for multiple comparisons. The second row reports average effects across both the corrections used for the Russia/Vermont story. The bottom row reports the difference in effects by ideology. This figure summarizes the regression models described in Table 1.

Table 1
Regression Models by Issue

	Pizzagate		Scaramucci/ Russia		Podesta brothers		Obama birth certificate		Trump pedophilia crackdown		Russia power hack	
Corr.	– 0.65***	– 0.43**	– 0.60***	– 0.45***	– 0.75***	– 0.80***	– 0.30***	– 0.37***	– 0.69***	– 0.76***	– 1.06***	– 0.93***
	(0.10)	(0.18)	(0.09)	(0.17)	(0.08)	(0.16)	(0.09)	(0.14)	(0.09)	(0.15)	(0.09)	(0.17)
Mod.		0.02		0.35**		– 0.28*		– 0.52***		– 0.65***		0.47**
		(0.19)		(0.17)		(0.17)		(0.15)		(0.17)		(0.21)
Lib.		– 0.86***		0.57***		– 0.70***		– 1.44***		– 1.42***		0.72***
		(0.16)		(0.14)		(0.13)		(0.13)		(0.13)		(0.17)
Corr. × Mod.		– 0.92***		– 0.07		0.10		– 0.08		0.05		– 0.05
		(0.28)		(0.26)		(0.24)		(0.21)		(0.24)		(0.25)
Corr. × Lib.		– 0.06		– 0.24		0.10		0.22		0.09		– 0.18
		(0.23)		(0.20)		(0.19)		(0.17)		(0.19)		(0.20)
Corr. eff. (*Cons*)		– 0.43*		– 0.45*		– 0.80***		– 0.37**		– 0.76***		– 0.93***
(*Mod.*)		– 1.35***		– 0.52**		– 0.71***		– 0.45**		– 0.71***		– 0.98***
(*Lib.*)		– 0.50***		– 0.69***		– 0.70***		– 0.16		– 0.66***		– 1.11***
Observations	670	670	667	667	715	715	711	711	724	724	723	723
R^2	0.06	0.16	0.07	0.09	0.10	0.16	0.02	0.27	.07	.29	.17	.21
Adjusted R^2	0.06	0.15	0.06	0.09	0.10	0.15	0.02	0.26	.07	.29	.17	.21

Note: For each issue, the first model measures the unconditional effect of a correction (larger values indicate agreement with inaccurate statement). The second model inside each issue reports the correction effect conditional on ideology. The auxiliary quantities underneath the coefficients report the significance of the corrections by ideology. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 2
Regression Models for Vermont Power Grid Hacking, by Correction Type

	Russia hacks power grid			
Greenwald correction	−1.09***	− 1.05***		
	(0.10)	(0.19)		
Washington Post correction	−1.04***	− 0.81***		
	(0.10)	(0.19)		
Moderate		0.47**		0.47**
		(0.21)		(0.21)
Liberal		0.72***		0.72***
		(0.17)		(0.17)
Greenwald × Moderate		0.25		
		(0.29)		
Washington Post × Moderate		− 0.38		
		(0.29)		
Greenwald × Liberal		− 0.12		
		(0.24)		
Washington Post × Liberal		− 0.24		
		(0.24)		
Overall correction × Moderate				− 0.05
				(0.25)
Overall correction × Liberal				− 0.18
				(0.20)
Overall correction			− 1.06***	− 0.93***
			(0.09)	(0.17)
Auxilary quantities: Correction effects by ideology				
Greenwald (Conservative)		− 1.05***		
Greenwald (Moderate)		− 0.81***		
Greenwald (Liberal)		− 1.17***		
WaPo (Conservative)		− 0.81***		
WaPo (Moderate)		− 1.19***		
WaPo (Liberal)		− 1.06***		
Conservative				− 0.93***
Moderate				− 0.98***
Liberal				− 1.11***
Differences in correction effects by ideology				
Washington Post—Greenwald (Cons.)		− 0.24		
Washington Post—Greenwald (Mod.)		0.38		
Washington Post—Greenwald (Lib.)		− 0.12		
Observations	723	723	723	723
R^2	0.17	0.22	0.17	0.21

Note: Both the *Washington Post* and the Glen Greenwald corrections are indistinguishably corrective, as indicated by insignificant differences in the *differences* in the correction effects (the second group of auxiliary quantities). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

accuracy overall, even among those ideological cohorts who had a clear political interest in a fake news story. For example, despite ubiquitous claims about Russian political interference in the 2016 election, even liberals showed a correction to a story alleging Russian infiltration of a Vermont power utility subsequently evinced more accurate beliefs ($\hat{\beta} = -1.11$; $p < 0.01$). Likewise, conservatives exposed to a correction that indicated that President Trump had not ordered an

Table 3
Conditional Balance

		Number of corrections			
		None	One	Two	Association
Education	HSD	10	9	10	
	Some coll	36	38	35	$\chi^2 = 2.25, p = 0.68$
	BA +	55	52	55	
Gender	Female	50	49	48	$\chi^2 = 0.52, p = 0.72$
	Male	50	51	52	
	Lib	53	51	54	
Ideology	Mod	20	21	19	$\chi^2 = 1.65, p = 0.79$
	Cons	28	28	27	
	Democrat	53	49	51	
Party	Independent	20	21	23	$\chi^2 = 3.61, p = 0.46$
	Republican	27	30	26	
	Clinton	52	48	52	
2016 Vote	Trump	29	33	28	$\chi^2 = 4.52, p = 0.37$
	Other	19	19	19	
Race	White	76	76	78	$\chi^2 = 3.69, p = 0.72$
	Black	7	7	7	
	Hispanic	10	9	9	
	Other	7	8	5	
Age		36.4	36.2	36.5	$F(1, 2102) = 0.0007, p = 0.98$
Income		$58,133	$59,095	$56,847	$F(1, 2102) = 0.07, p = 0.79$

Note: For categorical covariates, the three numerica columns report the proportional distribution of each variable within the variable class. For continuous variables, cells report correction exposure group means. Categorical relationships are tested with a chi-square test, continuous variables are tested with an *F*-test.

"unprecedented" crackdown on pedophilia became more accurate ($\hat{\beta} = -0.76$; $p < 0.01$). The second row of Figure 1 displays ideological results for all stories.

To be sure, there was some evidence of differential response to corrections by ideology. Furthermore, uncorrected subjects were credulous of the claims made by the fake stories. Yet, for no issue was a correction met with factual backfire (Nyhan Reifler, 2010; Wood and Porter, nd). As with non-fake stories, corrections led to large gains in factually accurate beliefs across the ideological spectrum. While fake news *may* have had a significant impact on the 2016 election, upon seeing a correction, Americans are willing to disregard fanciful accounts and hew to the truth.

SUPPLEMENTARY MATERIALS

To view supplementary material for this article, please visit https://doi.org/10.1017/XPS.2017.32

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