APTARA | AJPS Journal | ajps12293 MSP No. | Dispatch: January 17, 2017 | No. of pages: 3 | CE: n/a | PE: Martha

Erratum to *Making Young Voters: The Impact of Preregistration on Youth Turnout*

John B. Holbein and **D. Sunshine Hillygus**

The purpose of this erratum is to address an error in *Making Young Voters: The Impact of Preregistration on Youth Turnout*.[1] The error affects the size of the coefficient estimate on preregistration laws in the difference-in-difference model reported in Table 2 (column 1). Updating the difference-in-difference model estimate finds a smaller, but still positive effect of preregistration laws on youth turnout. Taken together with the results from other model specifications, data sources, and analytic approaches, the conclusion of the article remains the same: preregistration appears to be a viable electoral policy for increasing youth turnout.

The error in the difference-in-difference model comes from including state fixed effects, year fixed effects, and state*year fixed effects. Because our treatment variable—preregistration availability in the state and year—is defined by state and year, we should not include the interactions in the model. Stata version 11.2 (using code posted on the AJPS Dataverse[2]) estimated the model by dropping the fixed effect on Delaware in 2012, resulting in a misinterpretation of the treatment variable.[3] We are grateful to Ryan Enos, James Snyder, and the Harvard American Politics Summer Reading Group for alerting us to this error (email dated August 10, 2016) and to Anthony Fowler for following up with additional information (email dated November 22, 2016).

The more appropriate difference-in-difference model specification for a state-level exposure treatment variable would include state and year fixed effects without the interactions (e.g., Leighley and Nagler 2013, ch. 4; Leighley and Nagler 2009; Neiheisel and Burden 2013; Burden et al. 2014).[4] The updated results are shown below in Table E1. When we estimate this model, the revised estimate for our difference-in-difference model is 2 percentage points ($p = 0.117$ with fixed effects and clustered standard errors) or 2 percentage points ($p = 0.036$ with fixed effects but without clustered standard errors).[5] Given the ambiguity associated with these revised results, we also report on alternative specifications that help with drawing substantive conclusions. For example, if we slightly widen the age window used to define young people in our estimation sample, our estimate size does not change, but our levels of precision increase (18-23 year olds, 2 p.p., $p = 0.040$; 18–24, 2 p.p., $p = 0.048$; 18–25, 2 p.p., $p = 0.021$).[6] Moreover, if we remove the control for registration status—which was originally included as a stringent way to account for individuals' propensity towards participation, but may actually over control away some of preregistration's effect—the effect of preregistration

[1]Holbein, John B. and D. Sunshine Hillygus. "Making Young Voters: The Impact of Preregistration on Youth Turnout." *American Journal of Political Science*. 60(2): 364-382.

[2]Holbein, John; Hillygus, D. Sunshine, 2014, "Replication data for: Making Young Voters: The Impact of Preregistration on Youth Turnout," doi:10.7910/DVN/27672, AJPS Dataverse, V2

[3]We have verified that this incorrect model also runs in a more recent version of Stata (14.1).

[4]This means that the correct specification of equation (1) should omit γ_{st} and $\lambda\gamma$.

[5]There is some ambiguity in the literature as to when exactly fixed effects alone adequately account for cluster dependencies (Peterson 2009).

[6]As we noted in the paper, the exact data window to define young people under this approach is somewhat ambiguous.

American Journal of Political Science, Vol. 00, No. 0, xxxx 2017, Pp. 1–3

 DOI: 10.1111/ajps.12293

Table E1 Difference-in-Difference Model Results

	Diff/Diff Model 1	Diff/Diff Model 2	Diff/Diff Model 3	Diff/Diff Model 4	Diff/Diff Model 5	Diff/Diff Model 6
Preregistration	0.02*	0.02	0.02*	0.02*	0.02*	0.05*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	−0.01*	−0.01*	−0.01*	−0.003*	−0.003*	0.02*
	(0.00)	(0.00)	(0.001)	(0.001)	(0.001)	(0.002)
Married	−0.01	−0.01	0.00	0.01	0.00	−0.04*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Female	0.01*	0.01*	0.01*	0.01*	0.01*	0.05*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Family Income	0.003*	0.003*	0.003*	0.003*	0.003*	0.01*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.00)
College Degree	0.08*	0.08*	0.08*	0.09*	0.10*	0.16*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
White	−0.02*	−0.02*	−0.02*	−0.02*	−0.02*	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Hispanic	−0.02*	−0.02*	−0.02*	−0.02*	−0.02*	−0.10*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Registration Status	0.65*	0.65*	0.65*	0.65*	0.65*	.
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	.
Metropolitan Area	0.02*	0.02*	0.01*	0.01*	0.01*	0.02*
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Length of Residence	0.01*	0.01*	0.01*	0.01*	0.01*	0.03*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Business/Farm	0.02*	0.02*	0.02*	0.02*	0.02*	0.05*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
In-Person Interview	−0.02*	−0.02*	−0.02*	−0.01*	−0.02*	−0.04*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
DMV Registration	−0.09*	−0.09*	−0.08*	−0.07*	−0.08*	0.27*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.13*	0.13*	0.10*	0.07*	0.06*	−0.21*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	No	No	No	No	No	No
N (individuals)	44,821	44,821	53,688	62,766	71,811	44,821
N (state-years)	357	357	357	357	357	357
Age of Sample	18-22	18-22	18-23	18-24	18-25	18-22
R^2	0.53	0.53	0.52	0.52	0.52	0.17
Clustered SE	No	Yes	Yes	Yes	Yes	Yes

is around 4–5 percentage points and statistically distinct from zero at a high level (4.5 p.p.; $p = 0.001$ among 18–22 year olds, for example).[7]

We deeply regret our error. It reflects an oversight in our application of a modeling approach when the treatment is not collinear with the state*year fixed effects—in which case the interactions would be appropriate (Gelman and

[7]All estimates with standard errors clustered at the state-year level. If we omit registration status and whether the person registered at the DMV, the estimates are 5-6 percentage points, depending on the age range used ($p<0.001$ across all). The updated code, which includes alternate specifications, is available on the AJPS Dataverse.

Hill 2007, 228; Angrist and Pischke 2008; Murnane and Willett 2010). Although the Stata command "*xi: i.state* i.year*" provides model estimates, alternative commands, including *i.state##i.year*", "*areg*", or "*xtreg*," would have correctly identified the model as misspecified. We have updated the code on Harvard Dataverse to reflect these corrections.

This error does not affect the other analyses presented in the article. The regression discontinuity design (RDD) model results remain unchanged, finding a treatment effect of 8-percentage points among those registered in Florida. In the absence of experiments in which citizens are randomized to different electoral reforms, the estimation of causal effects is inherently imperfect, necessitating the use of multiple statistical approaches with various model assumptions. Across different approaches—including panel methods and a RDD—we have consistently found that preregistration is a viable electoral reform for increasing youth turnout, increasing voting by somewhere between 2 to 8 percentage points.

References

Angrist, Joshua D., and Jörn-Steffen Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, 2008.

Burden, Barry C., David T. Canon, Kenneth R. Mayer, and Donald P. Moynihan. "Election Laws, Mobilization, and Turnout: The Unanticipated Consequences of Election Reform." *American Journal of Political Science* 58, no. 1 (2014): 95–109.

Gelman, Andrew, and Jennifer Hill. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press, 2006.

Holbein, John B., and D. Sunshine Hillygus. "Making Young Voters: The Impact of Preregistration on Youth Turnout." *American Journal of Political Science* 60, no. 2 (2016): 364–382.

Leighley, Jan E., and Jonathan Nagler. *Who Votes Now? Demographics, Issues, Inequality, and Turnout in The United States*. Princeton, NJ: Princeton University Press, 2013.

Leighley, Jan E., and Jonathan Nagler. "Electoral Laws and Turnout: 1972-2008." In *CELS 2009 4th Annual Conference on Empirical Legal Studies Paper*. 2009.

Murnane, Richard J., and John B. Willett. *Methods Matter: Improving Causal Inference in Educational and Social Science Research*. Oxford University Press, 2010.

Neiheisel, Jacob R., and Barry C. Burden. "The Impact of Election Day Registration On Voter Turnout and Election Outcomes." *American Politics Research* 40, no. 4 (2012): 636–664.

Petersen, Mitchell A.. "Estimating standard errors in finance panel data sets: Comparing approaches." *Review of financial studies* 22, no. 1 (2009): 435–480.