Zelizer (2019) Paper Replication and Extension

Miroslav Bergam

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1 Abstract

Zelizer (2019) finds that the cues that legislators take from their peers, in addition to other credible sources of information like briefings, influence their policymaking decisions. I succesfully replicated Zelizer's results. Zelizer took a Bayesian approach to his findings, running a large number of simulations for each table using for-loops to produce estimates and standard deviations; however, this made his code very slow and hard to run. I used the rstanarm package to both simplify his code and to match his results as a robustness check. Finally, I graphed the posterior predictive distributions to analyze, overall, the Bayesian approach to this study. This paper serves as a robustness test of Zelizer's results, a simplification that makes the coefficient estimates more easily reproducable, and an analysis of the study's Bayesian model.

2 Introduction

Zelizer (2019) contributes to a body of literature identifying cue-taking from other legislators as an influential source of information in legislator's own policy-making experience. Early studies such as Matthews and Stimson (1975) and Kingdon (1973) find that cue-taking has a large influence on the decisions made by policy-makers. Zelizer uses 'interference' – the experimental nuisance of units interacting and affecting one another – as an opportunity to measure cue-taking. His first treatment variable, then, is whether or not the legislator shares an office suite, as self-selecting to be in an office suite and sharing a space with another legislator will inevitably lead to the exchange of ideas. The second treatment variable is whether or not the legislators were briefed on a particular bill. With this, the paper contributes the literature by finding that cues complement rather than substitute other sources of expertise, such as briefings.

I successfully replicated his results. We both used R, although I more heavily utilized the tidyverse, gt, and rstanarm packages. I retrieved his code and data from its posting on the Harvard Dataverse. Although I could successfully replicate every result using his data, the models I used in this paper fail to recreate his standard error values due to a fundamental difference in our models (See: Replication).

I simplified his code using functions from the rstanarm() package to greatly lower the amount of time and computing power needed to run his analyses. The methods I used maintained the Bayesian framework of the study. My producing the same coefficients also served as a robustness test for Zelizer's findings. Additionally, I graphed the posterior predictions for each model, visualizing how our respective Bayesian approaches are fitting albeit imperfect given the dataset.

3 Literature Review

Studies as early as Matthews and Stimson (1975) and Kingdon (1973) find that cue-taking has a large influence on the decisions made by policy-makers. Kingdon concluded that cue-taking influences around 40% of decisions while Matthews and Stimson pinned the number around 75%. More recent observational studies like Masket (2008) found the percentage of votes influenced by cue-taking to be 10%. Masket found that information was shared primarily through deskmates, while Matthews and Stimson found that it was shared between friends. Coppock (2014) found that information was shared between ideologically-similar legislators.

This paper abets the conclusion that cue-taking influences policy decisions while updating the approach and contributing a new layer of findings. It uses a large dataset from two legislative field experiments, lending it power that previous studies may have lacked, and focuses on legislators who share office suites as a measure of their influence on one another. The paper contributes the finding that cues complement rather than substitute other sources of expertise as well as that cue-making's influence occurs late in the decision-making process.

4 Replication

I was able to match all of the coefficient estimates from the original paper in my replicated figures. Zelizer gathers his Bayesian estimates using for-loops with thousands of iterations. His original code took a large amount of time to replicate on my own computer, so I used tools like stan_lm() from the rstanarm() package to maintain the Bayesian integrity of the study while greatly minimizing the computational power needed.

However, a clear downside to my approach are my inaccurate standard errors. I was able to replicate every standard error when using Zelizer's code, but my method didn't account for certian intricacies in the data. In one of the two studies captured in the data, legislators were not eligable for briefings from the staffer/advocate. This leads to implicit clustering in the data of those who were not briefed (one of the treatment variables). As a result, the standard errors produced by my Bayesian stan_lm models are too small because it assumes that all participants in the study receieved a briefing and that therefore is a large population of legislators (from that study) who by default have no variability in this briefing treatment.

Therefore, while I am able to replicate the standard errors using the original replication code, the method used in this paper produces overly narrow standard errors that don't take into consideration implicit clustering. Zelizer's more accurate method works around this issue with the data using a particular form of Randomization Inference.

5 Extension

See the figure "Posterior Predictive Distributions" in Appendix. In each of the plots, the darker line shows the distribution of the observed data regarding their treatments, cosponsorships, and other variables. The more faded lines show the how the model I passed in for each respective plot fits the associated data. The resulting finding apply across all of the models used in the study: a Bayesian approach is an effective but imperfect way of fitting this data to a model. The grey lines shows the Bayesian model use this discrete data in non-discrete ways, as seen by the continuous distributions. Additionally, it extrapolates the data, producing results that are below zero despite the data not dipping below 0. However, the peaks of the two lines both consistently center around the same value (around 0), showing that it is somewhat accruate. As a result, I've determined that the Bayesian model both Zelizer and I use to produce our coefficient results is a flawed but accurate way of fitting the data.

6 Conclusion

Zelizer (2019) identifies cue-taking from other legislators as an influential source of information in a legislator's policy-making decision. Making briefings a treatment variable in addition to contact with other legislators, Zelizer contributes to the literature that cue-taking is a complement rather than substitute for other modes of information.

I was successful in replication Zelizer's results, although when using my code as opposed to his, my standard errors fail to match his as they do not use Randomization Inference. In addition to simplifying his code while maintaining its Bayesian framework, producing the same coefficients served as a robustness test for Zelizer's findings. I also graphed the posterior predictions for each model to visualize how our Bayesian approach is a flawed but effective approach to this dataset.

Both approaches to the study come with pros and cons: Zelizer's original code allows for a more nuanced calculation of the standard error by using thousands of iterations to perform Randomization Inference. However, these iterations make the code slow and cumbersome for those looking to replicate the experiment. A future extension would involve performing Randomization Inference using the quicker, more efficient methods used by the rstanarm package.

[1]

7 Figures

7.1 Table 3

Table 3

Summary of Cosponsorship by Briefing and Cue-Taking Assignment (in pp)

Briefing	NO CUE-TAKING	YES CUE-TAKING
NO	10.4 (1127)	19.1 (372)
YES	20.8 (257)	19.7 (88)

7.2 Table 4

Table 4

Estimated Briefing and Cue-Taking Effects (in pp)

Value	Briefing	Cue-Taking	Combined
ITT	4.61	3.63	11.90
SE	0.72	0.73	0.98

7.3 Table 5

Table 5

Estimated Briefing and Cue-Taking Effects by Bill Progress (in pp)

Reached Floor?	Value	Briefing	Cue-Taking	Combined
Bills that failed in committee	ITT	5.43	1.21	9.72
	SE	0.82	0.84	0.89
Bills that reached floor	ITT	3.97	6.50	10.59
	SE	1.30	1.29	2.54

7.4 Table 6

Table 6

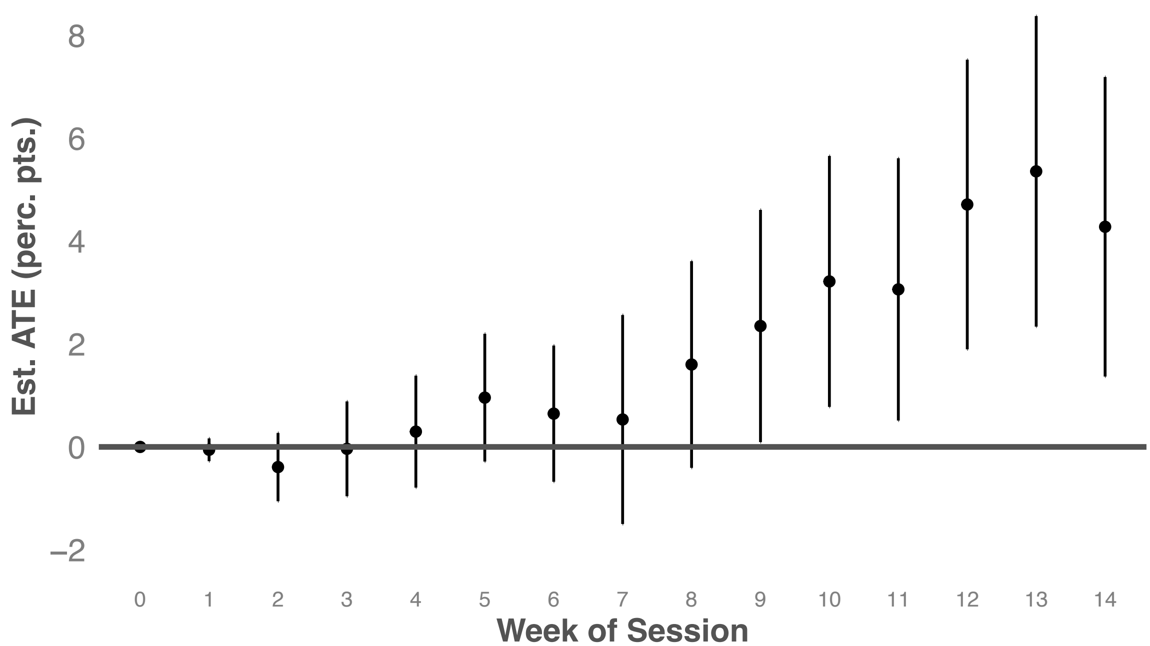
Estimated Briefing and Cue-Taking Effects Under Alternate Spillover Models (in pp)

Model (SE)	Office (SE)	Desks (SE)	Districts (SE)	Ideology (SE)
Briefing	4.69 (0.84)	2.93 (0.92)	5.86 (0.85)	4.16 (0.9)
Cue-Taking	3.71 (0.81)	2.34 (0.89)	3.67 (0.85)	2.42 (0.78)
Combined	10.31 (1)	16.71 (0.89)	8.4 (0.96)	14.32 (0.99)

[1] All analysis for this paper is availible at https://github.com/mirobergam/Bergam-Zelizer-Replication-Paper

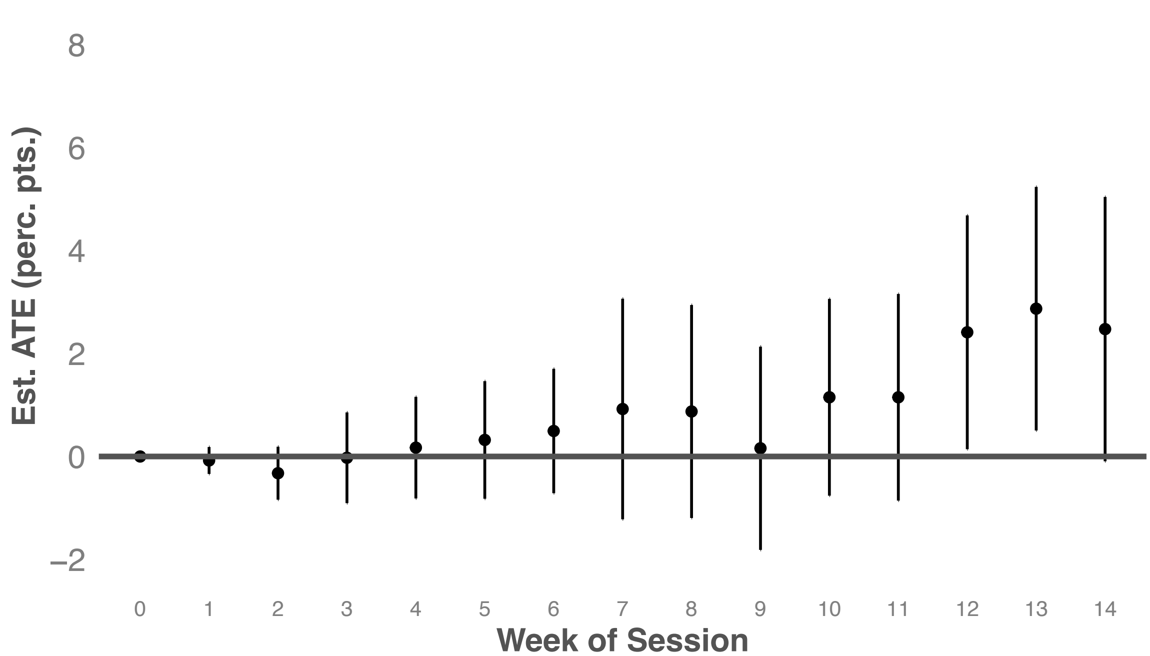
7.5 Figure 3

Figure 3. Briefing Effects by Date of Cosponsorship



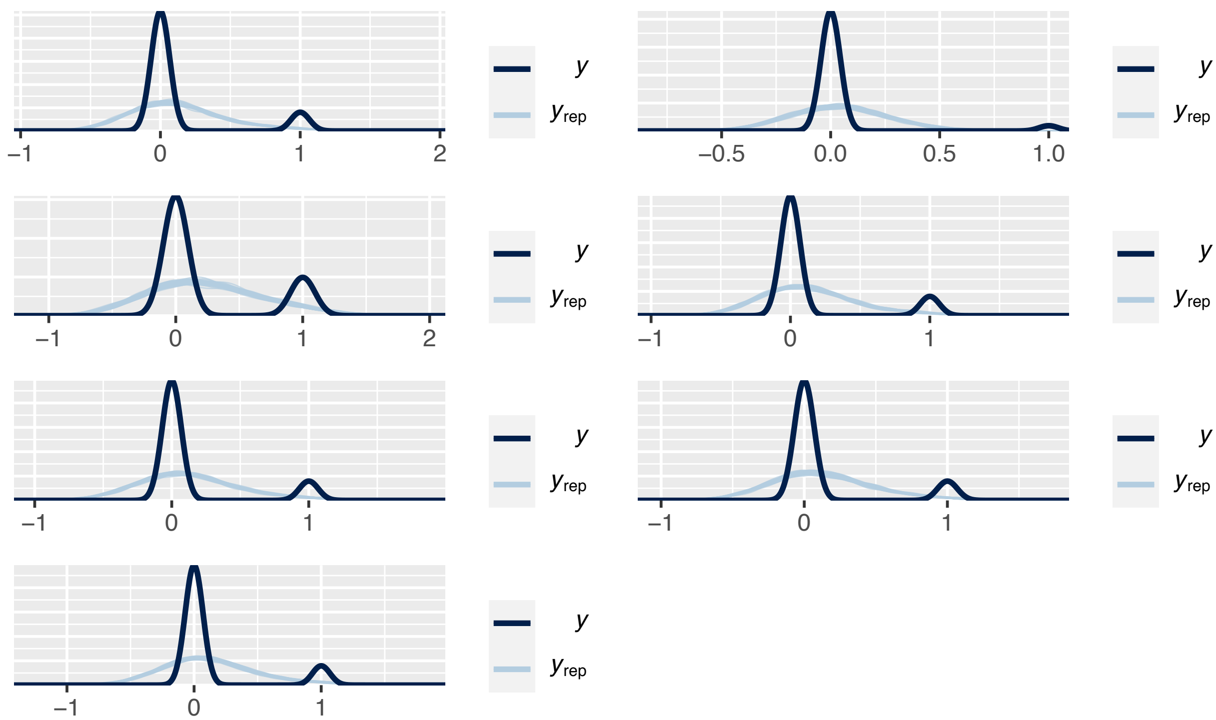
7.6 Figure 4

Figure 4. Cue–Taking Effects by Date of Cosponsors



7.7 Posterior Predictive Distributions

Posterior Predictive Distributions For All Models



Models from left to right: Table 4, Table 5 (bill didn't pass), Table 5 (bill passed), Table 6 (Offices), Table 6 (Desks), Table 6 (Districts), Table 6 (Ideology)

7.8 Bibliography

Zelizer (2019a) Matthews and Stimson (1975) Kingdon (1973) Zelizer (2019b) (*The R Project for Statistical Computing* 2020)

Kingdon, John W. 1973. *Congressmen's Voting Decisions*. https://www.cambridge.org/core/journals/american-political-science-review/article/congressmens-voting-decisions-by-john-w-kingdon-new-york-harper-row-publishers-1973-pp-313-895-cloth-450-paper/15D9C59791F2197BE31EBFC234E088A7.

Matthews, Donald R., and James A. Stimson. 1975. *Yeas and Nays: Normal Decision-Making in the U.s. House of Representatives*. https://www.cambridge.org/core/journals/american-political-science-review/article/yeas-and-nays-normal-decisionmaking-in-the-us-house-of-representatives-by-donald-r-matthews-and-james-a-stimson-new-york-john-wiley-1975-pp-xiv-190-1495/ACE1EF804F5A5E934F1DFFCEB5D54AA8.

The R Project for Statistical Computing. 2020. https://www.r-project.org/.

Zelizer, Adam. 2019a. *Is Position-Taking Contagious? Evidence of Cue-Taking from Two Field Experiments in a State Legislature*. https://www.cambridge.org/core/journals/american-political-science-review/article/is-positiontaking-contagious-evidence-of-cuetaking-from-two-field-experiments-in-a-state-legislature/1D1EF9146CF63241501C5E45B0FE6EA6.

———. 2019b. *Replication Data for: Is Position-Taking Contagious? Evidence of Cue-Taking from Two Field Experiments in a State Legislature*. https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/ZJTLSW.