

Combating capture in local politics: Evidence from eight field experiments*

Trevor Incerti[†]

June 6, 2022

Abstract

In the first field experiments to encourage participation in local civic bodies, I examine if outreach can reduce inequalities in who participates in city council meetings. Renter participation in local politics lags that of homeowners, who often participate to oppose housing growth. I randomized 19,951 renter households to receive emails encouraging them to comment at their city council meetings and support housing growth. Opening a message highlighting high costs of abstention increased public comments by 1.4 percentage points versus placebo. These effects are substantively large: treatment-induced comments represented 8% of total comments and 46% of pro-housing comments across all targeted meetings. The results suggest that even low-cost outreach strategies can meaningfully increase participation in lesser-known settings like city councils and make these bodies more reflective of the general public. Further, increasing the perception that abstention is costly appears to be an effective motivator of collective action.

Click [here](#) for the most recent version of the paper.

*I extend a special thank you to Abundant Housing LA, my partner in the implementation of this project. I also thank CSAP and ISPS at Yale University for generous support; P.M. Aronow, Moritz Bondeli, David Broockman, Alex Coppock, Charles Crabtree, Katherine Einstein, Matthew Graham, Gregory Huber, Devin Incerti, Joshua Kalla, Colin Moreshead, Mina Pollmann, Frances Rosenbluth, Kenneth Scheve, and Hikaru Yamagishi for invaluable feedback; and participants at the Yale Leitner Seminar in Political Economy and Junior Americanist Workshop Series. The human subject protocol of the research was evaluated and approved by an ethics committee at Yale University (IRB Protocol ID #2000030461). The research design and analyses were pre-registered at: <https://osf.io/c84j7>. Any and all errors are my own.

[†]Department of Political Science, Yale University.

Homeowners are more likely than renters to participate in local politics, such as attending city council meetings (Yoder 2020). Moreover, homeowners often participate to oppose housing development (Einstein, Palmer and Glick 2019; Fischel 2005; Hall and Yoder Forthcoming; Marble and Nall 2021). Yet policies that benefit homeowners often harm renters through decreased access to housing and higher rents (Charette, Herbert, Jakabovics, Marya and McCue 2015; Ganong and Shoag 2017; Glaeser and Gyourko 2018,0; Glaeser, Gyourko and Saks 2005a; Lens and Monkkonen 2016; Quigley and Rosenthal 2005; Reeves 2018). Renters therefore also have an economic incentive to participate in local politics and support housing development, but their participation lags homeowners.

Economic self-interest typically only motivates political behavior when benefits are “tangible, large, visible, and certain” (Citrin, Reingold and Green 1990). Homeowners can receive tangible benefits from blocking neighboring developments through preserved property value. For renters, increased housing will only reduce housing costs throughout a diffuse geographic region in the long term. Even moving city council meetings online in 2020 did not increase renter participation (Einstein, Glick, Puig and Palmer 2021). How then can those who only benefit through long-term and uncertain gains (like renters) be motivated to engage in personally costly political behavior?

In the first field experiments to motivate participation in local civic bodies, I randomly assigned 19,951 renter households to receive emails encouraging them to comment at their city council meetings in opposition to regulations that harm them. I also test three mechanisms for mobilization by randomizing messaging to: (1) provide attendance instructions only, (2) prime rational economic self interest, or (3) highlight the costs of abstention.

Receipt of any treatment increased public comments by 1 percentage point (pp) versus placebo, while highlighting costs of abstention increased comments by 1.4pp. Voters in local elections were more responsive to treatment (2.3pp) than non-voters (0.9pp). These effects are substantively large as council meeting attendance is typically low. Treatment-induced comments comprised 8% of total comments and 46% of pro-housing comments across all

meetings. A majority of comments were pro-housing in over 50% of treated meetings, in stark contrast with previous findings that pro-housing comments are typically in the minority in council meetings in equilibrium (Einstein et al. 2021; Yoder 2020).

These results suggest that in direct contrast with voter turnout, low-cost outreach strategies like email can increase political participation in remote settings such as commenting at city council meetings. As council meetings have low baseline rates of attendance, the increases in participation caused by such treatments are substantively large. Outreach targeted at underrepresented groups can therefore make civic bodies more reflective of the broader public, unlike allowing remote access alone. In terms of messaging, increasing perceived costs of abstention appears to be a particularly effective motivator of participation.

Motivation, theory and hypotheses

Motivation: Lack of renter participation in local politics

This paper examines if direct outreach can make participation in local civic bodies more reflective of the broader public. Homeowners are more likely than renters to participate in city council, planning, and zoning meetings (Yoder 2020), and to oppose new housing development (Einstein, Palmer and Glick 2019; Hankinson 2018). This participation is consistent with protection of property values (Hall and Yoder Forthcoming; Marble and Nall 2021; McCabe 2016; Yoder 2020).

The makeup of local political participation in majority-renter cities therefore does not typically reflect general public opinion. Unlike homeowners, renters do not consistently oppose new housing (Hankinson 2018; Marble and Nall 2021; Monkkonen and Manville 2019). This leads to discrepancies between the percentage of council meeting comments in favor of additional housing and the percentage of ballots cast in favor of additional housing (Einstein, Palmer and Glick 2019). Even moving council meetings online due to COVID-19 did not reduce the participation gap between renters and homeowners (Einstein et al. 2021).

The ability of residents to block new housing construction is also regularly cited as a

key cause of decreases in housing supply (Glaeser, Gyourko and Saks 2005a). These supply restrictions reduce real income for renters, and are estimated to be a net welfare loss for society (Glaeser and Gyourko 2018).

Theory: Encouraging political participation

Prior research offers lessons for encouraging participation inside and outside of the ballot box, as well as how to motivate renters in particular.

Get-out-the-vote (GOTV) experiments find email ineffective at increasing voter turnout (Green and Gerber 2019; Malhotra, Michelson, Valenzuela et al. 2012; Nickerson et al. 2007). However, the efficacy of email at increasing political participation that can itself be conducted remotely is less clear. Due to COVID-19, public comment at the time of this experiment was limited to email, telephone, or videoconference.

Past studies suggest that merely overcoming information costs should not have a large impact on turnout (Green and Gerber 2019; Riker and Ordeshook 1973), but that concrete instructions of how and when to participate can be effective (Milkman, Beshears, Choi, Laibson and Madrian 2011; Nickerson and Rogers 2010). Renters—who are on average less connected to their local political system (Ansolabehere 2012; McCabe 2016)—may also be less informed of how and when to participate.

Psychological motivators, such as comparing individuals’ behavior to neighbors and peers (Allcott 2011; Gerber, Green and Larimer 2008), have been shown to be more effective than highlighting economic self-interest alone (Citrin, Green, Muste and Wong 1997; De Rooij, Green and Gerber 2009; Ostrom 2000; Sears and Funk 1991). Relatedly, Aytaç and Stokes (2019) posit that high psychological costs of abstention can drive collective action. According to Aytaç and Stokes’ model,¹ a treatment that increases costs of abstention, decreases costs of participation, and adds social pressure should maximize participation.

For renters, highlighting “affordable” (i.e., government subsidized) housing developments

¹Where rewards of participation $P = A - C + D_E$ where P is rewards from participation, A is the cost of abstention, C is the cost of participation, and D_E is social pressure.

has been shown to increase support for more housing (Doberstein, Hickey and Li 2016). Messages encouraging renter collective action should therefore focus on the city-wide public benefits of increased housing and highlight affordable housing.

In sum, messaging strategies that: (1) lower participation costs with simple but detailed instructions of how and when to attend, (2) add social pressure by comparing abstainers to their neighbors, and (3) emphasize the costs of abstention should be particularly effective. While emails are typically ineffective at encouraging turnout, they may be more effective with remote public comment.

Hypotheses and treatment messages

The observations above leads to three (pre-registered) hypotheses of motivation to collective action, which I test with three distinct treatment messages. A treatment (T1) that lowers costs of participation with detailed instructions of how to participate should increase attendance, but the effects should be small in magnitude. All treatment messages therefore include a Zoom link for spoken comments, or link to submit a pre-filled sample public comment via email (while noting that individuals may draft their own comment) for written comments.² A treatment (T2) providing information that lack of housing supply increases rents should increase attendance more than attendance instructions only by priming economic self interest. A treatment (T3) that also highlights the costs of abstention should increase attendance more than treatments that lower costs of participation or economic self-interest alone.

Research design

Context

The experiment was fielded in LA County with a pro-housing NGO. Cities were in the process of updating their 2021-2029 “Housing Elements,” which are an analysis of a city’s housing needs and strategies to be used to meet those needs. The experiment therefore

²See [Sample comment](#) for the wording of the sample message.

targets council meetings in which the Housing Element is on the agenda.

COVID-19 moved city council meetings online, where comments can be made in spoken or written format. Written comments can be submitted by email and are either read aloud during the meeting or distributed to council members prior to the meeting. Council members should therefore be aware of the sentiments expressed in public comments, spoken or written.

While there is a vocal anti-development contingent in Los Angeles, the general voting public appears to support additional housing as anti-development ballot measures have recently failed.³ Only 28% of respondents in a survey of LA County residents oppose a hypothetical local development (Monkkonen and Manville 2019). The geographic and regulatory landscape in Los Angeles also leads to a majority of new housing developments replacing parking lots or commercial buildings, not existing housing stock.⁴

Interventions involving participation in governmental processes should be held to high ethical standards. For a detailed discussion of research ethics, please see [Ethics](#) in the appendix.

Experiment overview

The experiment proceeded in the following steps: (1) renters in the voter file were identified using LA City Planning records, (2) city council meetings discussing their Housing Element were targeted for the messaging campaign, (3) renters were randomly assigned to one of three email treatments encouraging them to submit a comment or a placebo control, (4) names in all treatment groups were matched with names of individuals who submitted a public comment, (5) analysis was performed using pre-registered outcomes and estimators.

³Measure S, which would have curbed high-density development in the city, failed with 30% support. Measure JJJ—which grants zoning changes to developments that include affordable housing—and Measure H—which instituted a sales tax increase to fund affordable housing—passed

⁴Roughly 14% of land, or over 200 square miles, is currently dedicated to parking (Chester, Fraser, Matute, Flower and Pendyala 2015). In addition, affordable housing is required for density above zoning limits.

Identifying renters and council meetings

Renters were identified by geo-matching addresses in the LA County voter file with Department of City Planning records of multi-unit apartment buildings using the FastLink probabilistic linkage algorithm (Enamorado, Fifield and Imai 2019). This resulted in 641,184 matched renters, 266,057 of whom listed their email addresses in the voter file. Partner organizations then monitored city council meetings in LA County for agenda items discussing the Housing Element throughout fall and winter 2021. Identified renters with email addresses living in all cities with Housing Element agenda items during this period then received emails prior to their meeting.⁵

Treatment assignment

Identified renters in the voter file were randomly assigned to an email treatment encouraging them to submit a public comment at their city council meeting, or a placebo control. Individuals were block randomly assigned by city and cluster randomly assigned by address.⁶ Treatment assignment probabilities were: 10% probability of assignment to a placebo message with no information on how to attend a meeting, and 30% probability of assignment to each of T1, T2, or T3.⁷ All treatments included identical subject lines and preview texts to ensure equal compliance rates across treatment arms.

Outcomes

The primary, pre-registered outcome of interest is a binary indicator of whether an individual submitted a spoken *or* written comment. I match the names of those in the treatment

⁵Recruitment starting and stopping dates were pre-registered. One council meeting in Santa Monica and two council meetings in Long Beach were selected for pilot studies, followed by pre-registration and treatment of individuals targeting meetings in the cities of (in chronological order) Beverly Hills, Santa Monica, Whittier, Rancho Palos Verdes, Manhattan Beach, Norwalk, Sierra Madre, and Culver City.

⁶While random assignment took place simultaneously for all cities, treatments were launched at different points in time for each city. If a unit number was available, clustering took place at the unit level. If a unit number was not available, clustering took place at the building level.

⁷Balance tables by treatment or placebo status, as well as for each treatment group can be found in Balance, and a map of all cities that received treatment can be found in Figure A.3.

groups with spoken or written comments using administrative records and video recordings of council meetings. I also examine *how* individuals commented by creating separate indicators for: spoken comments, written comments, comments that used our pre-written messages, custom comments, pro-housing comments, and anti-housing comments. In addition, I investigate whether the treatments changed the overall makeup of council meeting comments by comparing the number of pro-housing comments that were likely treatment induced with those that were not.⁸

Analytical procedures

The primary pre-registered estimand of interest is the complier average causal effect (CACE) of opening an email on submission of a public comment. In other words, the average treatment effect for individuals who opened the emails only (i.e., compliers). I employ a placebo-controlled design (rather than use assignment to treatment as an instrument) to mitigate statistical uncertainty (Broockman, Kalla and Sekhon 2017; Nickerson 2008). I estimate the CACE using the estimator derived by Lin (2013), including pre-registered pre-treatment covariates.⁹ Standard errors are clustered at the address level.

Results are analyzed as above (i.e., as one large experiment with city fixed effects), as well as aggregated using precision-weighted fixed effects and random effects meta-analysis. As the outcome data are “rare event” right-skewed binomial distributions (see Figure A.9), I also calculate randomization inference based p-values (RI p) free from distributional assumptions and re-estimate all models using penalized maximum likelihood as robustness tests (Cook, Hays and Franzese 2020; King and Zeng 2001).

I also examine pre-registered heterogeneous treatment effects by: building density, median area income, and turnout in the most recent local election. I regress comments on treatments and the treatment-covariate interaction, and use randomization inference as a robustness

⁸I define “likely treatment induced” comments as those submitted by individuals in the three treatment groups. This seems reasonable, as no comments were made by compliers in the placebo group.

⁹Covariates are listed in [Analytical procedure details](#), and results without covariate adjustment are reported in [Robustness](#).

check. Readers interested in more detailed description of the procedures in this section can explore [Analytical procedure details](#) in the appendix.

Results

Overall

Across all council meetings,¹⁰ the effect of opening any treatment email on submitting a public comment (i.e., the CACE) was 1.02 [RI p = 0.044; 95% CI 0.66, 1.38] percentage points (pp). The effect of being assigned to treatment (i.e., the ITT) on submitting a public comment was 0.19pp [RI p = 0.075, 95% CI 0.06, 0.31]. Both estimates are depicted in [Figure 1](#). Estimates in tabular form and without covariate adjustment are reported in the appendix. Compliance rates by treatment group were 17% in placebo, 17% in T1, 16% in T2, and 18% in T3 (see [Figure A.4](#)).

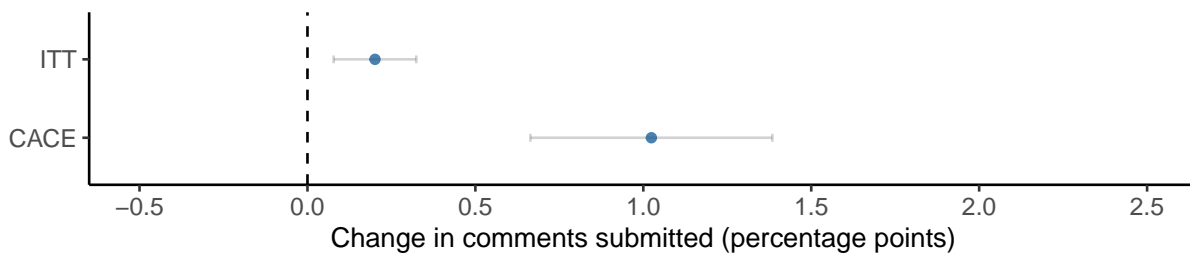


Figure 1: Intent-to-treat effect and complier average causal effect, all cities

Note: Tabular results can be found in [Table A.4](#) and [Table A.5](#)

CACEs for individual council meetings can be found in [Figure 2](#), which also contains meta-analytic estimates of the aggregate CACE. [Figure 2](#) also contains estimates from three pilot studies, increasing the sample size to over 27,000 households. The point estimate using fixed effects meta-analysis including the pilot studies is 0.78 [95% CI 0.51, 1.06], and excluding the pilot studies is 0.91 [95% CI 0.56, 1.25] (see [Figure A.8](#)).

¹⁰Not including pilot studies.

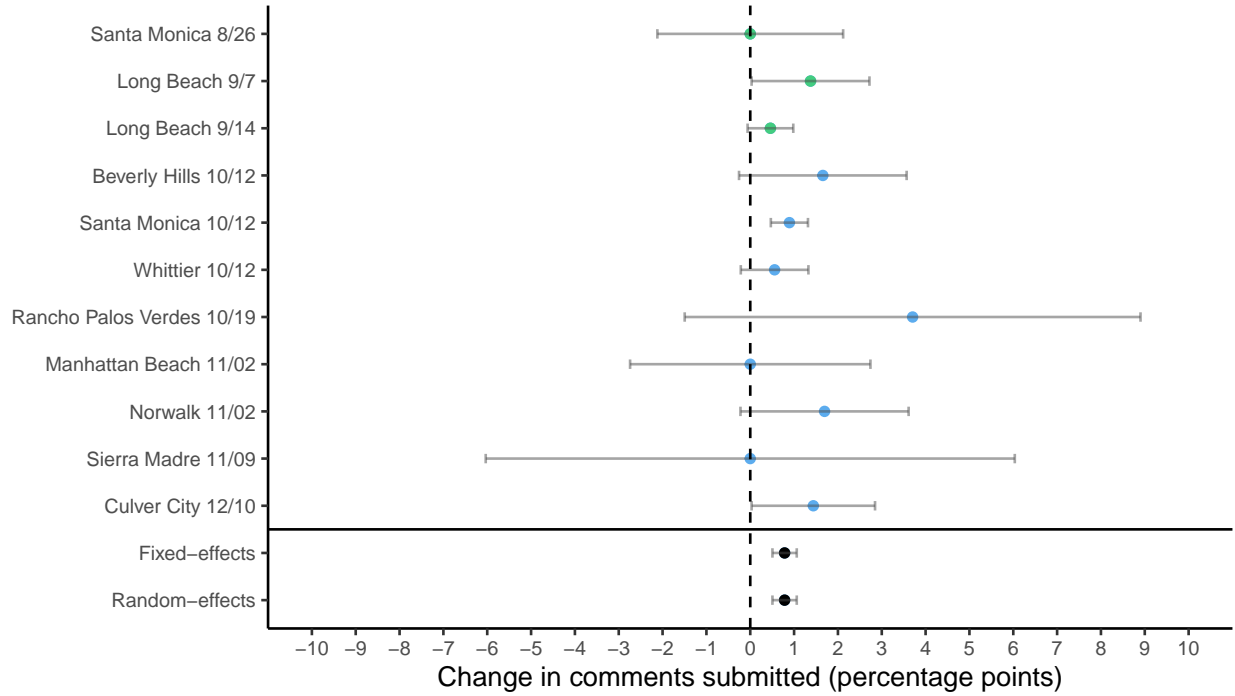


Figure 2: Meta-analysis of complier average causal effects, by council meeting

Note: Pilot studies in green. Tabular results can be found in [Table A.6](#) and [Table A.7](#).

By treatment group

In line with pre-registered hypotheses, [Figure 3](#) shows that highlighting the costs of abstention had the largest effect on turnout (CACE = 1.44pp; RI p = 0.011; 95% CI [0.73, 2.15]), priming economic self interest was the second most effective (CACE = 1.01pp; RI p = 0.071; 95% CI [0.39, 1.63]), and the instructions-only treatment was the least effective (CACE = 0.54pp; RI p = 0.386; 95% CI [0.06, 1.03]).¹¹ The estimates for the costly abstention and instructions-only treatments are significantly different from each other at the 5% level.¹²

¹¹ITT randomization inference p-values are: 0.380 for T1, 0.089 for T2, and 0.039 for T3.

¹²Based on a two-tailed linear hypothesis test.

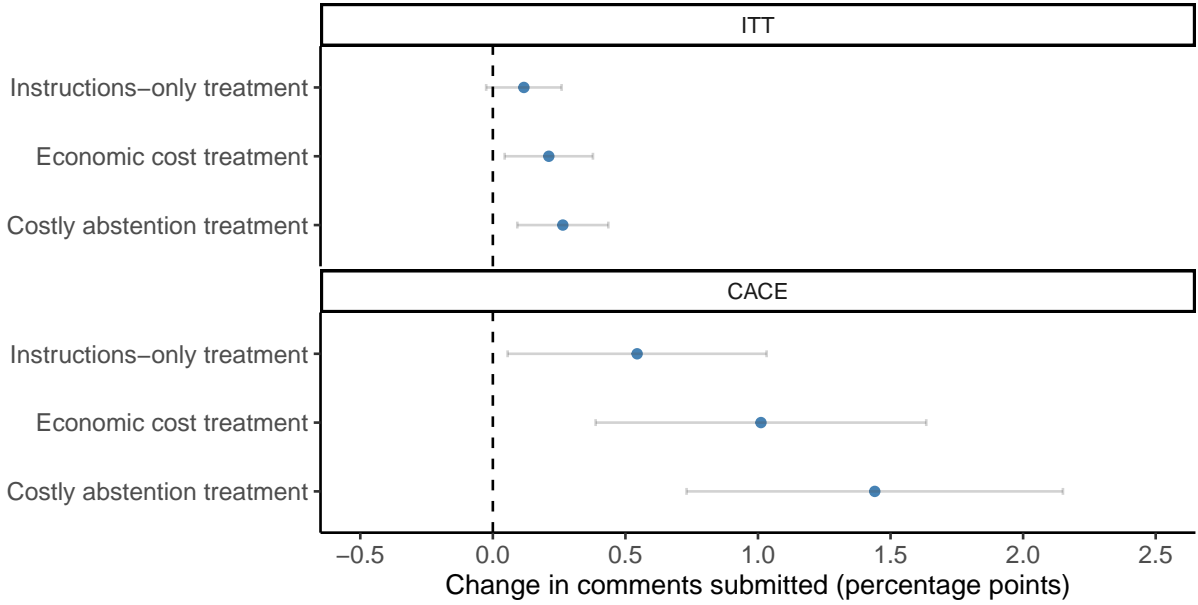


Figure 3: Effects by treatment group, all cities

Note: Tabular results can be found in [Table A.4](#) and [Table A.5](#)

To further assess confidence the costly abstention treatment was most effective and aid interpretation, I fit a Bayesian linear multilevel model using prior distributions from the power analysis in my pre-registration.¹³ I also compute Bayes factors¹⁴ for hypotheses that the differences between treatments are greater than zero. I find strong evidence that the null hypothesis the treatments are equivalent can be rejected, strong evidence the costly abstention treatment was more effective than the instructions only treatment, and moderate evidence the costly abstention treatment was more effective than the economic cost treatment.

These results align with the pre-registered [theoretical predictions](#). Providing instructions of how to participate may have increased attendance, but only marginally. Priming economic concerns appears to be more effective than lowering participation costs alone. The strongest

¹³Coefficient estimates and posterior distributions can be found in [Figure A.10](#). [Figure A.11](#) provides a visualization of the posterior distributions of each coefficient and the posterior distributions of the differences between each coefficient.

¹⁴The ratio of the likelihood of one particular hypothesis to the likelihood of another hypothesis. For example, a Bayes factor of 5 implies the alternative hypothesis is 5 times as likely as the null hypothesis given the data. The Bayes factor is 97 for the costly abstention treatment vs. the instructions only treatment and 5 for the costly abstention treatment vs. economic cost treatment.

evidence supports the theory that highlighting the perceived costs of abstention is more effective than lowering costs or economic self-interest alone.

Heterogeneous treatment effects

I find suggestive evidence that turnout in local elections is associated with a sizable increase in the likelihood of making a public comment.¹⁵ Voters who opened the messages were 1.4pp more likely to comment than non-voters (see [Figure 4](#), $p = 0.086$, RI $p = 0.06$).¹⁶ Voters were also more likely to open the emails across all treatment groups (see [Table A.3](#)). There is therefore suggestive evidence that participation in local politics in the form of voting begets willingness to participate in other forms, such as attending council meetings, submitting public comments, and engaging with outreach campaigns. Practitioners may therefore see higher returns to participation by targeting likely voters.

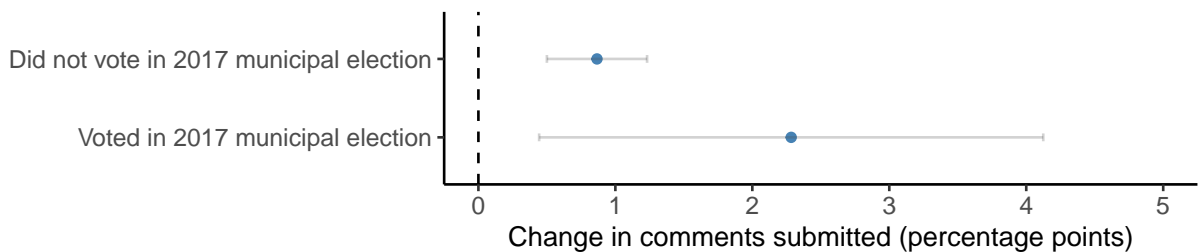


Figure 4: Complier average causal effects by turnout

Note: Tabular results can be found in [Table A.8](#).

Comment contents

I examine the content of each comment to determine if individuals submitted: spoken or written comments, custom comments or used the pre-written comment supplied in the emails, and pro or anti-housing comments (see [Figure 5](#)). The vast majority of individuals (93%) submitted written public comments, and the effect for spoken comments is only significant at the 10% level. However, even written submissions were not purely costless. While the ma-

¹⁵I do not uncover evidence that the other pre-registered covariates of interest—building density or median area income—are strongly associated with commenting.

¹⁶The uncertainty of the estimates are a result of low turnout (9.4% amongst the sample population)

jority of written comments used the sample message included in the email, 29% represented custom, personal comments. Many of these custom comments were deeply personal and reflected individuals' lived experiences with high housing costs.¹⁷ For example, some discussed near experiences with homelessness, senior commenters discussed fear of being priced out of subsidized senior housing, and young renters lamented their inability to purchase a home like their parents. While some anti-housing comments were submitted, they represented only 4% of total comments, and never comprised a majority of experimentally-induced comments in any council meetings.

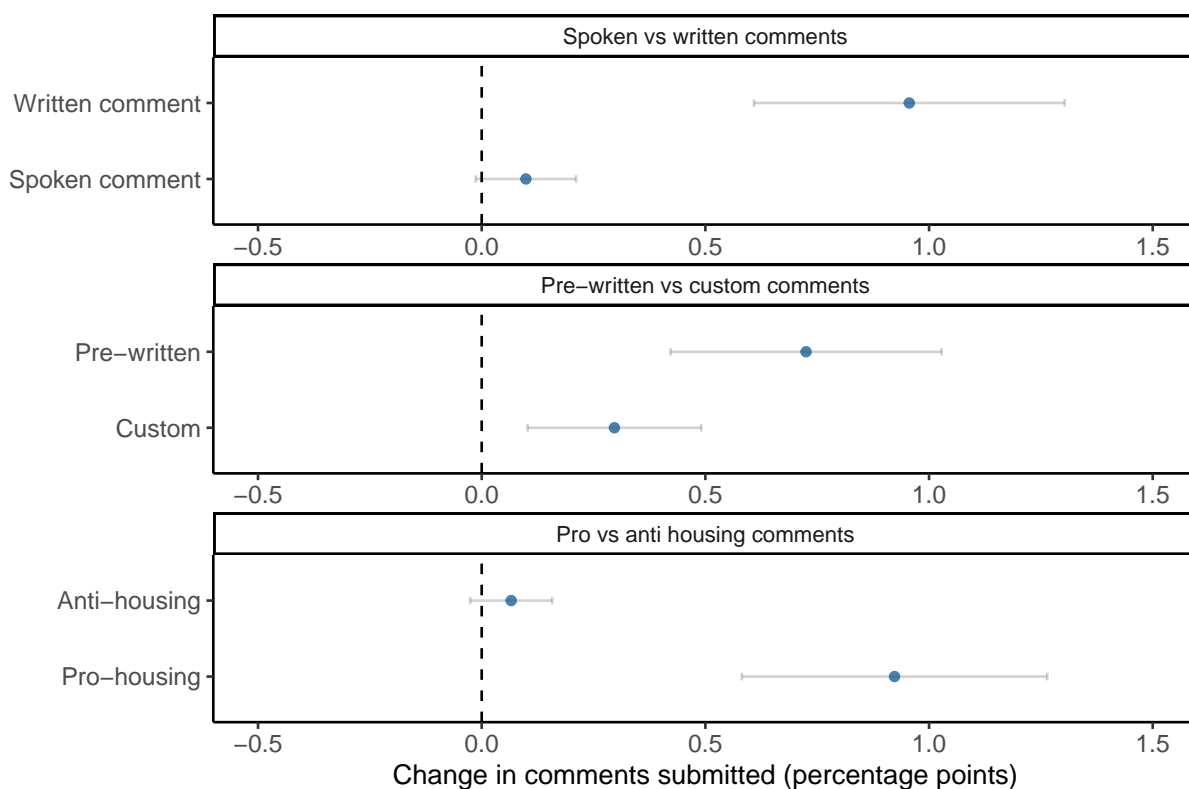


Figure 5: CACE by type of comment

Note: Tabular results can be found in [Table A.9](#).

¹⁷I do not provide quotes of custom experimentally-induced comments as I did not ask for consent to re-print individuals' public comments.

Substantive impact of comments and changes in representation

I also investigate the substantive impact of the campaigns on each council meeting. Table 1 shows that the treatments meaningfully changed the quantity and composition of comments in individual meetings. Comments by treated individuals represented 8% of total written public comments across all meetings, and 46% of all pro-housing comments. Treatment-induced comments swung the balance of pro-versus-anti housing comments toward a more equal footing, altering the imbalances of comment makeup highlighted by Yoder (2020) that were not corrected merely by moving to an online setting (Einstein et al. 2021). The treatments therefore caused the makeup of council meeting comments to be more reflective of the broader public where remote access alone did not.

Meeting	Total comments (incl. treatment induced)	Pro-housing comments (not incl. treatment induced)	Pro-housing comments (incl. treatment-induced)	Anti-housing comments (incl. treatment-induced)
Beverly Hills 10/12	19	4	1	5
Santa Monica 10/12	67	15	20	11
Whittier 10/12	4	0	1	0
Rancho Palos Verdes 10/19	121	2	3	54
Manhattan Beach 11/02	225	0	0	0
Norwalk 11/02	7	0	3	0
Sierra Madre 11/09	20	0	0	8
Culver City 12/10	71	25	21	23
Total	534	46	85	101

Table 1: Examination of public comments in treated council meetings

These large effects of contact on overall turnout contrast sharply with, e.g., GOTV. In voter turnout settings, the large number of individuals who regularly vote makes the change in overall turnout due to campaigns relatively small. By contrast, even a few new participants in city council meetings can drastically change the composition of comments due to low equilibrium participation rates.

Conclusion

Understanding how to motivate individuals to engage in personally costly collective action when gains from mobilization are long-term and uncertain is an enduring question in political economy. Homeowners with direct financial payoffs participate in local politics at disproportionately high rates. However, there is little evidence to suggest how to motivate renters—who face long-term and uncertain payoffs—to participate.

I contribute to our understanding of how to motivate underrepresented groups to engage in costly political behavior using 8 email-outreach field experiments encouraging renters to participate in local politics in the form of commenting at city council meetings. In addition, I document how these campaigns changed the balance of participation in civic bodies. Three treatment arms tested the effectiveness of messages that: (1) lowered the costs of participation only, (2) primed economic self-interest, or (3) highlighted the costs of abstention. Receipt of any treatment increased public comments by 1pp, while highlighting the cost of abstention increased comments by 1.4pp. Individuals already engaged in local politics were more responsive to treatment. Treatment-induced comments represented 8% of total comments and 46% of pro-housing comments across all city council meetings. The treatments therefore overcame many of the traditional barriers to renter collective action, and changed the representation of civic bodies to be more reflective of the broader public.

The results support the following theoretical and substantive conclusions. First, unlike voting, email can effectively increase political participation when participation can also be conducted remotely, particularly amongst those already engaged in politics. Second, low-cost outreach strategies can meaningfully increase political participation in low-turnout and lesser-known settings such as city council meetings. Third, outreach can change the representation of civic bodies to be more reflective of the broader public where increases in accessibility alone—such as online access—do not. Fourth, increasing perceived costs of abstention appears to be an effective motivator of collective action.

References

- Allcott, Hunt. 2011. “Social norms and energy conservation.” *Journal of Public Economics* 95(9-10):1082–1095.
- Ansolabehere, Stephen Daniel. 2012. “Movers, stayers, and registration: Why age is correlated with registration in the US.” *Quarterly Journal of Political Science* .
- Aytaç, S Erdem and Susan C Stokes. 2019. *Why Bother?: Rethinking Participation in Elections and Protests*. Cambridge University Press.
- Bovens, Luc. 2009. The ethics of nudge. In *Preference change*. Springer pp. 207–219.
- Broockman, David E, Joshua L Kalla and Jasjeet S Sekhon. 2017. “The design of field experiments with survey outcomes: A framework for selecting more efficient, robust, and ethical designs.” *Political Analysis* 25(4):435–464.
- Brueckner, Jan K. 2009. Government land use interventions: An economic analysis. In *Urban land markets*. Springer pp. 3–23.
- Cervero, Robert and Jin Murakami. 2010. “Effects of built environments on vehicle miles traveled: evidence from 370 US urbanized areas.” *Environment and planning A* 42(2):400–418.
- Charette, Allison, Chris Herbert, Andrew Jakabovics, Ellen Tracy Marya and Daniel T McCue. 2015. “Projecting trends in severely cost-burdened renters: 2015–2025.” *Harvard University’s Joint Center for Housing Studies and Enterprise Community Partners Inc* .
- Chester, Mikhail, Andrew Fraser, Juan Matute, Carolyn Flower and Ram Pendyala. 2015. “Parking infrastructure: A constraint on or opportunity for urban redevelopment? A study of Los Angeles County parking supply and growth.” *Journal of the American Planning Association* 81(4):268–286.
- Citrin, Jack, Beth Reingold and Donald P Green. 1990. “American identity and the politics of ethnic change.” *The Journal of Politics* 52(4):1124–1154.

- Citrin, Jack, Donald P Green, Christopher Muste and Cara Wong. 1997. "Public opinion toward immigration reform: The role of economic motivations." *The Journal of Politics* 59(3):858–881.
- Cook, Scott J, Jude C Hays and Robert J Franzese. 2020. "Fixed effects in rare events data: a penalized maximum likelihood solution." *Political Science Research and Methods* 8(1):92–105.
- De Rooij, Eline A, Donald P Green and Alan S Gerber. 2009. "Field experiments on political behavior and collective action." *Annual Review of Political Science* 12:389–395.
- Doberstein, Carey, Ross Hickey and Eric Li. 2016. "Nudging NIMBY: Do positive messages regarding the benefits of increased housing density influence resident stated housing development preferences?" *Land Use Policy* 54:276–289.
- Einstein, Katherine Levine, David Glick, Luisa Godinez Puig and Maxwell Palmer. 2021. "Zoom Does Not Reduce Unequal Participation: Evidence from Public Meeting Minutes." *Working Paper* .
- Einstein, Katherine Levine, Joseph T Ornstein and Maxwell Palmer. 2019. "Who Represents the Renters?" *Working Paper* .
- Einstein, Katherine Levine, Maxwell Palmer and David M Glick. 2019. "Who participates in local government? Evidence from meeting minutes." *Perspectives on Politics* 17(1):28–46.
- Enamorado, Ted, Benjamin Fifield and Kosuke Imai. 2019. "Using a probabilistic model to assist merging of large-scale administrative records." *American Political Science Review* 113(2):353–371.
- Fischel, William A. 2005. *The homevoter hypothesis: How home values influence local government taxation, school finance, and land-use policies*. Harvard University Press.
- Ganong, Peter and Daniel Shoag. 2017. "Why has regional income convergence in the US declined?" *Journal of Urban Economics* 102:76–90.
- Gelman, Andrew and Jennifer Hill. 2006. *Data analysis using regression and multi-*

- level/hierarchical models*. Cambridge university press.
- Gerber, Alan S, Donald P Green and Christopher W Larimer. 2008. “Social pressure and voter turnout: Evidence from a large-scale field experiment.” *American political Science review* pp. 33–48.
- Glaeser, Edward and Joseph Gyourko. 2018. “The economic implications of housing supply.” *Journal of Economic Perspectives* 32(1):3–30.
- Glaeser, Edward L and Joseph Gyourko. 2002. “The impact of zoning on housing affordability.”.
- Glaeser, Edward L, Joseph Gyourko and Raven E Saks. 2005*a*. “Why have housing prices gone up?” *American Economic Review* 95(2):329–333.
- Glaeser, Edward L, Joseph Gyourko and Raven Saks. 2005*b*. “Why is Manhattan so expensive? Regulation and the rise in housing prices.” *The Journal of Law and Economics* 48(2):331–369.
- Green, Donald P and Alan S Gerber. 2019. *Get out the vote: How to increase voter turnout*. Brookings Institution Press.
- Gyourko, Joseph and Raven Molloy. 2015. Regulation and housing supply. In *Handbook of regional and urban economics*. Vol. 5 Elsevier pp. 1289–1337.
- Hall, Andrew B and Jesse Yoder. Forthcoming. “Does homeownership influence political behavior? Evidence from administrative data.” *The Journal of Politics* .
- Hankinson, Michael. 2018. “When do renters behave like homeowners? High rent, price anxiety, and NIMBYism.” *American Political Science Review* 112(3):473–493.
- Hernández, Antonia. 2021. “Our Common Purpose: Reinventing American Democracy for the 21st Century.” *National Civic Review* 110(1):29–37.
- Hsieh, Chang-Tai and Enrico Moretti. 2019. “Housing constraints and spatial misallocation.” *American Economic Journal: Macroeconomics* 11(2):1–39.
- Judge-Lord, Devin. 2022. “The Environmental Justice Movement’s Impact on Technocratic Policymaking.” *Working paper* .

- King, Gary and Langche Zeng. 2001. “Logistic regression in rare events data.” *Political analysis* 9(2):137–163.
- Lens, Michael C and Paavo Monkkonen. 2016. “Do strict land use regulations make metropolitan areas more segregated by income?” *Journal of the American Planning Association* 82(1):6–21.
- Lin, Winston. 2013. “Agnostic notes on regression adjustments to experimental data: Re-examining Freedman’s critique.” *Annals of Applied Statistics* 7(1):295–318.
- Los Angeles Times. 2021. “Editorial: Some good from the pandemic era: Online access to government meetings.”
URL: <https://www.latimes.com/opinion/story/2021-04-28/require-livestreamed-public-meetings>
- Malhotra, Neil, Melissa R Michelson, Ali Adam Valenzuela et al. 2012. “Emails from official sources can increase turnout.” *Quarterly Journal of Political Science* 7(3):321–332.
- Marble, William and Clayton Nall. 2021. “Where self-interest trumps ideology: liberal homeowners and local opposition to housing development.” *The Journal of Politics* 83(4):1747–1763.
- McCabe, Brian J. 2016. *No place like home: Wealth, community, and the politics of homeownership*. Oxford University Press.
- McDermott, Mark. 2021. “BLACK LIVES MATTER: City Council spars over Bruce’s Beach plaque.”
URL: <https://easyreadernews.com/black-lives-matter-city-council-spars-over-bruces-beach-plaque/>
- McDermott, Rose and Peter K Hatemi. 2020. “Ethics in field experimentation: A call to establish new standards to protect the public from unwanted manipulation and real harms.” *Proceedings of the National Academy of Sciences* 117(48):30014–30021.
- Milkman, Katherine L, John Beshears, James J Choi, David Laibson and Brigitte C Madrian. 2011. “Using implementation intentions prompts to enhance influenza vaccination

- rates.” *Proceedings of the National Academy of Sciences* 108(26):10415–10420.
- Molloy, Raven et al. 2020. “The effect of housing supply regulation on housing affordability: A review.” *Regional Science and Urban Economics* 80(C).
- Monkkonen, Paavo and Michael Manville. 2019. “Opposition to development or opposition to developers? Experimental evidence on attitudes toward new housing.” *Journal of Urban Affairs* 41(8):1123–1141.
- Nickerson, David W. 2008. “Is voting contagious? Evidence from two field experiments.” *American political Science review* 102(1):49–57.
- Nickerson, David W and Todd Rogers. 2010. “Do you have a voting plan? Implementation intentions, voter turnout, and organic plan making.” *Psychological Science* 21(2):194–199.
- Nickerson, David W et al. 2007. “Does email boost turnout.” *Quarterly Journal of Political Science* 2(4):369–379.
- Olson, Mancur. 1965. *The Logic of Collective Action: Public Goods and the Theory of Groups*. Harvard University Press.
- Ortalo-Magné, François and Andrea Prat. 2014. “On the political economy of urban growth: Homeownership versus affordability.” *American Economic Journal: Microeconomics* 6(1):154–81.
- Ostrom, Elinor. 2000. “Collective action and the evolution of social norms.” *Journal of Economic Perspectives* 14(3):137–158.
- Quigley, John M and Larry A Rosenthal. 2005. “The effects of land use regulation on the price of housing: What do we know? What can we learn?” *Cityscape* pp. 69–137.
- Reeves, Richard V. 2018. *Dream hoarders: How the American upper middle class is leaving everyone else in the dust, why that is a problem, and what to do about it*. Brookings Institution Press.
- Riker, William H and Peter C Ordeshook. 1973. *An introduction to positive political theory*. Vol. 387 Prentice-Hall Englewood Cliffs, NJ.

- Schubert, Christian. 2017. “Green nudges: Do they work? Are they ethical?” *Ecological Economics* 132:329–342.
- Sears, David O and Carolyn L Funk. 1991. “The role of self-interest in social and political attitudes.” *Advances in experimental social psychology* 24:1–91.
- Sears, David O and Jack Citrin. 1982. *Tax revolt: Something for nothing in California*. Harvard University Press.
- Slough, Tara. 2019. “The Ethics of Electoral Experimentation: Design-Based Recommendations.” *Working Paper* .
URL: <http://taraslough.com/assets/pdf/eee.pdf>
- Slough, Tara and Scott A Tyson. 2021. “External Validity and Meta-Analysis.” *Working Paper* .
- The Boston Globe. 2021. “The pandemic taught us a better way to do public business.”.
URL: <https://www.bostonglobe.com/2021/05/27/opinion/pandemic-taught-us-better-way-do-public-business/>
- United States Census Bureau. 2020. “New Privately-Owned Housing Units Authorized by Building Permits in Permit-Issuing Places.”.
URL: <https://www.census.gov/construction/bps/pdf/annualhistorybystate.pdf>
- Wheeler, Stephen M, Christopher M Jones and Daniel M Kammen. 2018. “Carbon footprint planning: quantifying local and state mitigation opportunities for 700 California cities.” *Urban Planning* 3(2):35–51.
- Yoder, Jesse. 2020. “Does Property Ownership Lead to Participation in Local Politics? Evidence from Property Records and Meeting Minutes.” *American Political Science Review* 114(4):1213–1229.

A Appendix

Housing supply and housing prices

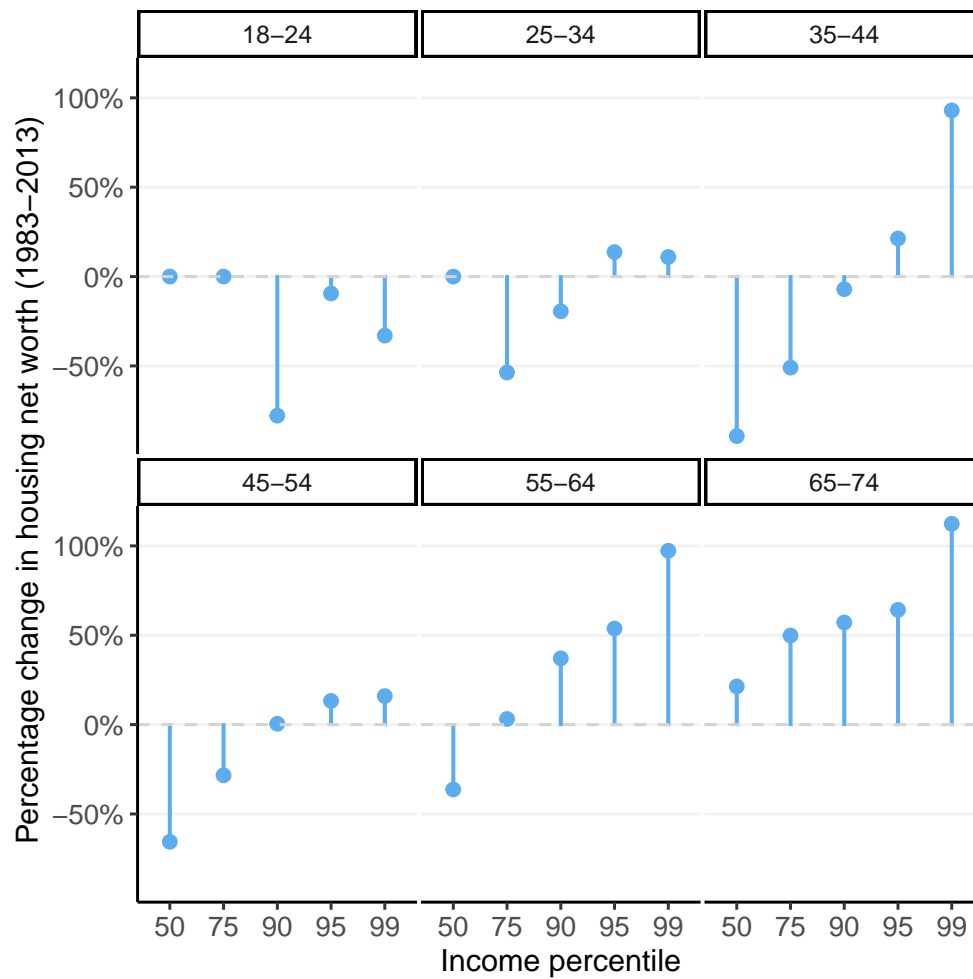


Figure A.1: Change in housing net worth by age and income percentile

Source: Glaeser and Gyourko (2018)

Treatment messages



Figure A.2: Example treatments and wording (Santa Monica experiment)

Treatment details

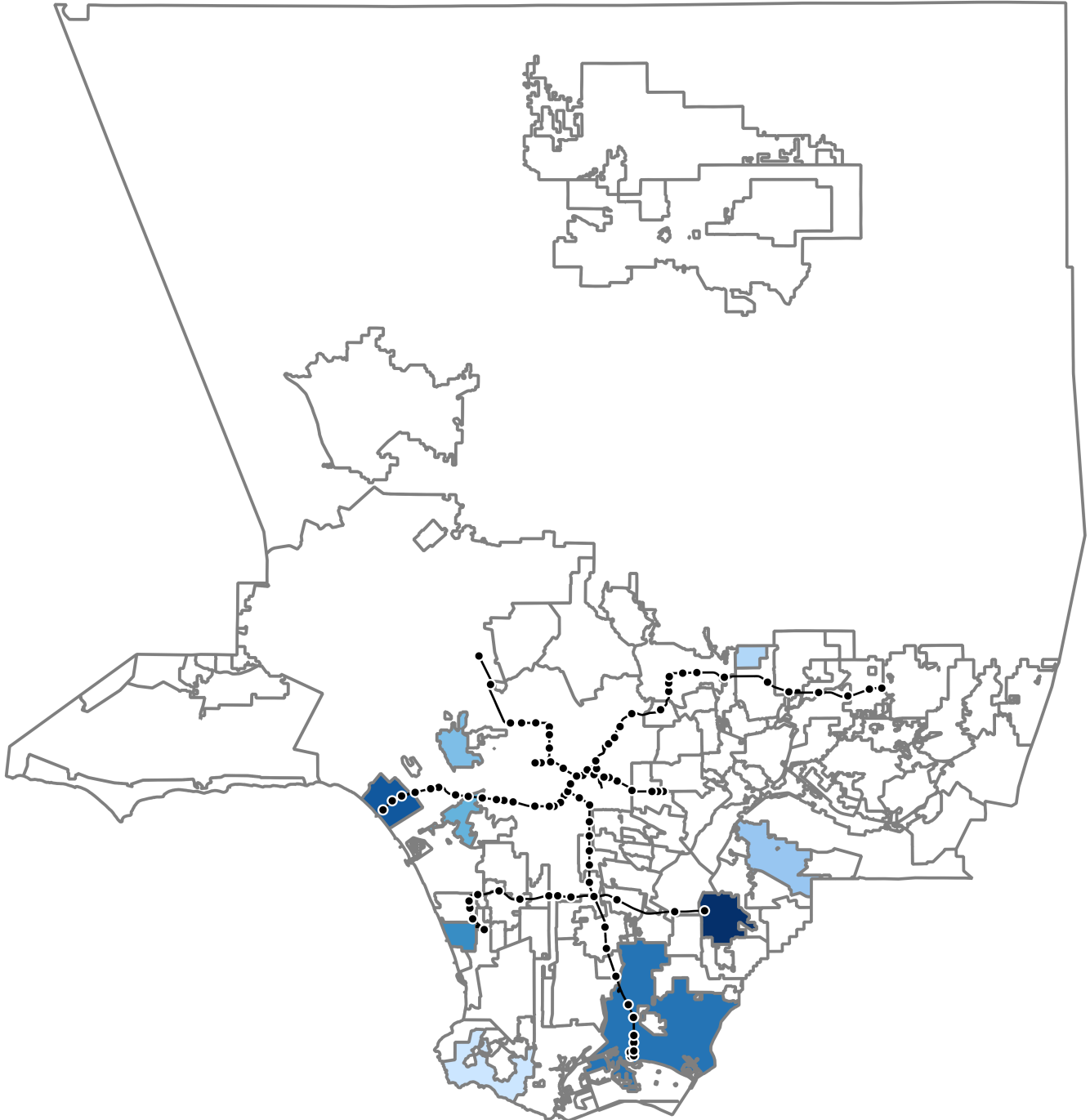


Figure A.3: Map of cities in Los Angeles county by experiment status

Note: Cities in which an experiment was launched in blue. Cities shaded by population density. Los Angeles Metro rail lines and rail stations in black.

Sample comment

Subject:

Public comment for [DATE] council meeting agenda item [ITEM NUMBER]

Body:

Dear City Council,

I'm writing to express my concern about our affordable housing shortage and its impact on the future of our city. Exclusionary zoning and land use practices have led to an undersupply of affordable medium- and high-density housing near jobs and transit, and have perpetuated segregated living patterns and the exclusion of historically disadvantaged communities.

[CITY] has an opportunity to address the need for more housing in a way that furthers equity, environmental sustainability, and economic recovery in its housing element update. We should update the housing element in a way that encourages historically high housing growth, while furthering fair housing opportunities and undoing patterns of discrimination in housing. We can't miss this opportunity to fix our city's housing crisis.

I urge you to legalize more housing, make housing easier to build, fund affordable housing and end homelessness, and strengthen tenants' rights.

Sincerely,

FIRSTNAME LASTNAME

Ethics

Any intervention motivating individuals to change their behavior should be held to high ethical standards, particularly when the intervention involves participation in and effects on governmental processes. Beyond IRB approval, I argue this project falls within ethical bounds for the reasons outlined below.

First, the interventions are designed to minimize a pre-existing imbalance in representation by increasing representation amongst a historically underrepresented group. Treatments are designed to encourage renters to participate (albeit not coercively) and make local governance more reflective of the general population.

Second, the interventions do not directly effect electoral outcomes (as highlighted by [Slough \(2019\)](#) and [McDermott and Hatemi \(2020\)](#)). I recognize that local officials may change their votes based on perceived changes in support levels that the experiment might cause. However, ultimate decisions and votes still rest with local elected officials.

Third, the interventions focus on increasing the supply of housing generally across the LA region, not on particular developments or neighborhoods. Treatment and sample messages also specifically encourage individuals to advocate for *affordable* (i.e., government subsidized) housing developments. We should therefore expect the targeted groups to benefit from the research through decreased rents and increased access to affordable housing.

Fourth, in social-welfare enhancing interventions such as “green nudges,” [Bovens \(2009\)](#) and [Schubert \(2017\)](#) argue that it should be possible “for everyone who is watchful to unmask the manipulation.” The interventions meet this criteria, as the messages come from an advocacy group that is transparent in their motivations.

While informed consent was not received from individuals prior to treatment, the research is: (1) minimal risk compared to similar outreach emails that individuals who listed their email addresses in the voter file would otherwise receive without researcher measurement, (2) permission to obtain the voter file and conduct the research was obtained from the Los Angeles County Registrar in addition to a university IRB, (3) individuals would have received

similar messages from advocacy organizations with or without researcher measurement, (4) treatment messages noted that they were part of a “collaboration between Abundant Housing Los Angeles and academic researchers at [redacted for peer review]” and were transparent in motivation, and (5) participant behavior may have changed if subjects were aware they were part of an academic study. The only potential deception was therefore anonymized data collection for the purpose of measurement.

Analytical procedure details

By randomly assigning individuals to a [placebo control](#) with no mention of council meetings, but featuring the same subject line and preview text as the treatment emails, I am able to observe the outcomes of a random sample of compliers (email openers) in the placebo group. Email opens are monitored using software that detects whether an individual opens a message. Tests for differential compliance by treatment group and differential covariate predictiveness of compliance can be found in [Figure A.4](#) and [Table A.3](#).

For the primary estimand (i.e., the CACE), I estimate the OLS specifications below:

$$Y_i = \alpha + \beta_1 Z_i + \beta_2 X_i^c + \gamma X_i^c Z_i + \delta_{city} + \epsilon_i \quad (\text{With Lin (2013) covariate adjustment})$$

$$Y_i = \alpha + \beta_1 Z_i + \delta_{city} + \epsilon_i \quad (\text{Without covariate adjustment})$$

where Y_i is the individual-level comment outcome, Z_i is an indicator for the treatment group, X_i^c is a vector of pre-treatment covariates for unit i that have been centered to have mean zero, and δ_{city} are city (block) fixed effects.

The following pre-registered pre-treatment covariates are included in the regression specification: *city, number of units in the building, gender, age, building age, primary language spoken, vote history, and party affiliation*. I show that these variables are balanced between the placebo and treatment groups in [Balance](#). Missing covariates are mean imputed.

Randomization inference p-values for the ITT are calculated by simulating a large number of “fake” random assignments for all units using the same procedure as the real random assignment, and estimate a treatment effect for each fake random assignment. I then calculate a p-value as the proportion of times fake treatment assignments resulted in an effect size larger than the actual treatment effect. For the CACE, I make the additional assumption that observed compliance would exist regardless of treatment status and hold compliers constant across simulations. I conduct 10,000 simulations for the CACE and 1000 simulations for the ITT. All simulations were performed without covariate adjustment due to high com-

putational demands. For CATEs, I generate the full schedule of potential outcomes under the null hypothesis that the true treatment effect is constant and equal to the estimated CACE. Then, I simulate random assignment 10,000 times and calculate the proportion of instances the simulated estimate of the interaction effect is at least as large (in absolute value) as the actual estimate.

In the precision-weighted fixed effects meta-analysis, weights are equal to the inverse of the variance. For council meetings where no comments are reported in treatment or placebo, I estimate standard errors according to the procedure described in [Gelman and Hill \(2006\)](#). See p. 17, footnote 1: “Consider a survey of size n with y Yes responses and $n - y$ No responses. The estimated proportion of the population who would answer Yes to this survey is $\hat{p} = y/n$, and the standard error of this estimate is $\sqrt{\hat{p}(1 - \hat{p})/n}$. This estimate and standard error are usually reasonable unless $y = 0$ or $n - y = 0$, in which case the resulting standard error estimate of zero is misleading. A reasonable quick correction when y or $n - y$ is near zero is to use the estimate $\hat{p} = (y + 1)/(n + 2)$ with standard error $\sqrt{\hat{p}(1 - \hat{p})/n}$.”

Note that while replication code is available for the creation of the identified renter sample (i.e., merging the voter file with Los Angeles Department of City Planning records of multi-unit housing developments), the full voter file cannot be provided for both legal and ethical reasons. However, all data used in the analyses described in this section are available in anonymized form.

Balance

	Placebo (N=2007)		Treatment (N=17944)		Diff. in Means	p
	Mean	Std. Dev.	Mean	Std. Dev.		
gender	0.52	0.50	0.53	0.50	0.02	0.11
english	0.98	0.12	0.98	0.14	0.00	0.27
age	41.60	15.76	41.25	15.62	-0.37	0.31
yearbuilt	1964.93	18.63	1964.83	18.03	-0.14	0.75
units	34.25	64.90	34.39	66.40	0.08	0.96
dem	0.57	0.49	0.58	0.49	0.01	0.41
rep	0.13	0.33	0.11	0.32	-0.01	0.21
npp	0.24	0.43	0.24	0.43	0.00	0.73
vote_2020_general	0.79	0.40	0.81	0.40	0.01	0.28
vote_2017_municipal	0.10	0.30	0.09	0.29	-0.01	0.28
vote_2016_general	0.45	0.50	0.44	0.50	0.00	0.75

Table A.1: Covariate balance and difference in means test: treatment vs. placebo

	Placebo (N=2007)		Treatment 1 (N=5984)		Treatment 2 (N=6002)		Treatment 3 (N=5958)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
gender	0.52	0.50	0.52	0.50	0.54	0.50	0.54	0.50
english	0.98	0.12	0.98	0.14	0.98	0.13	0.98	0.14
age	41.60	15.76	41.16	15.61	41.35	15.63	41.23	15.62
yearbuilt	1964.93	18.63	1964.83	17.88	1964.83	18.33	1964.84	17.88
units	34.25	64.90	34.31	66.10	34.01	66.54	34.86	66.56
dem	0.57	0.49	0.58	0.49	0.60	0.49	0.58	0.49
rep	0.13	0.33	0.11	0.32	0.11	0.31	0.12	0.33
npp	0.24	0.43	0.25	0.43	0.24	0.43	0.24	0.43
vote_2020_general	0.79	0.40	0.80	0.40	0.81	0.40	0.81	0.39
vote_2017_municipal	0.10	0.30	0.09	0.29	0.10	0.30	0.09	0.29
vote_2016_general	0.45	0.50	0.45	0.50	0.45	0.50	0.43	0.50

Table A.2: Covariate balance across all treatment groups

Tests for differential compliance

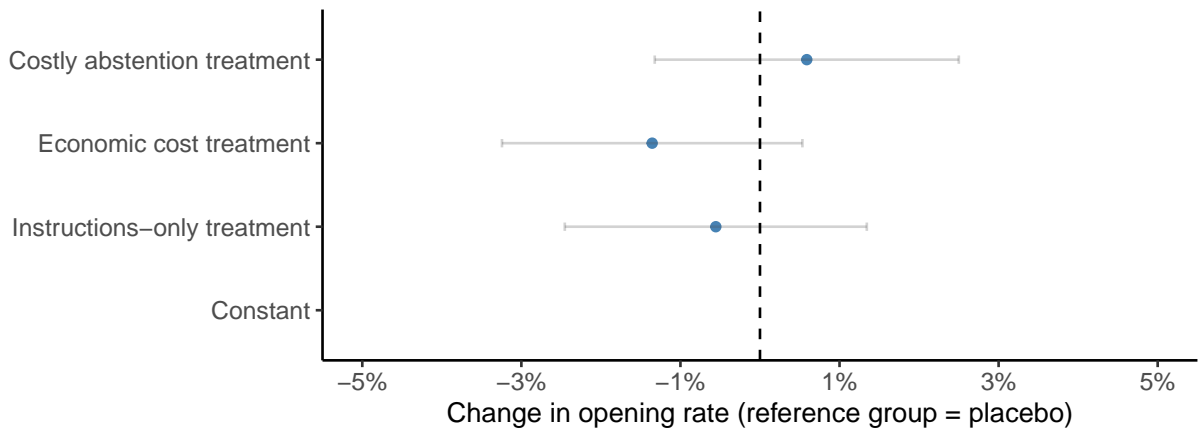


Figure A.4: Average treatment effect on email opening, all cities

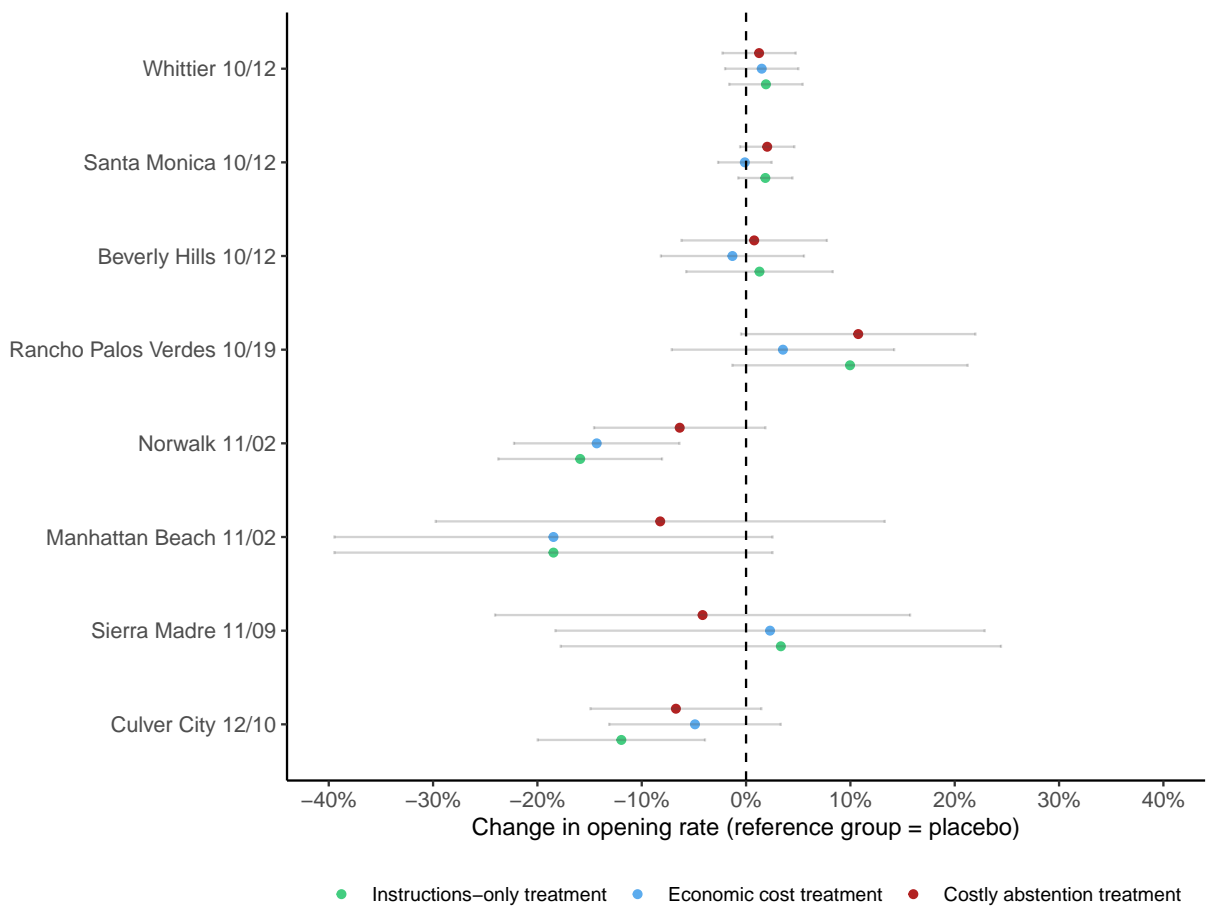


Figure A.5: Average treatment effect on email opening, by city

	Placebo	Treatment 1	Treatment 2	Treatment 3
(Intercept)	−0.321 (0.980)	−0.535 (0.569)	−0.565 (0.560)	0.216 (0.563)
gender	−0.028 (0.017)	0.004 (0.010)	−0.012 (0.010)	−0.004 (0.010)
english	0.009 (0.069)	0.045 (0.031)	−0.020 (0.037)	−0.042 (0.040)
age	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
yearbuilt	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
units	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)	0.000* (0.000)
dem	0.033 (0.033)	0.012 (0.020)	0.033+ (0.019)	0.030 (0.021)
rep	0.021 (0.039)	−0.008 (0.023)	0.003 (0.023)	−0.009 (0.024)
npp	0.054 (0.036)	0.000 (0.021)	0.017 (0.021)	0.011 (0.022)
vote_2020_general	0.028 (0.021)	0.031** (0.012)	0.062*** (0.011)	0.030* (0.013)
vote_2017_municipal	0.041 (0.033)	0.057** (0.020)	0.040* (0.018)	0.035+ (0.019)
vote_2016_general	−0.006 (0.019)	0.012 (0.011)	0.002 (0.010)	−0.019+ (0.011)
Num.Obs.	2007	5984	6002	5958

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Covariate predictiveness of compliance by treatment group

Tabular results

	All treatment groups vs. placebo		Individual treatments vs. placebo	
Constant	0.0005	0.0005	0.0005	0.0005
	(0.0005)	(0.0013)	(0.0005)	(0.0013)
	[−0.0005, 0.0015]	[−0.0022, 0.0031]	[−0.0005, 0.0015]	[−0.0022, 0.0031]
Treated	0.0020**	0.0020**		
	(0.0006)	(0.0006)		
	[0.0008, 0.0032]	[0.0007, 0.0032]		
Instructions-only treatment			0.0012	0.0011
			(0.0007)	(0.0007)
			[−0.0003, 0.0026]	[−0.0003, 0.0026]
Economic cost treatment			0.0021*	0.0021*
			(0.0008)	(0.0009)
			[0.0004, 0.0038]	[0.0004, 0.0038]
Costly abstention treatment			0.0026**	0.0027**
			(0.0009)	(0.0009)
			[0.0009, 0.0044]	[0.0009, 0.0044]
Covariate adjustment:	Yes	No	Yes	No
Num.Obs.	19 951	19 951	19 951	19 951

Notes: Standard errors clustered at the address level in parentheses. 95 percent confidence intervals in brackets.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: Intent-to-treat effects

	All treatment groups vs. placebo		Individual treatments vs. placebo	
Constant	0.0000	0.0061	0.0000	0.0063
	(0.0000)	(0.0086)		(0.0086)
	[0.0000, 0.0000]	[-0.0107, 0.0230]		[-0.0106, 0.0231]
Treated	0.0102***	0.0104***		
	(0.0018)	(0.0019)		
	[0.0066, 0.0138]	[0.0066, 0.0141]		
Instructions-only treatment			0.0054*	0.0052*
			(0.0025)	(0.0023)
			[0.0006, 0.0103]	[0.0006, 0.0098]
Economic cost treatment			0.0101**	0.0106**
			(0.0032)	(0.0033)
			[0.0039, 0.0163]	[0.0041, 0.0171]
Costly abstention treatment			0.0144***	0.0148***
			(0.0036)	(0.0037)
			[0.0073, 0.0215]	[0.0075, 0.0222]
Covariate adjustment:	Yes	No	Yes	No
Num.Obs.	3381	3381	3381	3381

Notes: Standard errors clustered at the address level in parentheses. 95 percent confidence intervals in brackets.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.5: Complier average causal effects

Table A.6: CACEs for each city council meeting

Meeting	CACE	95% CI	N
<u>Pilot studies</u>			
Santa Monica 8/26	0	[-2.119 , 2.119]	91
Long Beach 9/7	1.375	[0.031 , 2.719]	346
Long Beach 9/14	0.460	[-0.061 , 0.981]	727
<u>Primary studies</u>			
Beverly Hills 10/12	1.656	[-0.256 , 3.568]	194
Santa Monica 10/12	0.893	[0.47 , 1.317]	2,102
Whittier 10/12	0.556	[-0.216 , 1.327]	396
Rancho Palos Verdes 10/19	3.704	[-1.495 , 8.902]	57
Manhattan Beach 11/02	0	[-2.742 , 2.742]	70
Norwalk 11/02	1.695	[-0.223 , 3.613]	213
Sierra Madre 11/09	0	[-6.034 , 6.034]	31
Culver City 12/10	1.439	[0.031 , 2.847]	318

Note: Standard errors in parenthesis. Figures rounded to nearest thousandth decimal place. N is equal to the number of compliers in each city.

Table A.7: Meta-analysis estimates

Value	Estimate	95% CI	N
Weighted fixed effects, w/ pilot studies	0.008 (0.001)	[0.005 , 0.011]	4545
Random effects, w/ pilot studies	0.008 (0.001)	[0.005 , 0.011]	4545
Weighted fixed effects, w/o pilot studies	0.009 (0.002)	[0.006 , 0.012]	3381
Random effects, w/o pilot studies	0.009 (0.002)	[0.006 , 0.012]	3381

Note: Standard errors in parenthesis. N is equal to the number of compliers.

	CATE
Constant	0.006 (0.009)
Treated	0.009*** (0.002)
Voted in 2017 municipal election	0.000 (0.001)
Treated x Voted	0.014+ (0.008)
City fixed effects:	Yes
Num.Obs.	3381

Notes: CATE standard errors clustered at the address level.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.8: Conditional complier average causal effect

Comment type	Spoken	Written	Pro-housing	Anti-housing	Custom	Pre-written
Constant	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Treated	0.001+ (0.001)	0.010*** (0.002)	0.009*** (0.002)	0.001 (0.000)	0.003** (0.001)	0.007*** (0.002)
Num.Obs.	3381	3381	3381	3381	3381	3381

Notes: Standard errors clustered at the address level.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.9: Complier average causal effects by outcome

Robustness

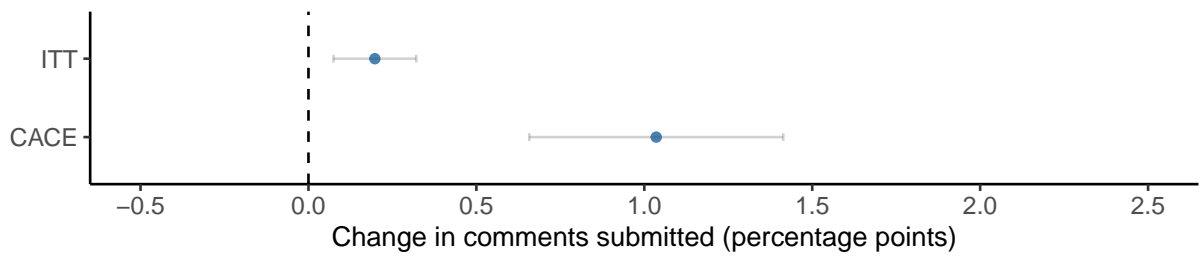


Figure A.6: Intent-to-treat effect and complier average causal effect, all cities (without covariate adjustment)

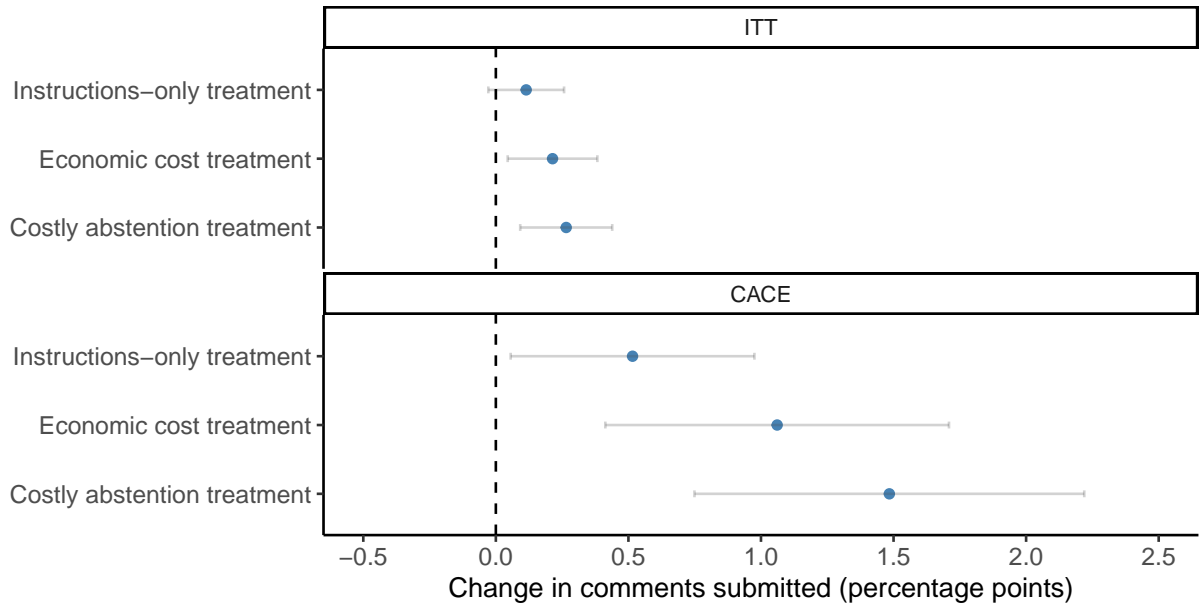


Figure A.7: Effects by treatment group, all cities (without covariate adjustment)

	All treatment groups vs. placebo		Individual treatments vs. placebo	
	ITT	CACE	ITT	CACE
Constant	-7.1987*** (0.8170) [-9.3648, -5.9318]	-6.5439*** (1.4173) [-11.3781, -4.6301]	-7.1987*** (0.8170) [-9.3648, -5.9318]	-6.5439*** (1.4173) [-11.3781, -4.6301]
Treated	1.2239+ (0.8304) [-0.0850, 3.4045]	1.9864* (1.4285) [0.0265, 6.8285]		
Instructions-only treatment			0.8548 (0.8735) [-0.5931, 3.0816]	1.3414 (1.4804) [-0.8391, 6.2197]
Economic cost treatment			1.3048+ (0.8534) [-0.0776, 3.5102]	2.0372+ (1.4509) [-0.0157, 6.8950]
Costly abstention treatment			1.4797* (0.8479) [0.1150, 3.6792]	2.3874* (1.4388) [0.3850, 7.2367]
Num.Obs.	19951	3381	19951	3381

Notes: Standard errors clustered at the address level in parentheses. 95 percent confidence intervals in brackets.

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.10: ITT and CACE estimates from penalized maximum likelihood

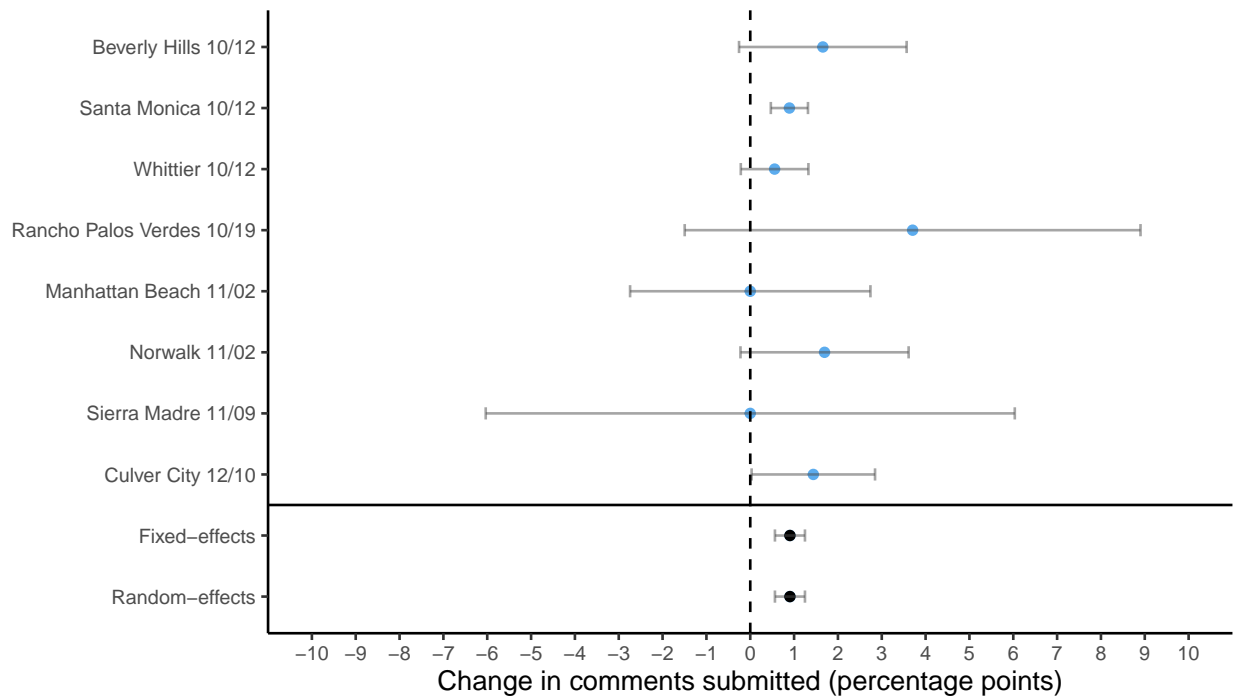


Figure A.8: Meta-analysis of complier average causal effects by city, excluding pilot studies

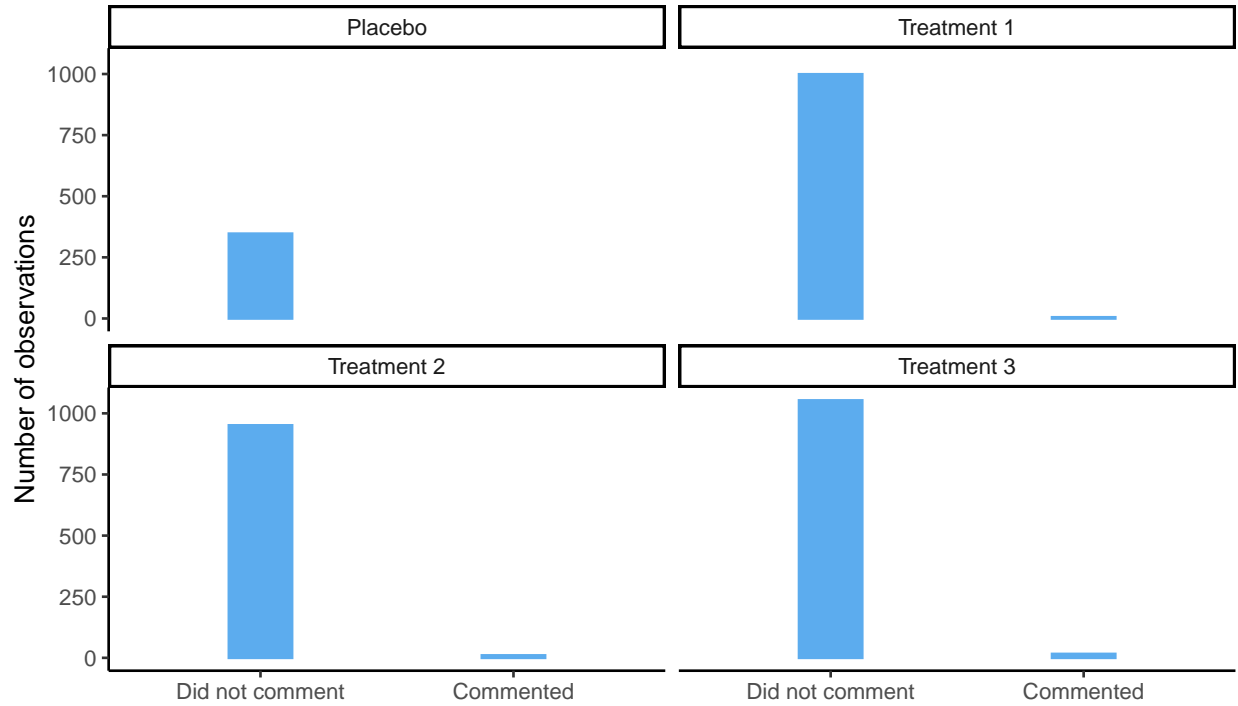


Figure A.9: Distribution of outcomes by treatment group (compliers only)

The Bayes factors in [the results section](#) are computed for hypotheses that the differences between treatments are greater than zero (e.g., costly abstention treatment - instructions only treatment > 0) and its alternative using the Savage-Dickey density ratio method. The Bayes factors are 97 and 5 for the costly abstention treatment vs. the instructions only treatment and costly abstention treatment vs. economic cost treatment, respectively. The posterior probability exceeds 95% for a one-sided hypothesis test in both comparisons, and exceeds 95% for a two-sided test in the first comparison. Given that the directionality and relative magnitudes of the treatment effects were pre-registered and negative treatment effects are theoretically implausible, a one-sided hypothesis test seems reasonable.

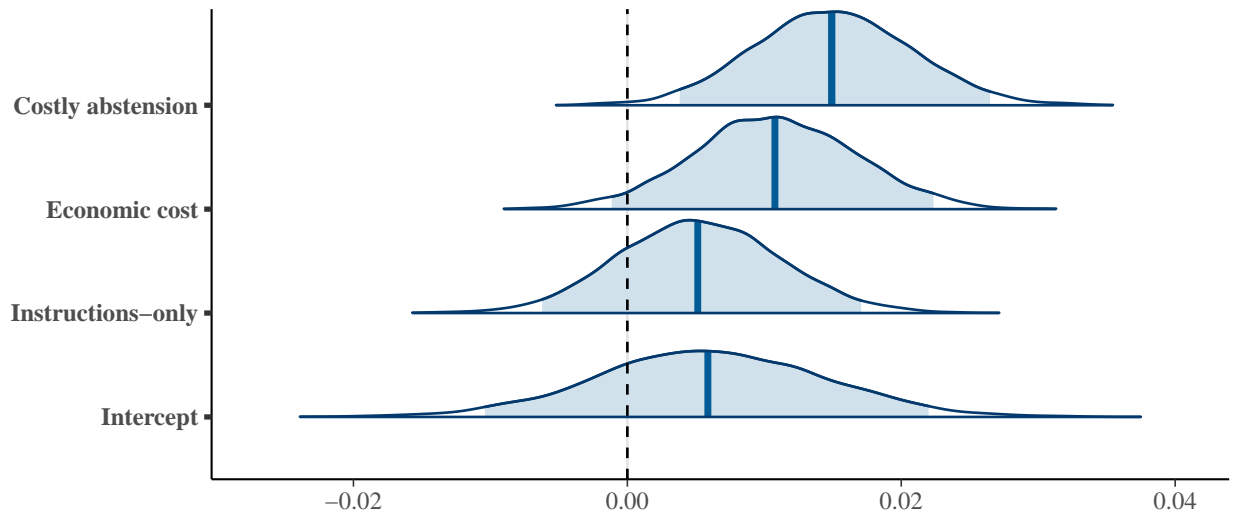


Figure A.10: Bayesian multilevel model: coefficient estimates and posterior distributions (includes city fixed effects)

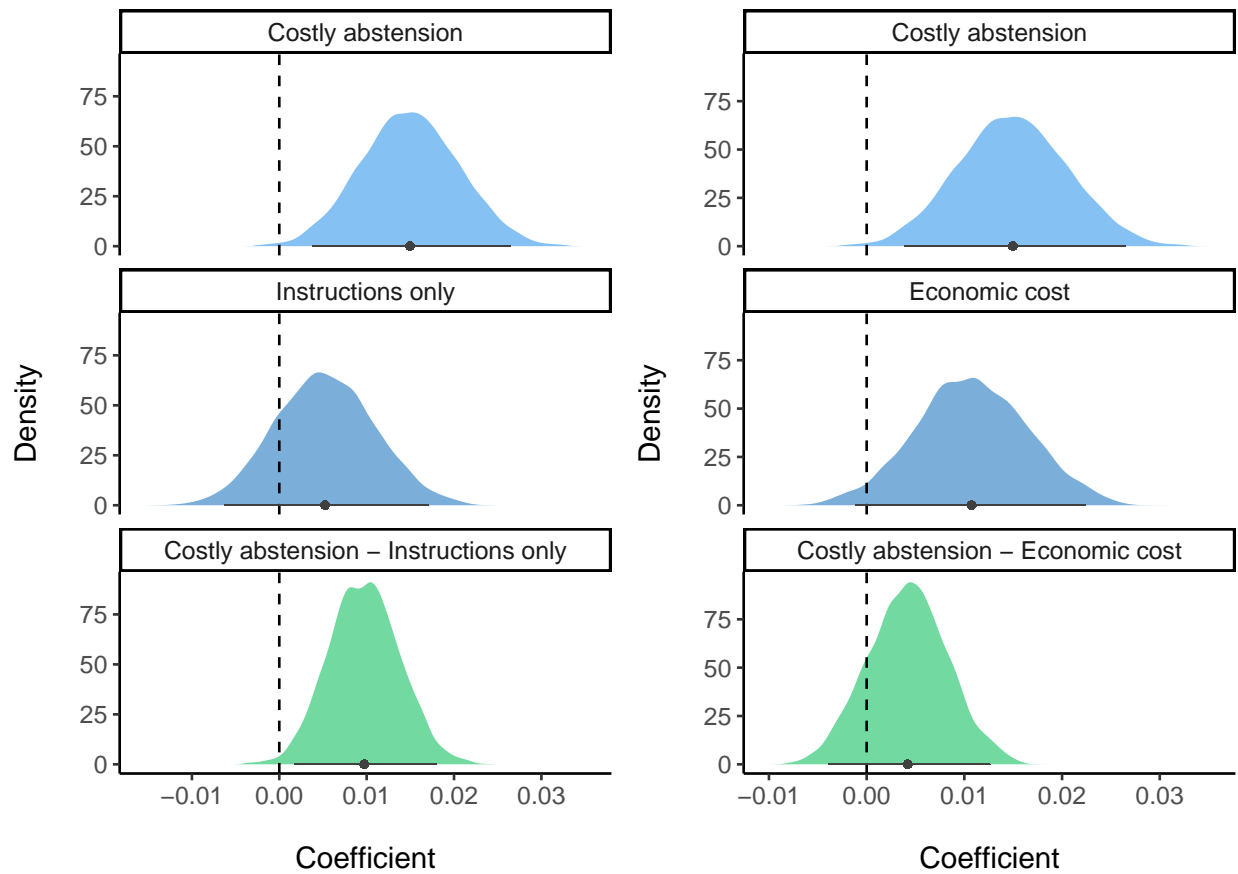


Figure A.11: Posterior distributions of costly abstention treatment, instructions only treatment, and difference

Pre-analysis plan:

Combatting capture in local politics: a field experiment

October 12, 2021

Project description

That individuals with a direct monetary stake in a political decision are more likely to participate in politics is at the heart of the collective action problem. This phenomenon impacts decision making through channels from lobbying of national legislatures to participation in local government. Recent work establishes that homeowners are far more likely to participate in local government, often to oppose development and support housing prices. However, renters are also directly impacted monetarily by anti-development decisions through higher rents caused by reduced housing supply. I partner with an NGO involved in abundant housing advocacy (Abundant Housing LA) to conduct a field experiment investigating whether direct outreach highlighting the real monetary costs of non-participation in local government can encourage individuals to attend city council meetings.

This document is a pre-analysis plan of the experimental design and analytical procedures. For any issues unaddressed in this pre-analysis plan, I commit to the defaults described in Version 1.05 of the Lin, Green, and Coppock (2016) standard operating procedures, available at: http://alexandercoppock.com/Green-Lab-SOP/Green_Lab_SOP.pdf.

Background

Design

The experiment will take the following steps:

1. Renters in Los Angeles County were identified by geo-matching addresses in the voter file with Los Angeles County Department of City Planning records of multi-unit housing developments using the *FastLink* probabilistic record linkage merging package in R (Enamorado, Fifield and Imai 2019).
2. AHLA is monitoring the dates of city council public comment periods during which time feedback on housing elements (required analyses of a community’s housing needs for all income levels and strategies to respond to provide for those housing needs) can be submitted.
3. Renters in the voter file will be randomly assigned to an email treatment asking them to turn out to support housing elements that expand the supply of housing in their city, or a placebo control. Multiple messages will be randomly assigned in the treatment group(s). The assignment will be block randomized by city and cluster randomized by address.
4. As participation in a public hearing is a matter of public record, I will match the names of those in the treatment group(s) with attendance in local meetings or letters of public support for increased housing supply. Attendance or sending a letter of support will represent the primary outcome measures in the experiment.
5. Results will be analyzed (details below). The primary treatment effect of interest will be defined as the covariate-adjusted treatment effect of opening an email on participating in a city council meeting by submitting a written or spoken public comment. Results will also be analyzed for spoken and written comments separately.
6. As multiple rounds of the experiment will be conducted across multiple municipalities in LA county, precision-weighted fixed effects meta-analysis will be performed to estimate an aggregate effect across municipalities.
7. An additional outcome of interest is whether individuals who attend one meeting attend future meetings. I will therefore also check for repeat attendance in future meetings.
8. Heterogenous effects analysis will be performed for density, area income, and political party affiliation.

Timeline

This pre-analysis plan was filed after treatment assignment and treatment implementation targeting three council meetings on October 12, 2021, but before treatment implementation of all remaining council meetings, and before data collection or analysis. *No outcome data has yet been gathered at the time of writing.*

Three pilot studies were conducted (Santa Monica, August 24, 2021 (N = 500), Long Beach, September 7, 2021 (N = 2000), and Long Beach September 14, 2021 N = 5000)) that inform the final research design. These pilots are identical to this pre-registration document, with the exception of: the absence of the third treatment group; the source of the consensus listed in the second treatment group (economic cost message below) randomized amongst economists, NGOs, and community leaders; and lack of cluster randomization at the address level.

All additional council meetings immediately prior to housing element deadlines between October 12, 2021 and January 2022 will be selected for treatment. In large cities (e.g., the city of Los Angeles), only up to a maximum of 15,000 individuals will be treated per council meeting for ethical purposes.

Hypotheses and treatments

Four treatment groups (including placebo control) using different messages will test the following hypotheses:

1. *Hypothesis 1:* Increased information about how to attend a meeting will increase attendance.
2. *Hypothesis 2:* Information that lack of housing supply increases rents will increase attendance more than attendance information only.
3. *Hypothesis 3:* Information that renters tend not to participate and that this lack of participation is costly (i.e., costly abstention theory) will increase attendance more than attendance information or rental price increase information only.
4. Funding permitting, future rounds of the experiment may add a nominal direct monetary incentive treatment arm. This pre-analysis plan will be updated in this event.

As these are competing hypotheses, each treatment group will contain a message designed to test each hypothesis. All three treatment groups will be analyzed in the aggregate compared to placebo, in addition to each treatment group separately to assess which has the largest effect.

Examples of treatment messages for one council meeting can be found in [Figure 1](#). Treatments for other council meetings will change the location, date, and attendance information only.

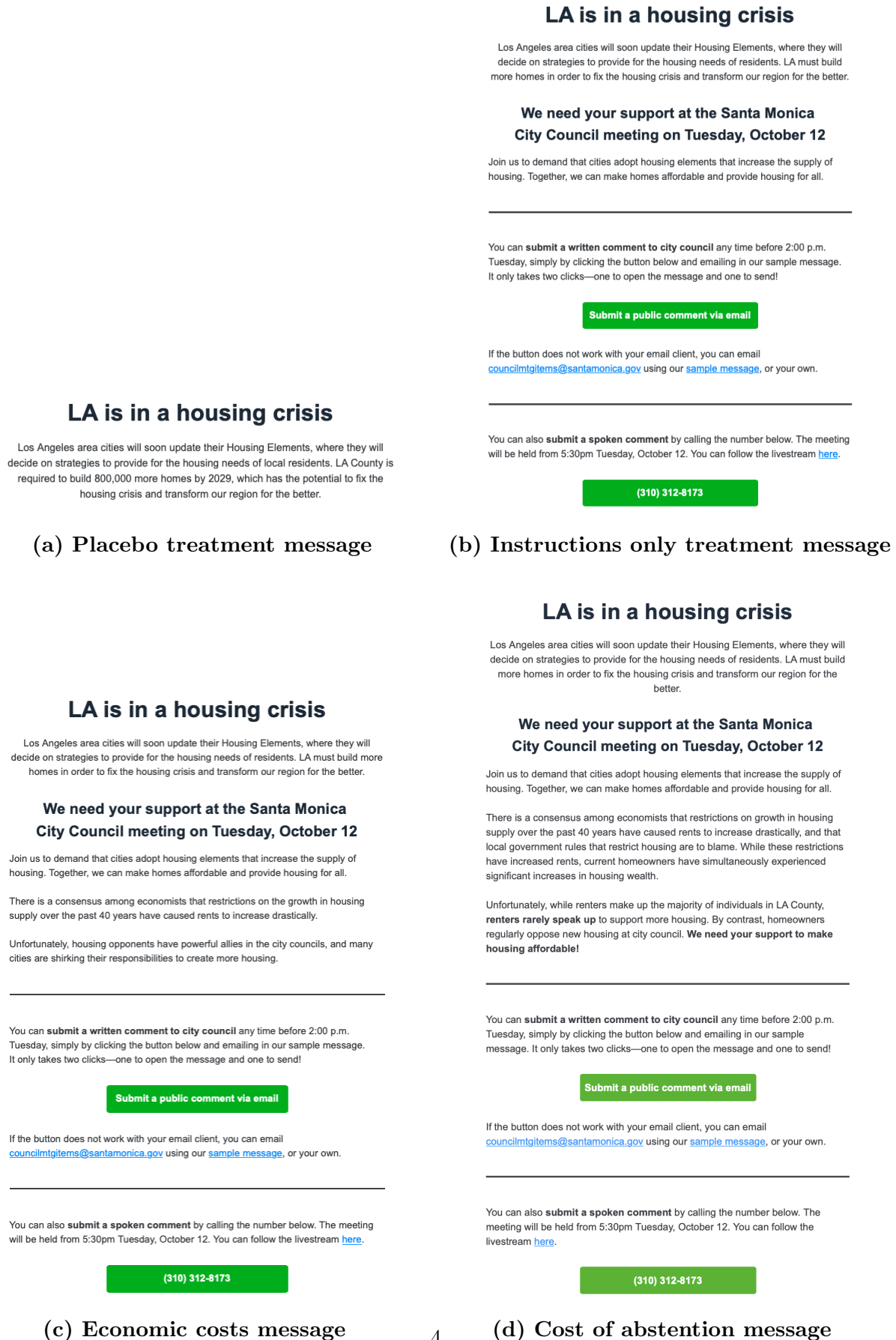


Figure 1: Treatment groups

Treatment assignment

Likely renters in the voter file were randomly assigned to an email treatment asking them to attend a meeting, or a placebo control.

Individuals were block randomly assigned by city and cluster randomly assigned by address, with 10% probability of assignment to a placebo message with no information on how to attend a meeting, 30% probability of assignment to the attendance instructions only treatment (T1), 30% probability of assignment to the informational treatment regarding how lack of housing supply impacts rents (T2), and 30% probability of assignment to a treatment identical to T2 but which also highlights lack of renter participation (T3).

Outcomes

The primary treatment outcomes of interest are a binary outcome indicating whether an individual:

- (1) Attended (virtually) a city council meeting, or
- (2) Wrote a message to city council.

This data will be collected by matching the names of individuals in each treatment group from the voter file with public records documenting both attendance and letters of support (both of which require a registration by name).

Treatment effect heterogeneity

I will examine the following heterogeneous treatment effects:

1. The density of the building (i.e., number of units) in which an individual lives.
2. The median income of the area in which an individual lives.
3. Turnout in local elections.

I may also conduct analysis using machine learning methods designed to automate the detection of heterogeneous treatment effects (e.g., Bayesian Additive Regression Trees). However, this analysis will be exploratory in nature, in contrast to the pre-registered variables denoted above.

Estimation procedures

My primary estimand is the CACE, and the estimator will include covariate adjustment. I will therefore estimate treatment effects using the Lin estimator (Lin 2013) and include the following pre-treatment covariates in the regression specification: *city, units, gender, age, building age, primary language spoken, vote history, and party affiliation*. Missing covariates will be mean imputed. As units were cluster randomly assigned by address, standard errors will be clustered at the address level.

This will be conducted using the “lm_lin” function in the “estimatr” package in R (Blair, Cooper, Coppock and Humphreys 2019; Lin 2013). The code that will be used is as follows:

`lm_lin(comment ~ treatment, covs, data = df, subset = opened == 1, clusters = address)`, where `covs` is the list of covariates above. Results will also be reported in the appendix without covariate adjustment. The code will be as follows: `lm_robust(comment ~ treatment + city, data = email, subset = opened == 1, clusters = address)`.

Heterogenous treatment effects will be estimated by regressing the outcome variables on treatments and the interaction between the treatment and the covariate. Heterogenous treatment effects will be estimated for density, median area income, and party affiliation. This will be conducted using the “`lm_robust`” function in the “`estimatr`” package in R.

Results will be analyzed both as one large experiment with city fixed effects, as well as aggregated using precision-weighted fixed and random effects meta-analysis. The meta-analysis will both include and exclude results from the pilot studies.

CACE vs ATE

Because I expect many emails to go unread, I wish to demarcate the complier average causal effect (CACE) vs. the ATE. I will monitor if an email is opened, and look at the CACE by examining whether an email was opened as the measure of treatment receipt.

Meta-analysis

Precision-weighted¹ fixed effects meta-analysis, including the pilot studies, will be performed to estimate an aggregate effect across council meetings. For council meetings where no comments are reported in treatment or placebo, I will estimate standard errors according to the procedure described in [Gelman and Hill \(2006, p.17, footnote 1\)](#). Random effects meta-analysis and meta-analysis excluding the pilot studies will also be performed for robustness purposes. This will be conducted using the `rma.uni` function in the *metafor* package in R. The code for this analysis can be found below:

Weighted fixed effects:

```
rma.uni(yi = estimate, sei = std.error, weighted = TRUE, method = "FE", data = meta_cace)
```

Random effects:

```
rma.uni(yi = estimate, sei = std.error, data = meta_cace)
```

Tests for proper implementation

1. I will test that contact rates in treatment and placebo are the same.
2. I will test that compliers in the placebo group have similar baseline values to compliers in the treatment group. For the covariates for this test, I use the baseline covariates mentioned above for covariate adjustment.

Pilot studies

A small-scale pilot study to test mechanics was conducted in Santa Monica, CA on August 24, 2021 (N = 500), and two larger pilot studies to test outcomes were conducted in Long Beach, CA on September 7, 2021 (N = 2000) and September 14, 2021 (N = 5000).

¹With weights equal to the inverse of the variance.

These pilot studies suggest a compliance rate of 15.5%, intent-to-treat effect of 0.0012, and complier average causal effect of 0.0077.

The power analysis below assumes this compliance rate and CACE for T2 (0.0077), a smaller effect size for T1 (0.004), and a larger effect size for T3 (0.01).

Power analysis

The LA County voter file possesses 266,057 individuals with email addresses who could be linked to a rental apartment address with posterior probability of a correct match of 99% or higher. An assumed compliance rate of 15% equals 39,909 individuals who will receive a message. However, as not all cities will undergo public comment periods for housing elements during the experiment timeline, a conservative estimate of number of individuals who will receive a message is likely around 6000.

The power analysis below assumes this compliance rate and CACE for T2 (0.0077), a smaller effect size for T1 (0.004), and a larger effect size for T3 (0.01).

Assuming a 0.1% turnout rate amongst compliers in the control group, 0.4% in the first treatment group, 0.77% in the second treatment group, and 1% in the third treatment group in a simulation reveals the statistical power between each treatment group and control in the table below. The “all treatments - control” simulation assumes a constant treatment effect of 0.77% across all treatment groups.

Estimate	Power	SE(power)
DIM (T1 - Control)	0.35	0.05
DIM (T2 - Control)	0.87	0.03
DIM (T3 - Control)	0.97	0.02
DIM (T2 - T1)	0.23	0.04
DIM (T3 - T2)	0.07	0.03
DIM (T3 - T1)	0.46	0.05
DIM (All treatments - Control)	0.99	0.01

References

- Blair, Graeme, Jasper Cooper, Alexander Coppock and Macartan Humphreys. 2019. “Declaring and diagnosing research designs.” *American Political Science Review* 113(3):838–859.
- Enamorado, Ted, Benjamin Fifield and Kosuke Imai. 2019. “Using a probabilistic model to assist merging of large-scale administrative records.” *American Political Science Review* 113(2):353–371.
- Gelman, Andrew and Jennifer Hill. 2006. *Data analysis using regression and multi-level/hierarchical models*. Cambridge university press.
- Lin, Winston. 2013. “Agnostic notes on regression adjustments to experimental data: Re-examining Freedman’s critique.” *Annals of Applied Statistics* 7(1):295–318.