Pathways of Local Opinion Formation: The Case of Housing Policy

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Abstract

Classic scholarship argues that local political behavior is guided by self-interest rather than partisanship or ideology, partly because local information environments often lack partisan and ideological information. When voters do have access to this information, do they sort along partisan and ideological lines, or do they continue to behave in self-interested ways? To answer this question, we turn to housing policy. We compile data on the partisan composition of state-level housing preemption policies and the ideological valence of YIMBY movement tweets between 2018-2024 to show that voters' subnational information environments have recently become rich with partisan and ideological information about housing policy. We then use this to develop realistic information treatments in a survey experiment with residents of major metro-areas (n = 7,734). We find that this information increases partisan divisions on housing policy, and even persuades some homeowners to support housing reforms that negatively impact their self-interest.

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Longstanding scholarship argues that voters behave differently in local politics than they do in national politics: instead of viewing issues and candidates through a "partisan lens" (Campbell et al. 1960), as they do in national politics, they tend to form opinions and make voting decisions based on their self-interest (Fischel 2001; Oliver and Ha 2007; Oliver, Ha, and Callen 2012). One reason for this difference is that local information environments often lack the partisan cues and ideological information that dominate national politics (Wood 2002; Schaffner and Streb 2002; Anzia 2021). When such information is available on national policies, voters tend to adopt opinions that conform to their party (Lenz 2012) and match their ideological predispositions (Zaller 1992). This raises the question: Is the same true of local politics? In other words, when voters have access to the partisan and ideological information they typically rely on in national politics, will they use it in the same way to form opinions on local issues, or will they continue to behave in ways that protect their self-interest?

To answer this question, we focus on an issue area that scholars typically view as dominated by self-interest, but that has recently become the subject of both partisan and ideological debate: housing policy. Amidst an escalating housing crisis concentrated in cities with growing demand but not enough supply, state legislative action and local political mobilization are providing new information about supply-side solutions to the housing crisis. At the state-level, legislatures across the country have begun passing laws to address the housing crisis (Brouwer and Trounstine 2024), with a particular focus on preemption laws that override local zoning regulations to encourage housing supply (Infranca 2019). As we show, these state legislative efforts provide partisan cues that Democrats are more likely to support supply-side interventions. At the local level, the nonpartisan Yes in My Backyard (YIMBY) movement has proliferated since 2016 (Dougherty 2020; Holleran 2020). Through their extensive engagement on social media, local YIMBY groups routinely make arguments in favor of more and denser housing that are likely to appeal to liberal and Democratic audiences, despite the movement's aversion to partisan and ideological labels.

Partisan and ideological information in voters' subnational contexts has the potential to teach voters how to think about housing policy in ways that conform to their partisan identities and ideological predispositions (Converse 2006). As such, we expect that once voters have access to that information, they will form preferences in line with what we have come to expect of voters in national politics.

More specifically, we expect that the information from state legislative contexts can provide partisan cues that convince Democrats to align their behavior with their copartisans (Lenz 2012), while YIMBY movement arguments at the local level can provide left-leaning ideological information that persuades Democrats to support denser housing (Druckman, Peterson, and Slothuus 2013; Zaller 1992). Both kinds of information, through different mechanisms, could therefore increase partisan divisions on housing policy.

We further expect that, when presented with this information, Democratic homeowners may increase their support for supply-side housing policies *even though it conflicts with their self-interest.* Existing research suggests that this group indeed tends to behave in self-interested ways on issues of housing policy and development (Sahn 2024; Einstein, Glick, and Palmer 2019; Marble and Nall 2021), but this scholarship predates the recent wave of partisan and ideological information about housing, to which many voters now have access. In the presence of such information, we expect that they may change their opinions.

To assess these expectations, we pair descriptive analyses of the actual housing policy information environment in states and localities across the country with a survey and survey experiment conducted with a large sample (n = 7,734) of residents in the twenty largest Metropolitan Statistical Areas (MSAs).

Our research design proceeds in two phases, building on the insight that partisan and ideological information about housing policy is reaching voters not just through the national media or party elites,[1] but also–and perhaps primarily–through local- and state-level contexts.

1. At the national-level, housing featured centrally in both the Harris and Trump campaigns during July, August, and September 2024. See the Wesleyan Media Project: https://mediaproject.wesleyan.edu/releases-081424/ and https://mediaproject.wesleyan.edu/releases-092624/.

In the first phase, we describe voters' actual subnational information environments on housing policy. We begin by collecting all state-level zoning preemption policies passed between 2016 and 2024, as well as the partisan composition of each state legislative vote (Hill and Huber 2019). Next, we collect data on the YIMBY movement to identify the most common frames the movement uses to mobilize people on social media. To do so, we scrape all tweets from YIMBY movement accounts between 2018 and 2024 (n = 410,689) and iteratively develop a human-validated codebook of common frames. We then use a jury of expert annotators and large language models (LLMs) to fit machine learning models that accurately classify tweets according to these frames, and perform design-based supervised learning to infer valid measures of frame prevalence in the corpus (Egami et al. 2024).

Through these analyses, we show that partisan and ideological information on housing are indeed available to millions of voters across the country – particularly those living in the largest metro areas that are facing the worst of the housing crisis (Divounguy 2024). Although the available cues in these cities are not uniformly Democratic or liberal, much of the information available to voters from their state and local contexts indicates that supply-side interventions are policies that Democrats and liberals support.[2]

The second phase of the research assesses the extent to which this information could cause voters to think about housing policy in more partisan ways. To do so, we turn to a survey experiment to assess the causal effects of this information on opinion formation. In a 2x2 design, we randomly assign participants to a state-level partisan information condition, a local-level ideological information condition, a combined condition, or a control. We maximize external validity by drawing on the descriptive analyses from the first phase of the research to design the treatments. More specifically, the state-level partisan condition informs participants that a majority of Democrats in their state supported a preemption bill, while the local-level ideological condition informs them that a local housing group supports the

2. In fact, we show that the most prevalent argument made by the YIMBY movement is a non-ideological supply-side argument in favor of housing reform; however, liberal-leaning arguments make up half of the movement's most common frames.

bill because it will make communities more affordable for working-class residents. To choose this argument, we pre-tested the seven most common YIMBY movement frames, using them as levels in a conjoint, and found it to be the most effective (Chong and Druckman 2007).[3] The combined treatment presents both state-level partisan cues and local-level ideological information.

We find that the state-level partisan and local-level ideological treatments, and particularly the combination of the two, can increase partisan divisions on supply-side housing policies by convincing Democrats to support these kinds of housing reforms. Moreover, the information has a similar effect on support among both Democratic renters and homeowners – despite the fact that the reforms may negatively impact the latter's self-interest. Finally, we show that *both* the state-level partisan and local-level ideological information polarize through the same mechanism: teaching respondents which party supports supply-side interventions.

As such, this study contributes to ongoing debates about how voters form preferences in local politics, and the conditions under which local political behavior might mirror the partisan and ideological divisions that dominate national political behavior (Anzia 2021; Hopkins 2018; Warshaw 2019). We show that self-interested behavior in local politics is indeed contingent on the information environment – when voters receive the partisan and ideological information they typically rely on to form opinions in national politics, they use it in similar ways to form opinions in local politics.

Moreover, our findings highlight that this information may come from surprising sources: subnational information environments. Existing scholarship has highlighted how information-rich local contexts tend to *localize* politics by providing voters with more information about local elections such that they do not need to default to low-cost partisan heuristics (Moskowitz 2021; Peterson 2017). But much of this research focuses on local news. By expanding the scope of our analyses to include policy contexts and digital media, we show that subnational information environments may equally be sources of *nationalizing* information – in other

3. This was also the second-most prevalent fame in our corpus.

words, information that exacerbates partisan divisions in local politics (Hopkins 2018).

These findings thus have implications for issue areas beyond land use politics, such as education, crime, and property taxes. Scholars are right to point out that national parties rarely take stances on local issues (Anzia 2021), but our findings emphasize that even in the absence of party position-taking, subnational political activity – whether local mobilization or state- and local-policymaking – can be an important source of partisan and ideological information about local issues.

Information Environments & Opinion Formation on Local Issues

Scholars have repeatedly concluded that opinion formation and vote choice at the local level are dominated by concerns that differ from those at the national level. Unlike in national politics, where partisanship and ideology explain much of the variance in political behavior (Bafumi and Shapiro 2009; Campbell et al. 1960; Achen and Bartels 2016), in local politics, residents are thought to behave as "homevoters," supporting the policies that will best uphold their property values (Fischel 2001).

One reason for this difference is the divergence of local and national information environments. On the one hand, research has shown that when voters better understand how their own fortunes are affected by a particular policy, they are more likely to favor outcomes that align with their self-interest (Chong 2013; Green and Cowden 1992). This may make it easier to vote in one's self-interest at the local-level, where the consequences of the policies are more visible (Marble and Nall 2021). On the other hand, voters in local elections rarely have access to the partisan and ideological information that typically guides their behavior in national politics (Zaller 1992; Lenz 2012). This is because many local elections are formally nonpartisan (Wood 2002) and national elites rarely make local issues central to their campaigns (Anzia 2021).

As a result, scholars have shown that local political behavior is often guided by residents' parochial concerns about issues that affect them directly (Oliver, Ha, and Callen 2012;

Oliver and Ha 2007). Local information environments can encourage this "localization" of political behavior by providing voters with nonpartisan information about local elections, allowing them to evaluate personal economic tradeoffs associated with local policy decisions (Moskowitz 2021; Peterson 2017).

But it is also possible that local information environments may contain the partisan and ideological information that scholars argue is typically missing from these contexts. Under such conditions, it is not clear whether local voters would continue to protect their self-interest (Marble and Nall 2021), or whether they might embrace policies that align with their partisan group and ideological predispositions.

To assess these possibilities, we focus on the case of housing politics. Amidst a growing housing crisis that has led to skyrocketing prices and rising rates of homelessness, many activists and policymakers have converged around supply-side solutions to the crisis: communities must build more (and often denser) housing. The housing policy information environment has become increasingly rich with both partisan and ideological information about supply-side housing policies, providing an opportunity to assess how these real-world changes are affecting behavior in local politics.

First, many state legislatures, often in states that have endured the worst of the housing crisis, have made housing a legislative priority, with a particular focus on supply-side interventions (Brouwer and Trounstine 2024). In so doing, many have turned to preemption laws, which override local zoning regulations by requiring municipalities to make residential development easier and less expensive. This "new generation" of state preemption laws since 2017 (Infranca 2019:828; see also: Goodman and Hatch 2023; Wielga 2023) has not emerged unimpeded: state legislative battles over housing have garnered extensive media coverage in states like Colorado, California, Oregon, Washington, and New York.

Much of this legislation has been encouraged by the YIMBY movement, which began in San Francisco in 2015 and has since spread to dozens of statewide and local organizations in 22 states and Washington, D.C. The YIMBY movement is a nonpartisan movement that

advocates for supply-side solutions to the housing crisis. Since its founding, the movement has focused its efforts on lobbying for more permissive zoning regulations at both the state- and local-levels (Dougherty 2020; Holleran 2020). It has also mobilized support at the grassroots, bringing pro-housing supporters to public meetings to counteract the once-dominant voice of local homeowners opposed to new development (Einstein, Glick, and Palmer 2019; Sahn 2024).

To build support at the grassroots level, YIMBY organizations provide information about the consequences of status quo housing policy through email lists, events, engagement at local public meetings, and extensive social media activity. In doing so, they make many arguments that frame housing as a particular kind of social problem in need of certain political solutions (Benford and Snow 2000). Others have recently shown that such advocacy group messaging can be effective in changing people's opinions about housing policy (Elmendorf, Nall, and Oklobdzija 2024). As demonstrated below, the YIMBY movement often makes *nonpartisan* but ideological arguments.

As such, the information from these state and local sources tells voters "what goes with what" politically (Converse 2006). State legislatures often provide explicit partisan cues, which could allow copartisans to follow their leaders (Hill and Huber 2019; Lenz 2012) and/or encourage outpartisans to move in the opposite direction (Nicholson 2012). YIMBY movement frames, on the other hand, contain ideological appeals rather than explicit partisan cues, which could allow people to map their housing policy preferences onto their existing predispositions (Zaller 1992; Gelman and King 1993).

Both sources of information thus have the potential to change voters' opinions about housing policy. But the direction of that change should depend on their self-interest and political commitments. The information should be most persuasive to people whose group attachments and predispositions align with the side advocating for more housing, and whose self-interest is not threatened by more housing (i.e., renters).

As we will show, the majority of information voters may receive about supply-side solu-

tions to the housing crisis from their state and local contexts suggests that these solutions are favored by Democrats and may achieve goals that appeal to liberals. To that end, this information should be most effective at persuading Democrats to support greater housing supply, and may even persuade Democratic homeowners to forego their self-interest and support housing reform.

Research Design & Analyses

The research design proceeds in two phases. In the first set of analyses, we establish several descriptive facts about the ideological and partisan content of local- and state-level information on housing policy. These analyses show that subnational information environments are indeed rife with partisan and ideological information about supply-side housing interventions, particularly Democratic partisan cues and liberal arguments if favor of these policies.

In the second set of analyses, we assess whether this information can affect public opinion in line with our expectations. First, we test whether exposure to partisan and ideological information that reflects voters' real-world housing policy information environments can exacerbate partisan divisions on housing issues–either by increasing Democrats' support, decreasing Republicans' support, or both. Then, we assess whether this exposure can persuade Democrats to support increased housing supply, even if this policy is against their self-interest.

Analysis I: Describing the Housing Policy Information Environment

To assess whether voters' real-world information environments indeed offer them partisan and ideological cues about housing policy, we begin by collecting data on state-level preemption policies and YIMBY movement frames.

State-level Information Environment. To identify all state-level preemption policies passed since 2016, we begin with secondary sources that have already tabulated state-level housing legislation, including the Mercatus Center (Kahn and Furth 2023) and the Terner

Center for Housing Innovation,[4] as well as data collected by N.R. Brouwer and Jessica Trounstine (see Brouwer and Trounstine 2024). We then expand our search to all states and years not included on existing lists. We ultimately collect a comprehensive set of state preemption laws that have been passed since 2016, along with two additional pieces of information about each law: the partisan composition of support for the bills and the "type" of action that the law allowed. About 90% of laws are categorized into one or more of the following categories: accessory dwelling unit (ADU) liberalization, encouraging multifamily housing in single-family zoned neighborhoods, incentivizing transit-oriented development, streamlining zoning, removing parking requirements, and offering density bonuses for more affordable housing.

Figure 1 shows the number of laws passed in each state since 2016 (a), and the average difference in the percentage of Democratic - Republican state legislators (in both houses) who supported all preemption laws in the state (b). As Figure 1(a) makes clear, the majority of laws have been passed in Democrat-led West coast states, particularly California, Oregon, and Washington, but several Republican-led states have also passed 1-2 preemption laws each.

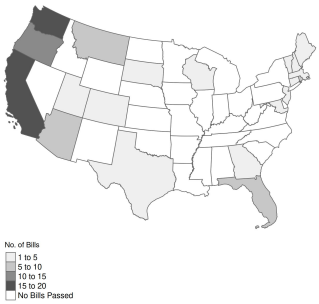
Figure 1(b) examines this partisan tilt more directly, showing the difference in the percentage of Democratic and Republican state legislators who supported all of the state's preemption laws. Values above zero therefore indicate states in which the partisan balance of support on preemption is Democratic, and values below zero indicate the opposite. As it shows, several states have indeed passed preemption laws with more Republican than Democratic support. However, many of these laws merely tinker around the edges with local zoning regulations. For example, Georgia passed one preemption law in 2023 that prohibits local governments from preventing mobile home owners from replacing their homes if they are located on nonconforming lots.[5]

In contrast, 60% of the 114 laws we identify fall into one of five categories that are more

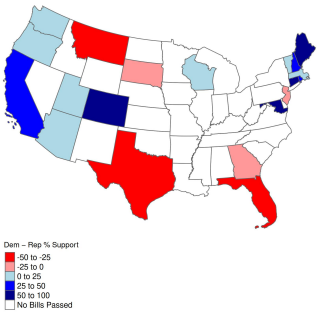
4. See: https://ternercenter.berkeley.edu/california-land-use-housing/
5. See Georgia Senate Bill 213.

Figure 1: The Geography of State Housing Preemption Laws

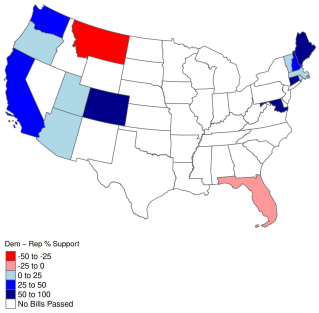
(a) Total No. of Laws Passed



(b) D-R Support in Legislature



(c) D-R Support in Legislature (Excluding streamlining zoning)



likely to generate media attention and provide cues to voters: allowing multi-family housing in single-family neighborhoods; allowing ADUs; changing zoning near transit to incentivize transit-oriented development; eliminating parking requirements; or offering density bonuses to developers who include more affordable housing in their projects. Figure 1(c) takes this into account, focusing just on the laws that fall into one of those five categories. As it shows, in just two states – Montana and Florida – more Republicans than Democrats have supported preemption. But in most states that pass meaningful reforms, support at least leans Democratic in the state legislature.[6]

In short, Figure 1 indicates that for many Americans, the state-level information environment contains partisan cues about supply-side solutions. And in many places, these partisan cues indicate that Democrats are the party more likely to support preemption: of the 20 states that have passed preemption laws, 14 have done so with more Democratic than Republican support; in all states, the majority of Democratic legislators have supported preemption legislation; across all legislation, the majority of laws were sponsored by only Democrats.

Local-level Information Environment. Next, we turn to assessing the ideological arguments in favor of supply-side interventions that are present in voters' local contexts. Although there are many local interest groups involved in housing policy disputes (Anzia 2022), from homeowners' associations to developers to anti-gentrification coalitions, we focus on one organization that is active across the country: the YIMBY movement.

To collect information about frames that the YIMBY movement has been using to persuade and mobilize people to their cause, we identify local YIMBY group Twitter accounts active from 2018-2024 using three sources: all groups affiliated with the national YIMBY Action organization (according to their website), all groups identified by Pearson and Schuetz 2022 in their Brookings Institute report on pro-housing groups emerging across the country, and any groups with "YIMBY" in their name in the United States section of the HousingWiki

6. We were unable to find the partisan voting record for seven laws passed in NH, RI, ME, VT, CA, WI, and NH.

page "YIMBY organizations directory." Using this method, we identify 137 unique accounts, including at least one account covering each of the 20 largest MSAs, with the exception of Riverside-San Bernadino. We collect data from Twitter as the YIMBY movement was started and led by Millenials (Holleran 2020), and is particularly active on Twitter during this period.

With this list of Twitter accounts, we then scrape all tweets from January 2018 to June 2024 from these accounts. This scraping generates a corpus of 410,689 total tweets. Figure A1 summarizes our corpus over time. Although we focus on YIMBY movement activity on social media, as this provides a record of their mobilization techniques, this information may reach voters both directly (if they read a tweet) or indirectly, through friends, neighbors, and family in the area (Shearer 2024).

Next, we identify the YIMBY movement's most common frames. To do so, we define the problem as k independent binary classification tasks, one per frame. We begin by randomly selecting 200 tweets for independent coding by two members of our research team.[7] This process generates a preliminary codebook of 14 distinct frames, as well as a prevalent category of "no frame."[8] The relative infrequency of many of our frames poses challenges for coding, so we use `GPT-4o-mini`[9] to search for tweets with frames to improve the expert coding. To do so, once the preliminary codebook was complete, we perform another 8 iterations of coding in which an expert (i) edited prompts instructing the model to perform binary classification of a tweet, (ii) coded a random subset of the corpus with `GPT-4o-mini` using those prompts, (iii) sampled tweets from that subset for manual annotation with 0.98 probability if the tweet was predicted to use any of the frames and 0.02 probability if not (Törnberg 2024).[10] Through this process, we find that six of the original 14 frames are extremely rare and focus instead

7. We stratify our random samples by MSA.

8. This category includes tweets geared toward mobilizing members to public meetings or events. Although these are important actions for the movement's policy success (Mendelsohn et al. 2024), they are less relevant for understanding how the movement's ideas are shaping public opinion via framing.

9. Accessed from 12/6/24 to 1/15/25 via the University Information Technology OpenAI Direct API.

10. We repeated this process until the intercoder reliability between an expert and `GPT-4o-mini` exceeded a Cohen's κ of 0.30 for each frame in a round of coding.

on the eight most common frames. Our final codebook can be found in Appendix A.

Finally, we validate our codebook of eight frames through expert intercoder agreement exercises and perform statistical analyses to estimate the frames' prevalence in the corpus. As a result of the rare incidence and large number of frames in our codebook, a traditional approach of annotating a large number of documents and then training a machine learning classifier for each of these frames is too difficult and the direct use of LLMs is inappropriate due to non-random errors in their predictions. Instead, we use design-based supervised learning, a method that allows for valid statistical inference when using predicted variables that may contain non-random prediction errors by correcting those predictions with expert annotations (Egami et al. 2024). We code our entire corpus for each frame using three LLMs (`GPT-4o-mini`, `Llama-3.2-1B-Instruct`, and `Qwen2.5-0.5B-Instruct`) (Grattafiori et al. 2024; Yang et al. 2024; Achiam et al. 2024).[11]

To perform human validation, improve the final prediction model, and enable more precise statistical inference, we then sample 100 tweets per frame[12] and have two members of our research team independently code each of these tweets. We find percent agreement ranges from 88% to 100% with a median of 96% and Cohen's kappa ranges from 0.37 to 1.0 with a median of 0.64 across our eight frames.[13] We then fit supervised machine learning models to serve as binary classifiers for each frame.[14] We fit a logistic regression, support vector machine, and multinomial Naive Bayes, using our expert annotations as labels[15], with two types of features: (1) TF-IDF weighted unigrams, bigrams, and trigrams, and

11. We used our each frame's entry in the final codebook as the system message, edited to elicit a Yes/No response from the model and supplemented with three positive and negative examples per frame to allow for in-context learning. We used each tweet as the prompt. `Llama-3.2-1B-Instruct` and `Qwen2.5-0.5B-Instruct` were run on the Harvard Faculty of Arts and Sciences Research Computing Cluster using the `vLLM` package. See footnote 12 for `GPT-4o-mini` use. Each LLM had its temperature parameter set to zero and the maximum number of output tokens parameter set to five.

12. We use a probability-based strategy where tweets coded as positive by all three LLMs were sampled with 0.7 probability, by two out of the three LLMs with 0.2 probability, by one out of the three LLMs with a probability of 0.09, and by none of the three LLMs with 0.01 probability. Many tweets appear multiple times in the data because of retweets, so we actually coded over > 300 tweets per frame.

13. Table A3 describes our complete intercoder reliability results after the final round of coding.

14. With non-random error that is then corrected by expert annotations in design-based supervised learning.

15. We classify a tweet as containing a given frame if at least one coder identified that frame in the tweet.

(2) the three LLM predictions. In addition, we fit a logistic regression that uses the 768-dimensional classification token embedding from the last hidden state of `bert-base-uncased`, a pre-trained transformer-based language model (Devlin et al. 2019), instead of the TF-IDF weighted ngrams. Table A4 presents our complete modeling results using five-fold cross-validation. In our design-based supervised learning, we use logistic regressions with BERT-based embedding and LLM prediction features trained on the complete dataset due to its best performance on an out of sample test set.

Figure 2 shows the results of the linear probability models (in blue) and logistic models (in green) using design-based supervised learning to estimate the percentage of our corpus that used each frame.[16] We find that the supply-side frame is precisely estimated to be our most prevalent frame at 12.3% of all tweets, followed by affordability with a prevalence of 5.3%. All other frames are predicted to appear more than 1% but less than 5% of the time, except homelessness at 0.4%.[17] Some of the tweets by YIMBY organizations use multimedia or external links as opposed to or in addition to the text of the tweet. Moreover, many tweets serve to publicize public meetings or events. As our analysis excludes any multimedia and those publicity tweets, we posit that these results serve as a lower bound for the use of these frames.[18]

This analysis tells us several things about the YIMBY movement's efforts to persuade voters to support supply-side interventions: first, that partisan arguments are rare but ideological arguments are common. While the supply-side and housing crisis frames are relatively non-ideological and technocratic arguments, the affordability, racial justice, homelessness, and regulation frames all have ideological content. Second, most of the ideological arguments

16. Table A5 reports the full set of regression coefficients.

17. As Figure A2 shows, frame usage does not vary much by MSA.

18. In addition to the LLMs used for the iterative coding of text documents, the authors used LLMs to generate and debug code from 2024-05-24 to 2025-03-06 using the best available models from Anthropic and OpenAI (Claude Code and Codex respectively) at the time each file was written. Detailed information on which model used was not recorded. The code performed data collection, statistical analysis, and figure and table generation. Every line of code was reviewed and approved by an author. The authors also used LLMs to copyedit the paper draft and format the LaTeX figures and images using Anthropic Sonnet 4.6 and OpenAI GPT 5.3. All model output was reviewed, edited, and approved by an author.

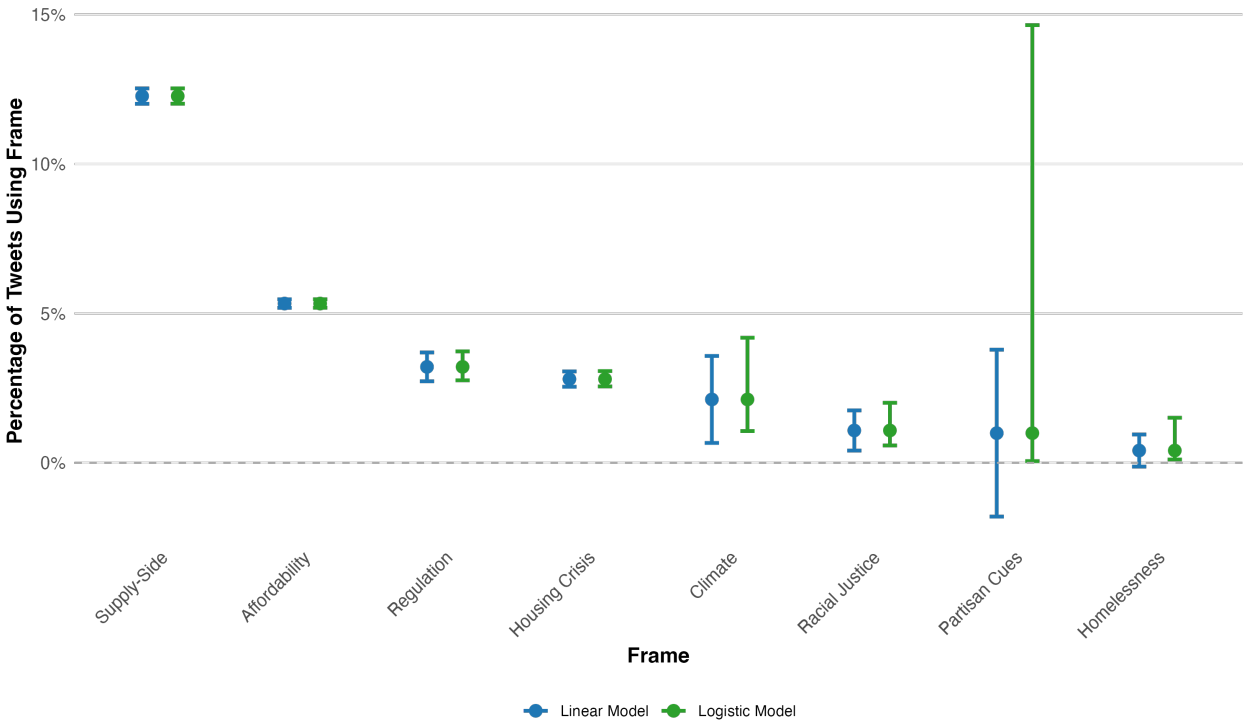


Figure 2: Design-based Supervised Learning Estimates of Frame Proportions

are likely to appeal to liberal rather than conservative predispositions. Half of the movement's most common frames appeal to standard liberal concerns (affordability, climate, racial justice, and homelessness), while only one appeals to conservative concerns (regulation).

Taken together, the preceding analyses indicate that voters in twenty states and most of the largest MSAs have access to partisan or ideological information about housing policy, or in some cases, both. The YIMBY movement is active in almost all of the largest MSAs across the country, where the housing crisis is most severe (Divounguy 2024). Eleven of those MSAs are located in states that have passed preemption legislation since 2016. And in six out of seven of those states, that legislation was passed with more Democratic than Republican support. This means that the 58 million Americans living in those MSAs have access to partisan and ideological information indicating that Democrats and liberals support supply-side interventions to address the housing crisis.

Analysis II: Assessing the Effects of Subnational Information Environments on Housing Policy Attitudes

But to what extent can this information cause voters to think about housing policy in more partisan, ideological and less self-interested ways? In other words, to what extent could this information cause housing politics to reflect divisions more typical of national vs. local politics?

To answer these questions, we draw on a survey experiment of respondents from the 20 largest metropolitan statistical areas (MSAs) (n = 7,734). The survey was conducted by the survey firm Dynata in September-October 2025, and respondents were quota-sampled to match demographic distributions in their MSA using Census data.[19] We focus on the largest MSAs because this is where the housing crisis is most severe and where, as our preceding analyses show, residents are most likely to have access to some ideological or partisan information about housing.[20]

Respondents first answered pre-treatment questions about their support for three policies designed to increase housing supply: changing zoning laws to make it easier to build apartments near commercial areas, changing zoning laws to make it easier to build townhomes and 2-4 unit apartments in neighborhoods with single-family homes, and allowing "granny flats" (accessory dwelling units) in backyards. Support was measured on 5-point Likert scale from "Strongly oppose" (0) to "Strongly support" (1). Participants also answered two questions to measure their pre-existing knowledge that the Democratic Party is more likely to support housing densification policies and that housing densification policies mostly help low-income Americans.

19. MSAs near state borders will only include residents of the state that includes the core metropolitan area (i.e. the New York MSA sample will not include residents of Jersey City). The Washington-Arlington-Alexandria, DC-VA-MD-WV Metropolitan Statistical Area will be excluded from the top 20 MSAs and the Orlando-Kissimmee-Sanford, FL Metro Area will be included to ensure comparability of the state legislative treatment.

20. This sample also follows previous research aimed at understanding attitudes toward housing policy (Marble and Nall 2021)

After answering these questions, participants were assigned to one of three treatments or a control condition, according to a 2x2 factorial design: state-level partisan information; local-level ideological information; or a combined state and local information. After viewing these treatments, respondents answered the same three policy support questions and two knowledge questions again, allowing us to measure differences in between-subject change in support between the pre- and post-treatment responses (Clifford, Sheagley, and Piston 2021).

We design each treatment to match the subnational information environment as closely as possible. First, the state-level information condition emphasizes Democratic support for supply-side interventions. This is because, as Table A2 shows, all states that passed preemption legislation did so with Democratic support of at least 80%; and in every state except Florida, legislation was passed with more Democratic than Republican support.

Next, for the local-level information condition, we sought to identify the *strongest* of the YIMBY movement's most common frames in order to guard against a null finding due to the weakness of the frame (Druckman, Peterson, and Slothuus 2013; Chong and Druckman 2007). To do so, we conducted a conjoint experiment with 1,596 urban and suburban residents recruited through the online survey platform CloudResearch, which asked participants to choose between four randomly generated pairs of proposed legislation that their states might consider adopting to increase housing supply.[21] These pairs varied across four dimensions, one of which contained arguments in favor of the proposed legislation, which were drawn from our Twitter analysis above.[22] Among all the YIMBY movement arguments in favor of supply-side interventions, the affordability frame led to the highest probability of selection. For this reason, we choose a local-level treatment that contains an affordability frame. For more information about the conjoint, see Appendix B.

Finally, the combined state- and local-level combined condition combines the partisan

21. Urban/suburban residence is based on respondent self-reports. Table A8 shows the sample demographic characteristics.

22. To generate each argument, we combined the common characteristics of tweets within each category to reflect the YIMBY movement's typical framing of the housing crisis. Table A10 shows the language used for each argument, and Figure A4 plots the Average Marginal Component Effects (AMCEs) for each level relative to the reference category. The format of each frame was kept as standardized as possible.

cue along with the affordability frame. In the local and combined conditions, respondents were shown a mock image of a social media post, designed to mirror an affordability argument they might commonly see from the YIMBY movement. See Appendix C for the actual text of the treatments and the image used. As noted above, we consider the affordability frame to be "liberal" because, as the codebook illustrates, tweets categorized in this way argued that supply-side interventions would not just increase affordability in general, but would help low-income people in particular. As Appendix C details, the text of the treatment also emphasizes this, focusing on benefits for "working class residents."

To further ground the experiment in respondents' actual information environments, only people living in states that have passed preemption laws were passed with majority Democratic support (Arizona, California, Colorado, Florida, Maryland, Massachusetts, or Washington, per Table A2) could receive the state or combined treatments.

For this reason, treatment was assigned through stratified randomization depending on respondents' state of residence: in non-preemption states, respondents were assigned trough simple randomization to either the local-level treatment or control conditions; and in preemption states, they were assigned with 8.3% probability each to the local-level treatment or the control and 41.7% probability each to the state-level or combined treatments.[23]

We use these data to assess our hypotheses: that when voters are aware of the partisan and ideological information available in their state- and local-contexts, they will offer opinions on housing policy that are more in line with their partisan group and ideological predispositions, thereby generating partisan polarization on these issues. We further expect that this information can persuade people to support policies in line with these political commitments, even when those policies conflict with their self-interest. To this end, in the analyses that follow, we measure the effects of each treatment on the *change in partisan sorting* for each of the three policy questions.

23. All analyses include inverse probability weights to account for the weighted randomization into treatment groups. All results include standard errors clustered at the state-level using HC2 estimators.

The results of these analyses are presented below.[24] Table 1 begins by showing that the treatments indeed increase partisan divisions on housing policy–particularly when people receive *both* partisan and ideological information together. It presents the coefficients from an OLS model regressing change in partisan sorting for each policy question (columns (1)-(3)), on each of the three treatment conditions (with the control as reference category). To measure partisan sorting, we reverse code support for Republicans and Democrats, such that Democrats receive higher values for supporting densification, and Republicans receive higher values for opposing densification. Positive coefficients in Table 1 thus indicate that exposure to the treatment increased the gap in support for densification between Democrats and Republicans, relative to the control.

Table 1: Treatment Effects on Partisan Sorting

	(1) Sorted Downtown	(2) Sorted SFH	(3) Sorted ADU
Local	0.024*	0.014	0.009
	[0.005, 0.042]	[−0.003, 0.030]	[−0.005, 0.023]
State	0.029**	0.014	0.002
	[0.015, 0.042]	[−0.011, 0.040]	[−0.009, 0.014]
Combined	0.022*	0.029*	0.003
	[0.004, 0.040]	[0.010, 0.047]	[−0.023, 0.029]
Num.Obs.	7.734	7.734	7.734
R2	0.002	0.002	0.001

95% confidence intervals in brackets. Standard errors clustered at the state level. * p < 0.05, ** p < 0.01, *** p < 0.001

[a] SFH: multifamily housing in single-family zoned neighborhoods.

[b] ADU: accessory dwelling units.

While ADU preferences are largely fixed, all three treatments increase partisan sorting on the question of allowing more multi-family housing development in downtown commercial districts. The local and combined treatments also increase partisan sorting on the question of

24. Consistent with our pre-analysis plan, all regression results include a control for attention based on three pre-treatment attention check questions as well as an alternative attention specification for those who provide a zip code matching their MSA. Results shown in Figures 3 and 4 are based on group means and do not control for attention. We run all analyses excluding inattentive respondents and find largely similar results.

whether to increase multi-family housing development in single-family zoned neighborhoods (although the effect of the local treatment is significant at $p < 0.1$). All other results are directionally consistent but fail to reach statistical significance.[25]

Taken together, these results thus suggest that the kinds of information increasingly available to voters about housing policy can indeed increase partisan polarization on this local issue – particularly if people are exposed to both the ideological and partisan information available in their subnational contexts.[26]

But to what extent is this polarization driven by Democrats moving to support supply-side housing interventions (either because they are following their partisan leaders or persuaded by liberal arguments that align with their predispositions) or by Republicans moving to oppose those policies for corresponding reasons? Figure 3 addresses this question: it plots average pre- and post-treatment support for an index of housing policies, across Democrats (in blue) and Republicans (in red). The index is a simple average of responses across all three policy questions.[27]

The circles on the left side of each panel show respondents' pre-treatment levels of support–revealing that Democrats were slightly more supportive of densification policies than Republicans before exposure to the partisan and ideological information. Then, as we can see, in all three treatment conditions that gap widened post-treatment because Democrats' support for the policies increased more than Republicans'.

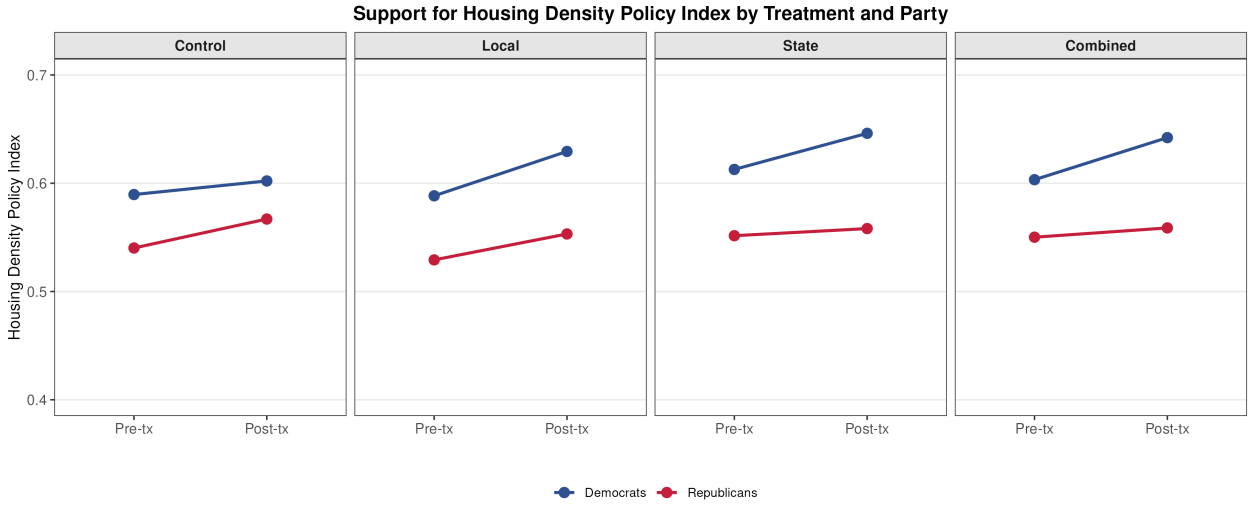
This is particularly true of the state and combined treatments, wherein Republican support largely remains unchanged post-treatment, while Democrats' support increases. In contrast, exposure to the YIMBY movement's affordability argument (the local treatment) actually increases Republican support somewhat, although not quite as much as it increases

25. We note that we are using a particularly conservative approach to estimate standard errors by clustering at the state-level and using a Bell-McCaffrey degrees-of-freedom correction. Without that correction, or with standard errors clsutered at the MSA-level or unclustered, the local treatment effect on increasing multi-family housing in single-family neighborhoods is significant at $p < 0.05$.

26. This is consistent with our pre-registered expectations that the combined treatment would be the most polarizing.

27. We create this for purposes of visualization. In the Appendix, we recreate Figures 3 and 4 for each policy question separately, as we did not pre-register formal expectations about the policy index.

Figure 3: Treatment Effects by Party Subgroup



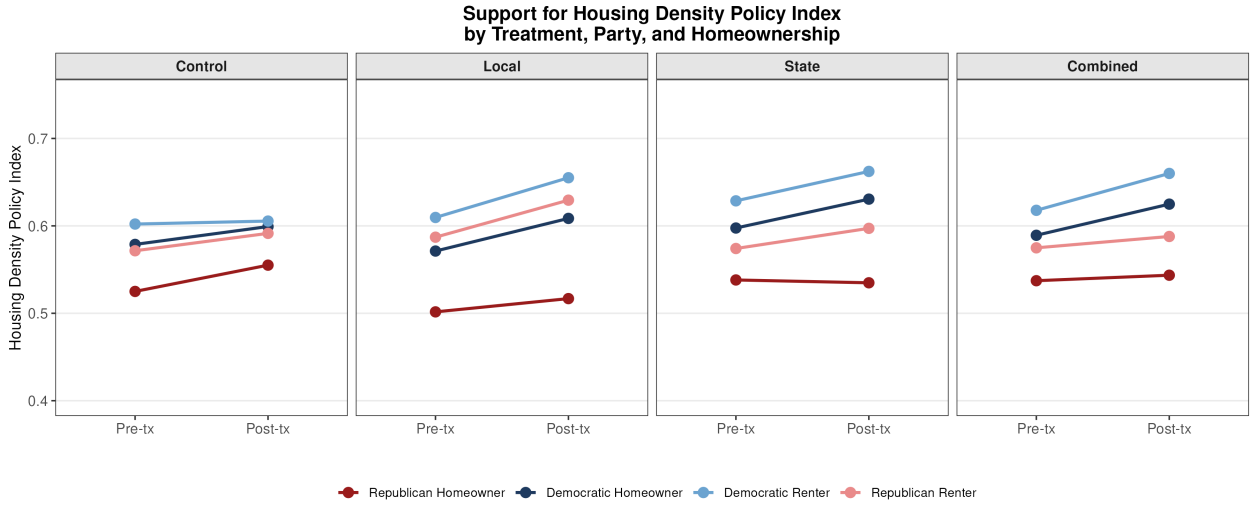
Note: The figure shows the change in support among partisan subgroups for a housing policy index, which is a simple average of the three housing policy support questions shown in Table 1. For full results, see Table A13.

Democrats' support.

Taken together, Table 1 and Figure 3 make clear that the kinds of ideological and partisan information available to millions of voters about housing policy indeed have polarizing effects, convincing people to think more like partisans than they otherwise would. Perhaps unsurprisingly, ideological arguments appear somewhat less polarizing than partisan cues, because they are somewhat persuasive to both Democrats and Republicans (on this point, see Coppock (2022)). But for the many people living in housing-crunched metro-areas, with both active YIMBY movements and state legislatures that are attempting to address the crisis, exposure to the dual ideological and partisan information available to them could serve to nationalize this issue.

Next, we assess whether this information can cause these national, partisan divisions to supplant the self-interested concerns that more typically dominate local politics. In other words, can partisan and ideological information convince even Democratic *homeowners* to support housing densification policies?

Figure 4: Treatment Effects by Party and Homeownership Subgroup



Note: The figure shows the change in support among partisan subgroups for a housing policy index, which is a simple average of the three housing policy support questions shown in Table 1. "Renter" includes those who say they live with a homeowner. For full results, see Table 4.

Figure 4 shows that it can. It replicates Figure 3, this time comparing pre- and post-treatment support for the housing policy index among four subgroups: Democratic homeowners (dark blue); Democratic renters (light blue); Republican homeowners (dark red); and Republican renters (light red).

Starting again with the pre-treatment levels of support, we can see that both partisan and self-interested divisions characterize housing policy opinion: across all four conditions, Democrats are typically more supportive of housing densification than Republicans, and renters are typically more supportive than homeowners – both only within partisan subgroups.

Post-treatment, this partisan sorting is exacerbated by Democrats' increase in support for housing reforms, rather than Republicans' backlash against it, as we have already seen.[28]

What Figure 4 further reveals is that this sorting is driven not only by Democratic

28. While Republican renters are somewhat persuaded by the YIMBY argument for affordability, Republican homeowners are not receptive to any of the three treatments, although they also do not demonstrate significant backlash in response to the state or combined treatments.

renters, but also by Democratic homeowners. In fact, across the three treatment conditions, Democratic homeowners increase their support for supply-side housing interventions just as much as Democratic renters and much more than Republican homeowners.[29] In other words, they are responding to partisan and ideological information as *Democrats* rather than as *self-interested homeowners*.

Table 2 reveals why: both the state-level partisan information and local-level ideological information teach voters that Democrats are more likely to support housing densification policies, thereby causing Democrats to align with their partisan group.

As described above, we hypothesized that increases in Democrats' support for housing densification would operate through different mechanisms: that the state-level partisan cue would cause Democrats to follow their leaders, and that local-level affordability argument would cause liberals to align their housing policy preferences with their ideological predispositions. To tease apart these mechanisms, participants also answered questions about their knowledge of the partisan and ideological stakes of housing densification policies. First, we assessed their knowledge of partisan divisions on housing by asking them which political party is more likely to support "Changing local zoning codes to make it easier to build new housing." Participants received a 1 if they answered that Democrats were the party most likely to change local zoning laws to make it easier to build housing; 0 otherwise. Then, we assessed their knowledge of the distributional consequences of housing densification by asking whether they thought "Building more housing" would "help low-income Americans, hurt low-income Americans, or have no effect." Participants received a 1 if they responded that building more housing would benefit low-income Americans; 0 otherwise.[30]

Both questions were asked pre- and post-treatment, such that we can estimate the effect of each treatment on the change in knowledge of the partisan divisions and distributional consequences of supply-side housing interventions. To do so, Table 2 reports the coefficients

29. The parallel increase in support among Democratic homeowners and renters was somewhat surprising to us: we had expected that, because the treatments would cross-pressure Democratic homeowners, they would increase their support less than Democratic renters.

30. Both questions were asked as part of larger batteries across a wide range of policies.

from an OLS model regressing change in knowledge on each of the three treatment conditions. The control, again, is the reference. Positive coefficients thus indicate that the treatment increased awareness that Democrats support changing local zoning laws (column (1)) or that building more housing benefits low-income Americans (column (2)).

Table 2: Treatment Effects on Party and Distributional Knowledge

	(1) Party Knowledge	(2) Distributional Knowledge
Local	0.065*	0.025
	[0.013, 0.118]	[−0.051, 0.102]
State	0.112*	−0.003
	[0.028, 0.195]	[−0.029, 0.023]
Combined	0.091*	0.011
	[0.023, 0.159]	[−0.026, 0.048]
Num.Obs.	7.734	7.734
R2	0.009	0.001

95% confidence intervals in brackets. Standard errors clustered at the state level. * p < 0.05, ** p < 0.01, *** p < 0.001

As the table shows, all three treatments increase respondents' awareness that the Democratic Party is more supportive of supply-side housing interventions. This is true even in the nonpartisan, local condition.

By contrast, contra our expectations, none of the treatments affect respondents' awareness that supply-side interventions benefit low-income Americans. Again, this is true even of the local-level information treatment, which explicitly offers an affordability argument in favor of supply-side housing intervention. This adds further support to existing evidence that voters are reluctant to believe that greater housing supply would reduce costs (Nall, Elmendorf, and Oklobdzija 2022). While pre-treatment knowledge of the distributional impact of housing densification is about twice as high as pre-treatment knowledge of partisan support for housing densification (62% vs. 29%), ceiling effects are unlikely to be a concern: 38% of respondents still answer the distributional knowledge question incorrectly, and both are below traditional political knowledge measures, with 70% correctly identifying Republican

control of the House and 69% correctly identifying Republican control of the Senate.

Taken together, these findings suggest that *both* the partisan and nonpartisan, ideological information increase Democrats' support for housing reforms through a "follow-the-leader" process, rather than convincing them to support policies that conform to their ideological predispositions.

Discussion

This paper demonstrates that self-interested behavior in local politics is conditional on the local information environment. We show that partisan and ideological information about housing policy is increasingly available in subnational contexts and that this information can meaningfully change policy preferences. When voters have access to the same kinds of information about housing policy that typically guides their opinion on national policies, they think in similar ways: as partisans rather than self-interested actors. Democratic homeowners react to partisan cues and liberal arguments about housing policy in nearly identical ways to Democratic renters.

These findings thus contribute to a growing body of research examining the conditions under which local political behavior may be guided by the same forces (partisanship and ideology) that tend to guide national political behavior. Existing scholarship has argued that partisan behavior in subnational politics may be the result of *a lack of information* (Hopkins 2018), in part because researchers have focused on traditional sources of local news, such as newspapers, which tend to provide nonpartisan information about local elections. By contrast, we focus on recent social movement mobilization on social media and state legislative policymaking in the case of housing policy, finding that many voters navigate local information environments increasingly rife with partisan and ideological cues. Our experimental results demonstrate the polarizing potential of these information inputs: when voters encounter partisan and ideological cues at the local level, they follow the leader just as they do at the national level. This is true even in a policy area where self-interest is more

easily discernible and influential in voters' policy preference formation (Fischel 2001; Hall and Yoder 2022).

Two surprising findings reveal paths for future research. First, the relationship between self-interest and partisan or ideological cues is not a simple trade-off. Though Democratic renters support densification policies at higher rates overall, Democratic homeowners are just as persuaded by polarizing cues as Democratic renters, despite cross-pressuring self-interest. On the other hand, Republican renters and homeowners show more divergent patterns in response to ideological cues. This complex interplay, particularly for cross-pressured voters, merits further research.

Second, partisan and ideological cues both operate through the same mechanism: updated knowledge of partisan policy stances. Despite the best efforts of the YIMBY movement, the experimental evidence suggests that voters are learning *partisan lessons* even from nonpartisan affordability arguments. This outcome may only be possible in the current context, in which the parties are clearly ideologically sorted (American Political Science Association Committee on Political Parties 1950; Levendusky 2009). This raises questions about the extent to which voters interpret other ideological arguments as partisan, and whether they interpret the YIMBY movement itself (or other social movements making ideological arguments) as partisan.

Third, long-run structural changes in local information environments suggest that the dynamics we document may generalize beyond housing policy. The collapse of local newspapers, and their substitution by social media, has shifted local information environments away from nonpartisan sources and toward more partisan and ideological content. Two trends could accelerate this process: social movements are increasingly using social media as a tool for informing and mobilizing voters, and state and local politicians are communicating directly with constituents through social media rather than through mass media intermediaries. As local news deserts expand, the patterns we observe in housing may be better understood as an early signal of how local political opinion formation will operate in an era in which

social media serves as the primary source of local political information, rather than as a peculiarity of a uniquely nationalized policy debate.

These findings suggest that partisanship may become even more influential in local politics in coming years, particularly as state legislatures and local activist groups mobilize around local environmental, criminal justice, school curriculum, and public health policies. Even as some local activist groups eschew explicit partisan labels, the specific frames they employ may generate partisan polarization, particularly in places where traditional sources of local news (e.g., newspapers) are not readily available. A local political arena ruled by partisanship rather than self-interest in a polarized era presents new challenges to democratic governance.

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Online Appendix for: "Pathways of Local Opinion Formation: The Case of Housing Policy"

Contents

Appendix A: State preemption Legislation & YIMBY Movement Frames

State preemption Legislation

As noted in the main text, we identified a total of 114 state preemption laws that were passed between 2016-2024. Table A1 shows the breakdown of these laws by category.

Table A1: Categories of preemption Legislation Across All States, 2016-2024

	Percentage
Streamlining zoning	39.5
Legalizing/liberalizing ADUs	20.2
Other	11.4
Transit-Oriented Development	7.0
Lessening Parking Requirements	7.0
Offering Density Bonuses	4.4

Table A2 shows further details on preemption laws passed in the states included in our survey sample. As described in the main text, in every single state in the sample, a majority of Democrats supported preemption.

Table A2: Preemption Legislation Among States in Survey Sample, 2016-2024

State	ADUs	MFH in SFH neighbor-hoods	Transit-/city-center oriented development	Parking require-ments	Den-sity bonus	Avg % Dem Vote in Favor	Avg % Rep Vote in Favor
AZ	Yes	Yes	No	No	No	80	67
CA	Yes	Yes	Yes	Yes	Yes	94	59
CO	Yes	No	Yes	Yes	No	88	5
FL	No	No	Yes	Yes	No	84	96
MD	No	No	No	No	Yes	95	6
MA	Yes	No	Yes	No	No	99	81
WA	Yes	Yes	No	Yes	No	97	74

Coding YIMBY Movement Tweets

Figure A1 shows the distribution of Tweets over time. We find that while certain MSAs (Seattle, San Francisco) lead in volume, most MSAs are well represented and volume over time is reasonably balanced in our corpus.

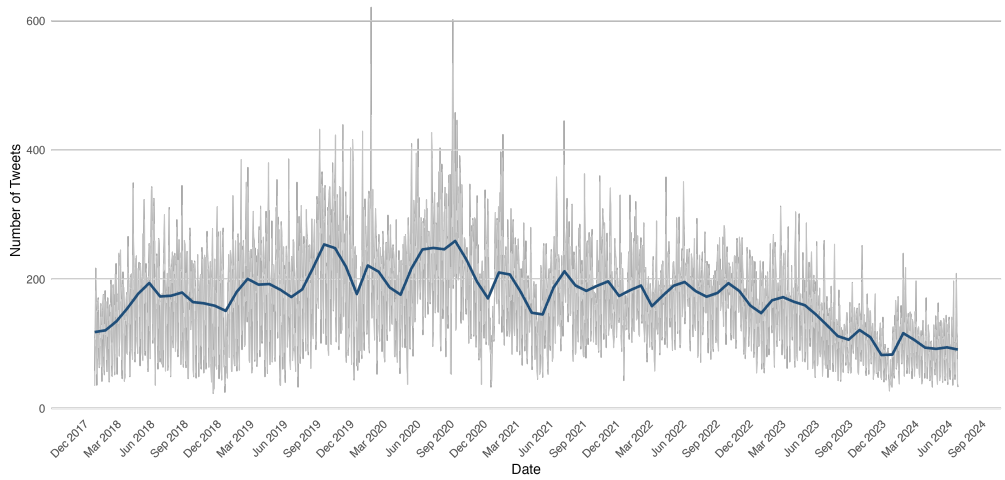


Figure A1: Tweet Corpus Distribution Over Time

Below we provide further information as to how we measured the prevalence of each frame. First, we include the full text of the codebook.

Codebook for YIMBY Tweets

1. supply-side: This includes calls for more housing, abundant housing, market-rate housing, housing regardless of income or at all prices, denser housing, missing middle housing, or explicit calls for building more housing or celebration of building more housing. Only include if there is a call for abundance or more development that is separate from calls for affordability. If the document only includes calls for more development as a way to increase affordability, then it will be coded elsewhere as affordability and will not be included here. Do not include updates on specific developments unless there is a celebration of that development that ties it to broader encouragement of increased housing production.

2. affordability: Discussions of how increased development lowers housing costs, housing as a poor people's issue, addressing housing affordability, or calls to build more low-income or affordable housing. Includes any tweets that discuss impacts of development on housing prices and the need to lower housing prices through more development. Does not include mentions of a housing crisis or need for government action to address rapidly rising housing costs.

3. homelessness: Mentions of addressing homelessness through housing policy, how more development reduces homelessness, or framing homelessness as a housing issue. Tweets that discuss homelessness without mentioning housing development or housing policy should not be coded here.

4. regulation: Calls to upzone, deregulate, streamline regulation, or discussions of how regulations affect housing costs. Does not include legislative updates or anything that is too in the weeds about specific bills or regulations. This category is about how regulations in the abstract increase housing costs by reducing development. This includes discussions of bans on certain types of housing or development, restrictive zoning laws, and parking minimums.

5. climate: Framing housing as a climate issue, discussing how density improves walkability and decreases carbon emissions, or arguing for sustainable, walkable communities with denser housing. Includes documents that discuss how increased density is better for the environment or ties housing justice to environmental justice. This should not be coded yes for any mention of conservation or environmentalism; rather the tweet should be tying climate change, environmentalism, or conservation to housing supply and housing policy to be coded yes.

6. racial_justice: References to racially exclusionary zoning, redlining, segregation, or framing housing as a racial justice issue. Includes calls for housing development to create racially and ethnically diverse/multicultural neighborhoods. Mentions of "di-

versity" by themselves without specific reference to race or ethnicity should be coded under inclusivity.

7. housing_crisis: Calls to address the housing crisis, identifying housing costs as a social problem that needs to be addressed urgently, or discussing rapidly rising costs of housing as an emergency. Includes explicit mentions of an affordability crisis or a housing crisis. Also includes implicit mentions of urgency or emergency in dealing with rising housing costs as a social issue. There should be some indication of urgency, emergency or crisis in order to be coded here.

8. partisan_cues: Noting that pro-housing is liberal/progressive, calling NIMBYs Republicans or Trump supporters, or describing YIMBYs as liberal/progressive. This frame should only be coded yes when there is an explicit partisan tie between housing policy/housing development/NIMBYism and partisanship or ideology.

Next, Table A2 shows our intercoder reliability results. Tables A3-A4 show our complete modeling results using five-fold cross-validation and the full regression results from Figure 2, respectively.

Table A3: Inter-annotator Agreement

Frame	**N**	**Agreement (%)**	**Cohen's κ**
Affordability	50	92	0.62
Climate	50	100	1.00
Homelessness	50	96	0.65
Housing Crisis	50	98	0.85
Supply-Side	50	88	0.63
Partisan Cues	50	96	0.48
Racial Justice	50	98	0.85
Regulation	50	94	0.37

Table A4: Model Performance Metrics

Values shown as mean (standard deviation) from 5-fold cross-validation.

Topic	Model	Accuracy	Precision	Recall	Binary F1	ROC AUC
Affordability	BERT + LR	.92 (.01)	.77 (.04)	.81 (.03)	.79 (.03)	.89 (.04)
	Logistic Regression	.94 (.01)	.81 (.05)	.85 (.08)	.83 (.06)	.96 (.04)
	Naive Bayes	.91 (.01)	.55 (.20)	.51 (.03)	.50 (.05)	.79 (.03)
	SVM	.95 (.03)	.87 (.11)	.80 (.11)	.83 (.11)	.98 (.01)
Climate	BERT + LR	.97 (.01)	.81 (.06)	.74 (.05)	.76 (.05)	.91 (.03)
	Logistic Regression	.97 (.01)	.80 (.06)	.75 (.06)	.77 (.06)	.94 (.02)
	Naive Bayes	.96 (.00)	.48 (.00)	.50 (.00)	.49 (.00)	.56 (.12)
	SVM	.97 (.01)	.86 (.11)	.73 (.08)	.77 (.08)	.93 (.04)
Homelessness	BERT + LR	.97 (.01)	.74 (.23)	.63 (.11)	.66 (.14)	.87 (.09)
	Logistic Regression	.97 (.01)	.69 (.25)	.58 (.11)	.61 (.15)	.85 (.12)
	Naive Bayes	.97 (.01)	.48 (.00)	.50 (.00)	.49 (.00)	.60 (.23)
	SVM	.97 (.01)	.69 (.25)	.58 (.11)	.61 (.15)	.90 (.05)
Housing Crisis	BERT + LR	.93 (.03)	.80 (.08)	.82 (.07)	.80 (.06)	.94 (.04)
	Logistic Regression	.98 (.02)	.97 (.04)	.87 (.11)	.91 (.09)	.98 (.02)
	Naive Bayes	.92 (.01)	.46 (.00)	.50 (.00)	.48 (.00)	.84 (.05)
	SVM	.98 (.01)	.97 (.04)	.89 (.04)	.93 (.04)	.97 (.02)
Supply-Side	BERT + LR	.90 (.04)	.79 (.07)	.80 (.09)	.79 (.08)	.89 (.09)
	Logistic Regression	.90 (.02)	.79 (.04)	.79 (.06)	.79 (.05)	.90 (.04)
	Naive Bayes	.87 (.01)	.73 (.25)	.52 (.02)	.50 (.03)	.70 (.11)
	SVM	.91 (.02)	.85 (.03)	.77 (.06)	.79 (.05)	.94 (.03)
Partisan Cues	BERT + LR	.97 (.01)	.79 (.19)	.70 (.11)	.73 (.14)	.64 (.12)
	Logistic Regression	.98 (.01)	.84 (.20)	.70 (.11)	.74 (.14)	.83 (.13)
	Naive Bayes	.97 (.01)	.48 (.00)	.50 (.00)	.49 (.00)	.69 (.05)
	SVM	.98 (.01)	.89 (.20)	.70 (.11)	.76 (.14)	.90 (.12)
Racial Justice	BERT + LR	.97 (.02)	.94 (.10)	.79 (.06)	.84 (.07)	.96 (.04)
	Logistic Regression	.96 (.02)	.78 (.19)	.68 (.12)	.71 (.14)	.95 (.04)
	Naive Bayes	.94 (.01)	.47 (.00)	.50 (.00)	.49 (.00)	.67 (.15)
	SVM	.97 (.01)	.88 (.21)	.69 (.12)	.74 (.15)	.95 (.05)
Regulation	BERT + LR	.93 (.03)	.81 (.06)	.77 (.10)	.77 (.08)	.90 (.04)
	Logistic Regression	.93 (.01)	.81 (.19)	.63 (.08)	.66 (.11)	.86 (.06)
	Naive Bayes	.91 (.00)	.45 (.00)	.50 (.00)	.48 (.00)	.67 (.12)
	SVM	.94 (.02)	.87 (.21)	.65 (.11)	.69 (.14)	.90 (.04)

Table A5: Regression Results by Category (Method: grf, Rule: or, Cross-fit: 5, Sample-split: 10)

Category	Model	Estimate	Std. Error	95% CI
Affordability	Linear	0.053***	0.001	[0.052, 0.055]
	Logistic	0.053***	0.001	[0.052, 0.055]
Climate	Linear	0.021**	0.007	[0.007, 0.036]
	Logistic	0.021***	0.007	[0.011, 0.042]
Homelessness	Linear	0.004	0.003	[-0.001, 0.009]
	Logistic	0.004***	0.003	[0.001, 0.015]
Housing Crisis	Linear	0.028***	0.001	[0.025, 0.031]
	Logistic	0.028***	0.001	[0.026, 0.031]
Partisan Cues	Linear	0.010	0.014	[-0.018, 0.038]
	Logistic	0.010**	0.014	[0.001, 0.146]
Racial Justice	Linear	0.011**	0.003	[0.004, 0.018]
	Logistic	0.011***	0.003	[0.006, 0.020]
Regulation	Linear	0.032***	0.002	[0.027, 0.037]
	Logistic	0.032***	0.002	[0.028, 0.037]
Supply-Side	Linear	0.123***	0.001	[0.120, 0.125]
	Logistic	0.123***	0.001	[0.120, 0.125]

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

Figure A2 shows the results of models estimating prevalence of frame by MSA.

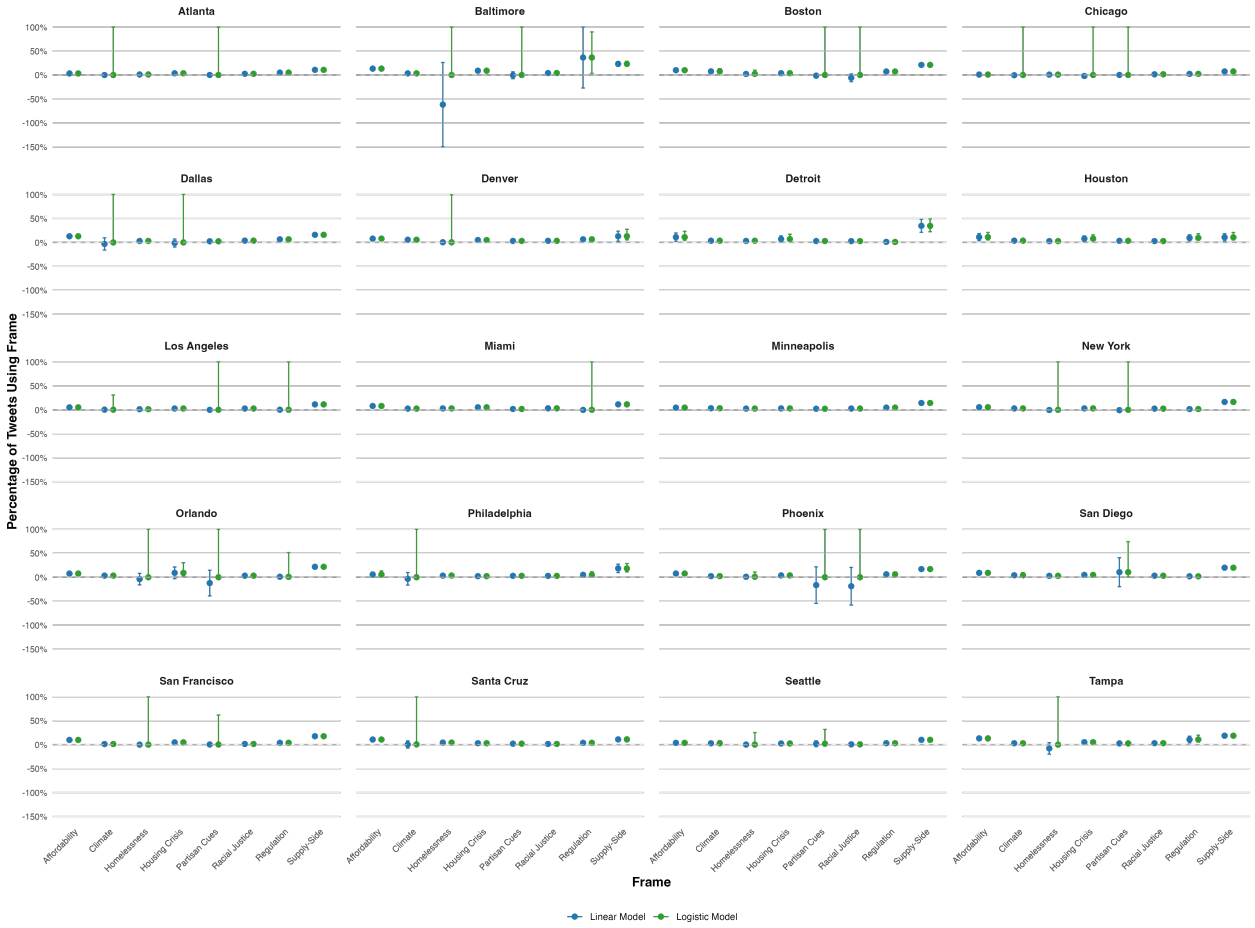


Figure A2: Regression results

Finally, Figure A3 shows the predicted change in engagement (measured by likes and log likes) when each frame is predicted to be used. Table A6 and A7 show the full regression results.

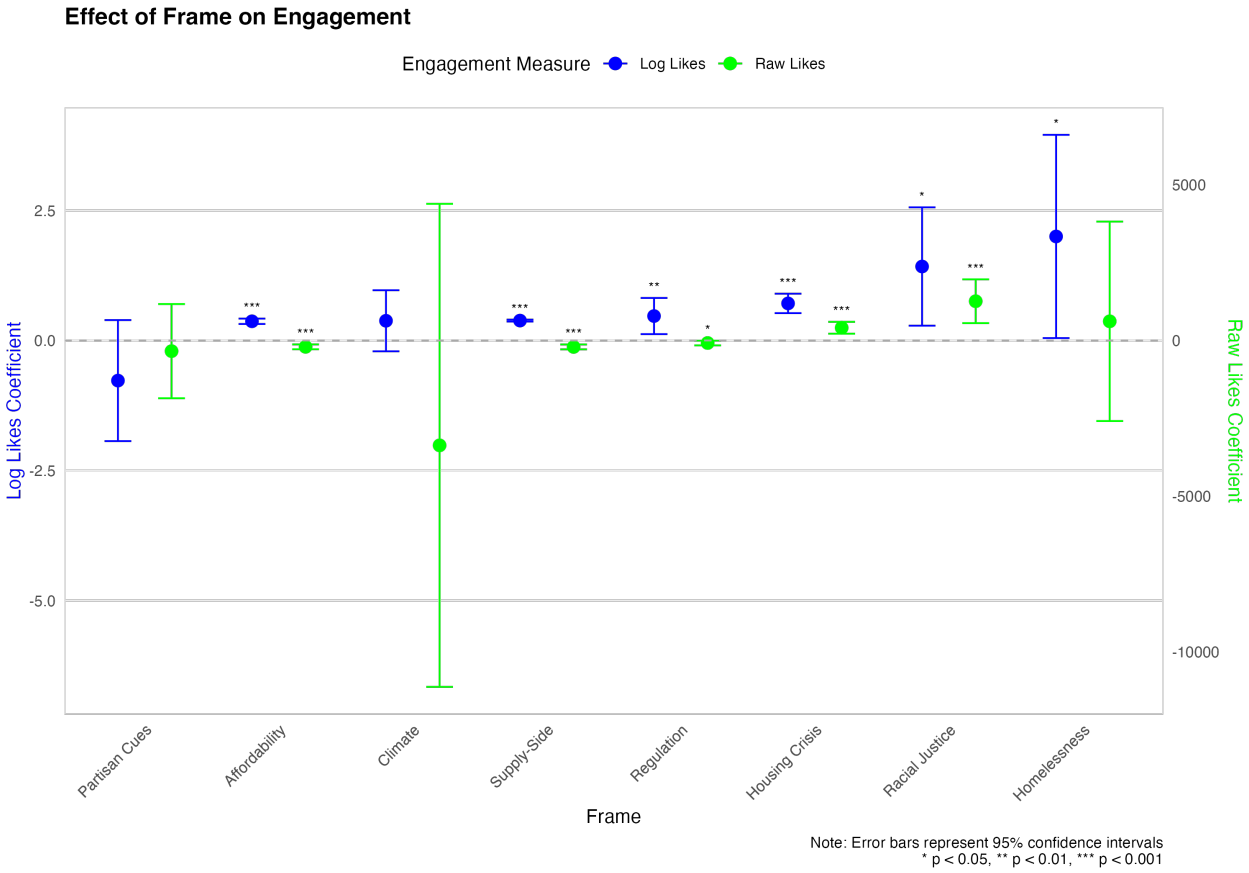


Figure A3: Frames and engagement

Table A6: Effect of Frame on Likes (Log Scale) (Log Scale, Method: grf, Rule: or)

Frame	Coefficient	Estimate	Std. Error	CI Lower	CI Upper	N
Affordability	human	0.369***	(0.026)	0.317	0.420	391
Climate	human	0.378	(0.300)	-0.209	0.965	980
Homelessness	human	1.999*	(0.997)	0.046	3.953	398
Housing Crisis	human	0.712***	(0.095)	0.525	0.899	396
Supply-Side	human	0.382***	(0.009)	0.364	0.401	487
Partisan Cues	human	-0.772	(0.594)	-1.935	0.392	354
Racial Justice	human	1.422*	(0.580)	0.284	2.559	344
Regulation	human	0.469**	(0.177)	0.122	0.817	326

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$
Coefficients represent approximate percentage changes in engagement

Table A7: Effect of Frame on Likes (Raw Likes) (Raw Likes, Method: grf, Rule: or)

Frame	Coefficient	Estimate	Std. Error	CI Lower	CI Upper	N
Affordability	human	-204.719***	(39.662)	-282.457	-126.981	391
Climate	human	-3368.214	(3956.494)	-11122.943	4386.515	980
Homelessness	human	614.958	(1633.772)	-2587.236	3817.152	398
Housing Crisis	human	407.441***	(97.152)	217.024	597.859	396
Supply	human	-207.296***	(40.231)	-286.150	-128.442	487
Partisan Cues	human	-342.836	(771.625)	-1855.220	1169.549	354
Racial Justice	human	1259.647***	(358.515)	556.957	1962.337	344
Regulation	human	-81.270*	(39.230)	-158.161	-4.379	326

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$
Coefficients represent absolute changes in engagement count

Appendix B: Additional Information about the Conjoint

As described in the main text, once we had identified the YIMBY movement's most common frames, we sought to choose the "strongest" frame so as to guard against a null finding due to a weak frame. To do so, we conducted a conjoint experiment on CloudResearch, which showed us that the affordability frame was the strongest. Below, we provide more details on that experiment.[31] Table A8 shows summary demographic statistics for the conjoint.

Table A8: Demographic Characteristics of Prolific Sample

Characteristic	**Proportion**
Age 18-29	**21.1%**
Age 30-49	**55.8%**
Age 50-64	**17.6%**
Age 65+	**5.5%**
Female	**48.0%**
Male	**50.4%**
Less than College Degree	**32.0%**
College Degree+	**67.9%**
Low Income	**10.3%**
Middle Income	**39.5%**
High Income	**50.1%**
Single-Family Homeowner	**45.7%**
Non-single-family Homeowner	**5.6%**
Renter	**36.0%**
Live with homeowner	**12.6%**
Democrat	**49.7%**
Republican	**22.4%**
Independent	**27.8%**
Democrat Leaning Independents	**17.2%**
Republican Leaning Independents	**10.5%**

Participants were asked to choose between four randomly generated pairs of proposed legislation that their states might consider adopting. These pairs varied across four dimensions: Makes it easier to build (X kind of housing), Changes zoning laws in (X neighborhood),

31. The experiment was deemed exempt from IRB review. The experiment was pre-registered.

Support among state legislators; and Arguments in favor. Each policy dimension was chosen at random from k possible levels, as shown in Table A9.

Table A9: Conjoint Attributes & Levels

Attributes	Levels
Makes it easier to build:	Single-family homes/Accessory dwelling units, or "granny flats"/2-4 unit apartments/Apartment buildings with less than 10 units/Apartment buildings with more than 10 units
Changes zoning laws in:	Neighborhoods zoned for single-family homes/Downtown, commercial, and transit-rich neighborhoods/All neighborhoods
Support among state legislators:	Most Democrats Support/Most Republicans Support/There is Bipartisan Support
Arguments in favor:	Supply-Side/Affordability/Regulation/Housing Crisis/Climate/Racial Justice/Homelessness

We estimate the Average Marginal Component Effect (AMCE), using ordinary least squares regression with standard errors clustered at the respondent level. The AMCE reflects the effect of viewing one level of a dimension on the probability that a respondent chooses the policy, estimated over the joint probability of all other policy dimensions and the sampling distribution of respondents (Abramson, Koçak, and Magazinnik 2019; Bansak et al. 2022). In other words, it assesses how much more or less likely a randomly-generated policy is to be chosen, when the level of one dimension switches from 0 to 1 (Bansak et al. 2022).[32] Because AMCEs depend on the respondent distribution, which has implications for generalizability, we recruited a sample for the conjoint that is likely to match the survey sample in Phase III (urban and suburban residents). We estimate AMCEs for the entire sample, as well as for split-samples defined by partisanship.[33]

32. Because of the way AMCEs aggregate preferences according to both the distribution of policies and the sample, they reflect both the intensity of preferences and the direction of preferences (Abramson, Koçak, and Magazinnik 2019). Although this means they do not reflect a simple majority preference, they can be used to estimate the effect of an attribute on the probability of selecting a profile (and on vote share in an election with the same specifications as the conjoint) (Bansak et al. 2022).

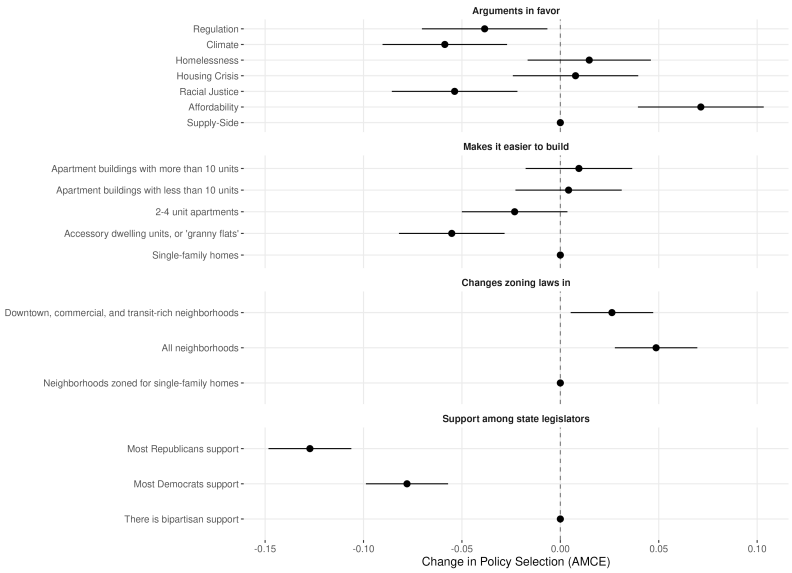
33. We include leaners as partisans and drop one pure Independent from the analysis. Figure Figure **??** shows the results when we include leaners as Independents and analyze them as a third subgroup.

Table A10: YIMBY Movement Frames

Label	Frame Used in Conjoint
Supply-Side	"This bill will allow residents to build more housing throughout the state. If our state is serious about ending the housing shortage, we need to make housing more abundant."
Affordability	"This bill will make housing more affordable for working class residents, the foundation of our state's economy, by making it easier to build more and denser housing of all kinds."
Regulation	"This bill helps reduce the cumbersome regulations that make it more expensive to build housing. Our state needs to legalize more and different kinds of housing."
Housing Crisis	"This bill is essential for addressing the housing crisis. The crisis is decades in the making, and our state cannot afford to wait any longer to take serious action."
Climate	"This bill is a key part of the state's efforts to address climate change. Building denser housing helps mitigate climate change by discouraging car use and lowering air pollution."
Racial Justice	"This bill will help address a long history of systemic racism in our state. Exclusionary zoning that preserves single family neighborhoods contributes to racial segregation."
Homelessness	"This bill is an important step towards addressing homelessness in the state. Homelessness is a housing issue, and to address it our state needs to start building more housing, quickly."

Figure A4: Conjoint Results

(a) Full Sample



(b) By Partisan Subgroup

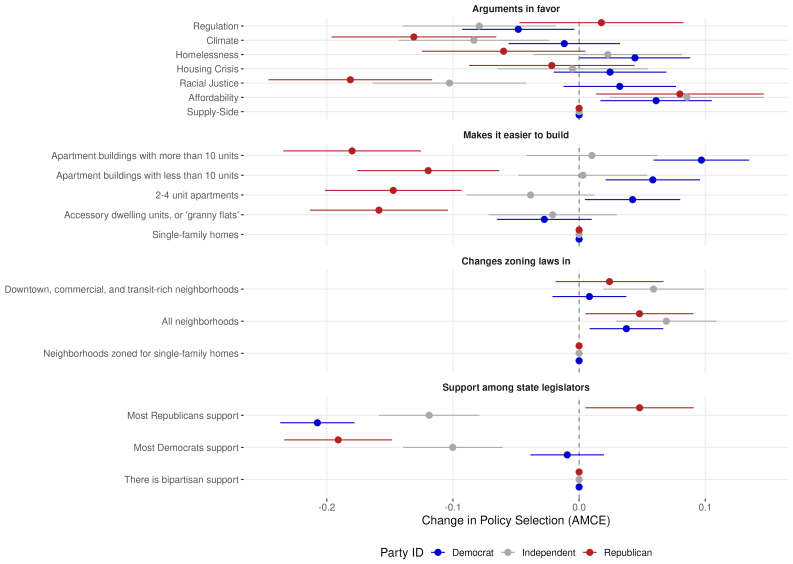


Figure A4 plots the AMCEs for each level relative to the reference category (supply-side frame, single-family homes, neighborhoods zoned for single-family homes, and bipartisan support), for all respondents in panel (a) and by partisan subgroup in panel (b).[34] As panel (a) shows, among all the YIMBY movement arguments in favor of supply-side interventions, the affordability frame leads to the highest probability of selection. The racial justice, climate, and regulation frames lead to a lower probability of selection than the supply-side frame, and the housing crisis and homelessness frames lead to a similar outcome.

Moreover, as panel (b) indicates, the affordability frame is also the only frame that is uniformly persuasive for both Republicans and Democrats. All others either fail to persuade anyone (housing crisis) or generate polarization between Democrats and Republicans (regulation, climate, homelessness, and racial justice). This is particularly true with the racial justice and climate frames: Republicans are far less likely to select a policy with either of those frames attached.

Appendix C: Additional Information about the Survey Experiment

As described in the main text, we sampled voters living in the 20 largest MSAs (excluding Washington, D.C. because it is not in a state). Given the experimental design that relied on state-level information, only residents of the state in which the central city of the MSA is located were recruited for the survey. For example, residents of New Jersey were excluded from the sample for the New York City MSA, but residents of Yonkers were included. Respondents were quota sampled to match ACS estimates by race/ethnicity, age, and gender. For more information about the sample and to compare the sample with the quota targets, see Table A11.

34. Our analyses exclude all respondents who failed the attention check (a total of 17).

Table A11: Survey Sample vs. MSA Population Targets (%)

		Gender						Race/Ethnicity												Age								
		Male			Female			White			Black			Hispanic			Other			18–34			35–64			65+		
MSA	N	S	Q	D	S	Q	D	S	Q	D	S	Q	D	S	Q	D	S	Q	D	S	Q	D	S	Q	D	S	Q	D
Atlanta-Sandy Springs-Alpharetta, GA	384	39.6	48.5	-8.9	60.4	51.5	8.9	42.7	43.5	-0.8	41.4	34.1	7.3	6.0	12.1	-6.1	9.9	19.7	-9.8	28.6	30.5	-1.9	58.9	52.4	6.5	12.5	17.1	-4.6
Baltimore-Columbia-Towson, MD	393	42.7	48.3	-5.6	57.3	51.7	5.6	40.7	53.0	-12.3	46.1	29.0	17.1	4.3	7.8	-3.5	8.9	16.2	-7.3	26.7	28.6	-1.9	59.8	50.4	9.4	13.5	21.0	-7.5
Boston-Cambridge-Newton, MA-NH	389	48.3	48.8	-0.5	51.7	51.2	0.5	66.3	64.3	2.0	8.7	8.1	0.6	14.1	12.9	1.2	10.8	24.8	-14.0	18.0	30.9	-12.9	58.9	48.6	10.3	23.1	20.4	2.7
Chicago-Naperville-Elgin, IL-IN-WI	386	45.6	49.2	-3.6	54.4	50.8	3.6	63.0	49.0	14.0	20.2	16.1	4.1	9.6	24.3	-14.7	7.3	29.1	-21.8	18.9	29.7	-10.8	59.6	50.4	9.2	21.5	19.8	1.7
Dallas-Fort Worth-Arlington, TX	378	50.0	49.5	0.5	50.0	50.5	-0.5	55.6	43.0	12.6	20.1	16.2	3.9	12.4	29.4	-17.0	11.9	31.1	-19.2	20.1	32.0	-11.9	60.6	52.1	8.5	19.3	15.9	3.4
Denver-Aurora-Lakewood, CO	388	39.2	50.4	-11.2	60.8	49.6	11.2	68.3	61.7	6.6	7.5	5.6	1.9	14.7	23.6	-8.9	9.5	25.3	-15.8	23.5	31.7	-8.2	53.1	50.7	2.4	23.5	17.6	5.9
Detroit-Warren-Dearborn, MI	395	42.3	49.0	-6.7	57.7	51.0	6.7	52.4	64.1	-11.7	38.2	21.5	16.7	3.3	5.1	-1.8	6.1	12.9	-6.8	28.4	27.8	0.6	50.9	50.0	0.9	20.8	22.2	-1.4
Houston-The Woodlands-Sugar Land, TX	393	43.3	49.7	-6.4	56.7	50.3	6.4	41.5	33.6	7.9	28.8	17.3	11.5	18.8	37.8	-19.0	10.9	37.5	-26.6	23.9	31.8	-7.9	62.8	52.0	10.8	13.2	16.2	-3.0
Los Angeles-Long Beach-Anaheim, CA	376	47.9	49.5	-1.6	52.1	50.5	1.6	42.6	28.2	14.4	9.0	6.3	2.7	25.0	44.8	-19.8	23.4	55.6	-32.2	25.0	30.9	-5.9	58.8	50.2	8.6	16.2	18.9	-2.7
Miami-Fort Lauderdale-Pompano Beach, FL	383	47.5	49.0	-1.5	52.5	51.0	1.5	39.7	28.2	11.5	21.7	20.3	1.4	32.9	46.0	-13.1	5.7	36.0	-30.3	25.1	25.8	-0.7	58.7	50.4	8.3	16.2	23.8	-7.6
Minneapolis-St. Paul-Bloomington, MN-WI	395	43.0	49.9	-6.9	57.0	50.1	6.9	76.2	71.5	4.7	9.4	9.3	0.1	2.8	6.8	-4.0	11.6	17.7	-6.1	16.2	29.2	-13.0	53.9	51.1	2.8	29.9	19.6	10.3
New York-Newark-Jersey City, NY-NJ-PA	373	51.2	48.4	2.8	48.8	51.6	-2.8	55.8	40.2	15.6	16.4	18.5	-2.1	16.1	26.2	-10.1	11.8	36.6	-24.8	26.5	29.7	-3.2	54.2	49.4	4.8	19.3	21.0	-1.7
Orlando-Kissimmee-Sanford, FL	386	39.6	49.1	-9.5	60.4	50.9	9.5	50.3	43.1	7.2	22.3	16.0	6.3	19.7	32.5	-12.8	7.8	31.6	-23.8	27.7	30.4	-2.7	51.6	49.8	1.8	20.7	19.7	1.0
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	393	46.1	48.4	-2.3	53.9	51.6	2.3	59.8	58.3	1.5	29.3	21.2	8.1	4.6	9.7	-5.1	6.4	18.4	-12.0	19.3	29.8	-10.5	59.5	48.8	10.7	21.1	21.4	-0.3
Phoenix-Mesa-Chandler, AZ	387	42.4	49.9	-7.5	57.6	50.1	7.5	59.4	53.6	5.8	11.9	5.7	6.2	14.7	30.8	-16.1	14.0	31.1	-17.1	22.0	30.4	-8.4	57.9	48.3	9.6	20.2	21.3	-1.1
Riverside-San Bernardino-Ontario, CA	382	39.5	50.1	-10.6	60.5	49.9	10.6	46.3	29.0	17.3	14.4	7.2	7.2	27.2	52.5	-25.3	12.0	52.1	-40.1	26.2	32.1	-5.9	54.7	49.5	5.2	19.1	18.4	0.7
San Diego-Chula Vista-Carlsbad, CA	383	37.9	50.6	-12.7	62.1	49.4	12.7	54.8	43.2	11.6	8.1	4.7	3.4	17.5	34.3	-16.8	19.6	42.3	-22.7	21.1	32.6	-11.5	51.4	48.3	3.1	27.4	19.1	8.3
San Francisco-Oakland-Berkeley, CA	387	52.7	49.8	2.9	47.3	50.2	-2.9	47.0	36.0	11.0	11.1	7.0	4.1	11.6	23.0	-11.4	30.2	53.0	-22.8	18.3	28.2	-9.9	59.4	51.2	8.2	22.2	20.6	1.6
Seattle-Tacoma-Bellevue, WA	391	49.9	50.5	-0.6	50.1	49.5	0.6	60.4	58.1	2.3	10.0	6.1	3.9	12.0	11.4	0.6	17.6	33.1	-15.5	17.9	31.6	-13.7	64.5	50.6	13.9	17.6	17.8	-0.2
Tampa-St. Petersburg-Clearwater, FL	392	37.5	48.9	-11.4	62.5	51.1	11.4	63.0	59.4	3.6	15.8	11.8	4.0	13.0	21.1	-8.1	8.2	22.2	-14.0	20.7	26.0	-5.3	53.6	48.9	4.7	25.8	25.0	0.8

S = Survey, Q = Quota target, D = Difference (pp). All values are percentages.

Table A12: Balance Table: Covariate Means by Treatment Condition

	Control	Combined	Local	State
Homeowner	0.59 (0.49)	0.57 (0.50)	0.60 (0.49)	0.56 (0.50)
Single-Family Homeowner	0.48 (0.50)	0.47 (0.50)	0.49 (0.50)	0.45 (0.50)
Age	47.97 (16.50)	48.93 (16.71)	48.70 (16.55)	48.25 (16.42)
Male	0.44 (0.50)	0.45 (0.50)	0.44 (0.50)	0.44 (0.50)
White	0.54 (0.50)	0.53 (0.50)	0.57 (0.50)	0.53 (0.50)
Black	0.26 (0.44)	0.17 (0.37)	0.24 (0.43)	0.17 (0.38)
Hispanic	0.10 (0.30)	0.18 (0.38)	0.11 (0.31)	0.17 (0.38)
Asian	0.06 (0.24)	0.09 (0.28)	0.05 (0.22)	0.09 (0.28)
Bachelor's Degree or Higher	0.58 (0.49)	0.61 (0.49)	0.58 (0.49)	0.61 (0.49)
Income over $100k	0.35 (0.48)	0.37 (0.48)	0.36 (0.48)	0.37 (0.48)
Democrat	0.44 (0.50)	0.40 (0.49)	0.44 (0.50)	0.39 (0.49)
Democrat (with leaners)	0.61 (0.49)	0.59 (0.49)	0.60 (0.49)	0.58 (0.49)
Suburban Resident	0.66 (0.47)	0.73 (0.44)	0.68 (0.46)	0.74 (0.44)

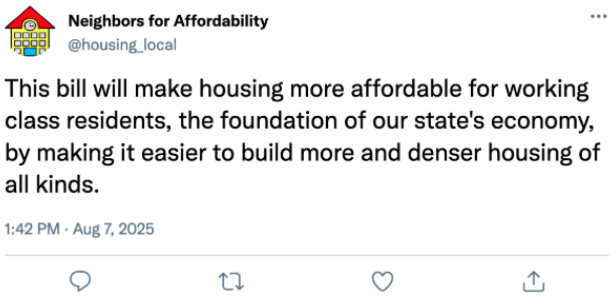
Standard deviations in parentheses. All variables are binary (0/1) except Age.

Treatment was assigned via stratified weighted randomization. Residents in non-preemption states received either the local treatment or control with 50% probability. Residents of preemption states were assigned to either the local treatment or control with 8.3% probability or to either the state or combined treatments with 41.7% probability. All analyses include inverse probability weights to correct for differential likelihood of treatment assignment. Table A12 shows the covariate balance across all four treatment conditions.

The actual text of the treatments are shown below:

- *State Information*: The [X state] legislature has recently passed legislation, with majority Democrat support, that requires cities and towns to change local zoning laws to enable more housing development. The goal of these changes is to make it easier to build housing, which will increase the supply and density of housing.

- *Local Information*: A local organization focused on housing affordability in your area has been advocating for new policies in the [X state] legislature, which would require cities and towns to change local zoning laws to enable more housing development. The goal of these changes is to make it easier to build housing, which will increase the



supply and density of housing. The organization posted the following on social media (see below for image):

- *State & Local Information:* The [X state] legislature has recently passed legislation, with majority Democrat support, that requires cities and towns to change local zoning laws to enable more housing development. The goal of these changes is to make it easier to build housing, which will increase the supply and density of housing. A local organization focused on housing affordability in your area posted the following on social media (see below for image):

- *Control:* The [X state] legislature has recently passed a resolution to recognize the outstanding achievements of the [X state] Mycological Society in helping to identify a new species of fungus.

The local and combined conditions also included the following image.

Aside from the policy index used to simplify visualizations in Figures 3 and 4, all analyses in the main text were pre-registered. The policy index was created by simply averaging across all three policy outcomes and reporting the results by subgroup. We also pre-registered three additional hypotheses, which we summarize below.

Full results for figures 3 and 4 are presented in tables A13 and A14.

Table A15 reports the treatment effects on overall support for densification policies rather than changes in partisan sorting. Consistent with the findings in Figure 3, the effects are weakly positive, reflecting small increases in Democrats' support for densification policies but

Table A13: Treatment × Party Effects on Support for Densification Policies

	(1) Downtown	(2) SFH	(3) ADU
Local	−0.011	0.017	−0.003
	[−0.034, 0.012]	[−0.017, 0.052]	[−0.045, 0.038]
State	−0.046**	0.019	−0.009
	[−0.072, −0.020]	[−0.024, 0.063]	[−0.039, 0.021]
Combined	−0.028	−0.006	0.003
	[−0.059, 0.004]	[−0.052, 0.041]	[−0.049, 0.054]
Democrats/Leaners	−0.017	0.002	0.003
	[−0.039, 0.005]	[−0.031, 0.034]	[−0.030, 0.036]
Local × Democrats/Leaners	0.044*	0.017	0.017
	[0.006, 0.082]	[−0.018, 0.053]	[−0.020, 0.053]
State × Democrats/Leaners	0.065**	0.020	0.007
	[0.037, 0.094]	[−0.032, 0.071]	[−0.019, 0.034]
Combined × Democrats/Leaners	0.048*	0.050*	0.004
	[0.015, 0.082]	[0.006, 0.095]	[−0.055, 0.064]
Num.Obs.	7734	7734	7734
R2	0.006	0.005	0.001

95% confidence intervals in brackets. Standard errors clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] SFH: multifamily housing in single-family zoned neighborhoods.

[b] ADU: accessory dwelling units.

Table A14: Treatment × Party and Homeowner Effects on Support for Densification Policies

	(1) Downtown	(2) SFH	(3) ADU
Local	−0.023	−0.011	−0.019
	[−0.055, 0.010]	[−0.056, 0.033]	[−0.052, 0.013]
State	−0.060*	−0.001	−0.029
	[−0.103, −0.017]	[−0.037, 0.035]	[−0.062, 0.005]
Combined	−0.019	−0.021	−0.022
	[−0.071, 0.032]	[−0.078, 0.036]	[−0.079, 0.036]
Democratic Homeowner	−0.028*	−0.013	−0.007
	[−0.048, −0.008]	[−0.032, 0.006]	[−0.057, 0.044]
Democratic Renter	−0.014	0.000	−0.010
	[−0.058, 0.030]	[−0.066, 0.066]	[−0.043, 0.022]
Republican Renter	−0.013	−0.024	−0.034
	[−0.066, 0.039]	[−0.093, 0.045]	[−0.094, 0.027]
Local × Democratic Homeowner	0.048	0.034	0.034
	[−0.021, 0.117]	[−0.028, 0.095]	[−0.014, 0.082]
State × Democratic Homeowner	0.092**	0.043	0.021
	[0.050, 0.133]	[−0.001, 0.086]	[−0.018, 0.060]
Combined × Democratic Homeowner	0.044**	0.078**	0.013
	[0.021, 0.067]	[0.034, 0.122]	[−0.068, 0.095]
Local × Democratic Renter	0.063*	0.058	0.032
	[0.015, 0.111]	[−0.008, 0.125]	[−0.006, 0.069]
State × Democratic Renter	0.065*	0.037	0.033
	[0.010, 0.121]	[−0.061, 0.135]	[−0.012, 0.077]
Combined × Democratic Renter	0.036	0.053	0.044
	[−0.033, 0.105]	[−0.033, 0.139]	[−0.020, 0.107]
Local × Republican Renter	0.034	0.082	0.047
	[−0.019, 0.087]	[−0.020, 0.185]	[−0.029, 0.123]
State × Republican Renter	0.038	0.057	0.056
	[−0.054, 0.130]	[−0.038, 0.152]	[−0.037, 0.148]
Combined × Republican Renter	−0.024	0.045	0.071*
	[−0.102, 0.055]	[−0.071, 0.161]	[0.023, 0.119]
Num.Obs.	7734	7734	7734
R2	0.007	0.009	0.003

95% confidence intervals in brackets. Standard errors clustered at the state level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] SFH: multifamily housing in single-family zoned neighborhoods.

[b] ADU: accessory dwelling units.

null results for Republicans.

Table A15: Overall Treatment Effects on Support for Densification Policies

	(1) Downtown	(2) SFH	(3) ADU
Local	0.015*	0.028*	0.006
	[0.000, 0.030]	[0.004, 0.051]	[−0.017, 0.029]
State	−0.008	0.031*	−0.005
	[−0.025, 0.009]	[0.004, 0.057]	[−0.025, 0.015]
Combined	0.001	0.024	0.005
	[−0.025, 0.027]	[−0.001, 0.049]	[−0.016, 0.025]
Num.Obs.	7734	7734	7734
R2	0.002	0.003	0.000

95% confidence intervals in brackets. Standard errors clustered at the state level. * p < 0.05, ** p < 0.01, *** p < 0.001

[a] SFH: multifamily housing in single-family zoned neighborhoods.

[b] ADU: accessory dwelling units.

Table A16 reports results for an alternative outcome measure — support for the hypothetical legislation presented in a given treatment condition. Partisan sorting is significantly higher in all three treatment conditions relative to the control, mirroring the main results for each of the three policy outcomes. This alternative outcome suggests that partisan and ideological cues generate polarization in a more direct way by sorting partisan attitudes on the given legislation itself, not just the broad policy goals.

Table A16: Treatment → Legislation Support Polarization

	(1) Sorted Legislation Support
Local	0.055**
	[0.029, 0.080]
State	0.048*
	[0.013, 0.083]
Combined	0.059**
	[0.027, 0.092]
Num.Obs.	7734
R2	0.011

95% confidence intervals in brackets. Standard errors clustered at the state level. * p < 0.05, ** p < 0.01, *** p < 0.001

Finally, Table A17 reports results for an additional pre-registered subgroup analysis. Consistent with the idea that partisan and ideological cues are most valuable to those who have low levels of existing knowledge, we hypothesize smaller treatment effects for those with high levels of knowledge. Respondents are categorized as having high state knowledge if they correctly identify their governor and self-report following state-level news "very closely." Respondents are categorized as having high local knowledge if they correctly identify the goals of the YIMBY movement and self-report following local news or neighborhood news "very closely." The results of this subgroup analysis are uniformly null, suggesting that these cues may be helpful even for those with high levels of existing knowledge. This finding obtains regardless of the knowledge specification.

Table A17: Treatment × Knowledge → Polarization

	(1) Down-town	(2) SFH	(3) ADU	(4) Down-town	(5) SFH	(6) ADU
Local Treatment	0.015	0.002	0.002	0.022*	0.011	0.008
	[−0.010, 0.040]	[−0.024, 0.029]	[−0.014, 0.019]	[0.004, 0.039]	[−0.005, 0.026]	[−0.006, 0.021]
State Treatment	0.016	0.007	−0.007	0.027**	0.014	0.001
	[−0.005, 0.038]	[−0.019, 0.033]	[−0.023, 0.009]	[0.013, 0.040]	[−0.009, 0.036]	[−0.009, 0.012]
Combined Treatment	0.017	0.019	−0.002	0.021*	0.027*	0.000
	[−0.001, 0.036]	[−0.007, 0.045]	[−0.029, 0.025]	[0.001, 0.041]	[0.002, 0.051]	[−0.024, 0.024]
State Knowledge	−0.019	−0.031	−0.023			
	[−0.062, 0.025]	[−0.062, 0.000]	[−0.054, 0.009]			
Local Treatment × State Knowledge	0.037	0.046	0.026			
	[−0.037, 0.111]	[−0.023, 0.115]	[−0.020, 0.072]			
State Treatment × State Knowledge	0.052	0.029	0.038			
	[−0.009, 0.112]	[−0.017, 0.075]	[−0.002, 0.077]			
Combined Treatment × State Knowledge	0.020	0.039	0.018			
	[−0.012, 0.052]	[−0.008, 0.087]	[−0.022, 0.058]			
Local Knowledge				−0.050*	−0.030	−0.042
				[−0.099, −0.001]	[−0.157, 0.098]	[−0.117, 0.033]
Local Treatment × Local Knowledge				0.052	0.063	0.030
				[−0.101, 0.204]	[−0.072, 0.198]	[−0.050, 0.109]
State Treatment × Local Knowledge				0.048	0.020	0.020
				[−0.040, 0.136]	[−0.105, 0.146]	[−0.092, 0.132]
Combined Treatment × Local Knowledge				0.033	0.041	0.057
				[−0.028, 0.094]	[−0.153, 0.234]	[−0.045, 0.158]
Num.Obs.	7734	7734	7734	7733	7733	7733
R2	0.003	0.003	0.002	0.003	0.002	0.002

95% confidence intervals in brackets. Standard errors clustered at the state level. * p < 0.05, ** p < 0.01, *** p < 0.001

[a] SFH: multifamily housing in single-family zoned neighborhoods.

[b] ADU: accessory dwelling units.