Housing Narratives: The Mental Models Underlying Skepticism Towards Housing Development

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1 Abstract

What are Americans' mental models of housing markets, and how do these models relate to their support for local housing development? Americans' responses to proposed housing development have often been framed either in terms of self-interested homeowners blocking housing or renters failing to organize collectively. Political scientists have tended to assume self-interested behavior without fully understanding how people think about—and often misunderstand—housing markets. Building on economists' recent survey-based research on mental models, we focus on the apparent phenomenon of Supply Skepticism: the belief, heavily promoted by leftist housing advocacy campaigns, that additional housing supply will not reduce housing prices (Been et al, 2018). While people generally have market-skeptical beliefs, we suspect they are more widespread for housing. In two national surveys, we present hypothetical scenarios describing sudden increases

in housing supply, then elicit predicted price changes in regional housing markets. We link these predictions to respondents' generalized beliefs about markets and their tendency toward "zero-sum thinking." Preliminary findings from a March 2022 survey suggest that Supply Skepticism is widespread, weakly related to belief in basic "Econ 101" facts, and moderately associated with opposition to housing development. We discuss whether these beliefs reveal something unique about public understandings of housing markets or are a product of more generalized Manichaean, zero-sum beliefs about markets and economic elites. In this document, we present our preliminary results and a preanalysis plan for our second-round survey.

2 Introduction

Local political economy scholars have recently engaged with a puzzle: why is there so little organized support for housing development even though many Americans would benefit from more accessible and affordable housing? Most explanations from political science and economics alike have used the 'logic of collective action' (Olson 1965), focusing on disparities across groups in the costs and benefits of organizing for, or against, new development. Homeowners are well-organized and locally attached (often through HOAs), and committed to protecting their neighborhood's quality of life and the home values that go with it (Fischel 2001; Einstein, Glick, and Palmer 2019). Renters, meanwhile, would benefit from lower housing prices that come with development, but the market-wide price impacts of new development are diffuse. Moreover, some housing projects may have local amenity effects that put upward pressure rents in the immediate vicinity of the project, and thus renters who live near a proposed development may oppose it even if they support expanding the citywide or regional housing stock in principle (Hankinson 2018). Previous research has found that renters only lukewarmly favor additional housing development, and more strongly favor policies that deliver them focused and immediate benefits (such as rent control and renter tax credits) but do little to address underlying market scarcity (Marble and Nall 2021).

The logic-of-collective-action story presupposes that renters and homeowners are self-interested, economically rational actors who understand how policy reforms would affect their welfare and who participate in (or abstain from) politics accordingly. However, unexplored still by the political science literature is another plausible pathway which does not presuppose a polity dpminated by homo economicus. It is possible that the politics of housing are rooted in fundamental misunderstandings about markets. The "mental models" of housing markets that ordinary tenants and homeowners use to interpret events and guide their politics may be quite different from the standard classical model in which exogenous increases in the supply of housing tend to bring down the price of housing across all market segments.

This paper examines the mental models that people develop around housing and the correlations among desired outcomes, subjective beliefs about the operation of housing markets, and preferences for supply-expanding policies. Using data from two original surveys of nationally representative samples of urban and suburban respondents, we first assess the population prevalence of "supply skepticism"–that is, the belief, frequently endorsed by some activist groups, that building more housing in a metropolitan area does not reduce housing prices and may even increase them (Been, Ellen, and O'Regan 2019). In Survey 1, conducted in March 2022, we asked respondents to predict the quantity and price effects of a hypothetical rezoning scenario that would allow larger duplex and triplex buildings in neighborhoods of single family homes. Later in the survey, respondents were also asked to predict effect of an exogenous 10% increase the regional housing stock caused by the removal of development restrictions. Survey 2, described in the pre-analysis plan here, uses a conjoint-like design (Hainmueller, Hopkins, and Yamamoto 2014) to check the robustness of the Survey 1 results, and it poses a series of questions that assess 1) how people think the housing-supply shock would affect certain regional and neighborhood outcomes and 2) how changes in such outcomes would affect prices. Survey 2 also includes a battery of more general questions designed to tap zero-sum thinking, and it elicits beliefs about the effect of supply shocks in several other markets. Both surveys ask whether the respondent supports zoning reforms to allow more and denser housing.

2.1 Defining Supply Skepticism

A significant share of Americans indicate support for "housing for all," but do not support specific measures to develop more housing. Previous scholarship has concluded that self-interest is responsible: that homeowners are interested in protecting both their home and its adjoining turf (Babcock, n.d.; Fischel 2001; Einstein, Glick, and Palmer 2019; Marble and Nall 2021). Regardless of their self-reported ideology or support for the generalized goal of housing for all, homeowners of all political stripes oppose the development of dense, multifamily housing in their communities (Marble and Nall 2021; Trounstine 2021). The focal point of political science research has been on homeowners as the main agents of opposition to additional housing development, as they are more likely to be fixtures of their community (McCabe 2016; Einstein, Glick, and Palmer 2019) and to be extremely involved in local politics (Yoder 2020). Moreover, their opposition to more housing, and their support for restrictive zoning regimes, frequently is rooted in financial self-interest that bolsters segregation (Trounstine 2018, 2021).

Within political science, scholars have fixated on low support for housing development–even among renters–as a manifestation of self-interest and the collective action problem. Homeowners and their local political power are so important to extant research that their self-interest and opposition to housing development tends to be a focal point–and foil–for additional research on the topic. A natural extension of this logic is that self-interested renters would be diametrically opposed to homeowners, and support building more dense housing, including rental housing. To the extent that renters oppose new development, the standard assumption is that this is an artifact of the piecemeal nature of development approvals: no single project will make a whit of difference for citywide or regional prices, but it might annoy nearby renters or elicit worries about a localized gentrification effect. If renters' collective action problem (Olson 1965) could be solved by setting development policy on a citywide, regional or statewide basis, renters would more strongly support new development (Hankinson 2018). Or so it is said.

This story has gained traction in the absence of any evidence about what owners or renters believe about housing markets and the effect of new supply on prices, rents, and other outcomes. In this paper, we take a step back to evaluate economic beliefs about housing markets, bearing in mind that few Americans "think like an economist" (Caplan 2001; Caplan and Miller 2010). Those who do may generate crude but reasonable mental models of supply and demand curves in regional markets when asked about the effects of adding housing stock in an area. Individuals who accept the value of housing development will be able to do more than parrot back "Econ 101" facts such as "supply and demand," but will integrate the logic into reasoning about important public policy matters. Our tentative preliminary evidence, which we used to generate and test hypotheses, suggests that people resort to other heuristics when anticipating the effects of housing development. They associate it either with highly localized externalities (such as positive spillovers from nice new buildings and a livelier local scene, or disamenities such as noise, congestion, and disorder) or may think only about their own experiences, not housing markets as a whole. Finally, the idea of increased housing development may elicit the zero-sum thinking associated with "folk economics." That is, if policies are changed to facilitate market-rate development, it must only be to benefit for-profit (i.e., greedy) developers at the expense of renters, local homeowners, or the public at large. Recent research suggests that such zero-sum thinking is often intractable, anchored in innate intuitions developed over the course of prehistoric human evolution, where individuals thrived by identifying economically predatory cheaters (Rubin 2003; Boyer and Petersen 2018; Cosmides and Tooby 1992). Evolutionary psychologists conclude that the evolutionary mindset conflicts with modern economic systems, where self-interested parties stand to benefit from gains in trade (Cosmides and Tooby 1992), and even ruthless capitalists can deliver social benefit through fair trades in open markets.

In this paper, we examine the mental models that people develop around housing. First, estimate the population prevalence of supply skepticism–the belief, frequently endorsed by community activist groups on the Left, that building more housing in a metropolitan area does not reduce housing prices and may even increase them (Been, Ellen, and O'Regan 2019). To do so, we present results from two surveys of nationally representative samples of urban and suburban respondents. These respondents evaluate various housing production scenarios, including an exogenous 10% increase in their metro region's housing stock, and we ask them to predict the effect of the scenario on home prices or rents in five years. We assess the robustness of supply-skeptical beliefs by independently randomizing numerous aspects of the scenario, including the type and location of the new housing, counterfactual prices in the absence of the shock, and the format of the question through which we elicit price and rent predictions.

To shed light on the mental models of the economy tied to such predictions, our second survey also asks respondents a series of questions that assess 1) how people think housing supply changes will affect certain regional and neighborhood outcomes and 2) how changes in such outcomes will affect prices. In addition, we assess the extent to which supply skepticism about housing is correlated with zero-sum thinking in general.

3 Defining Supply Skepticism

This paper is especially concerned with a manifestation of folk-economic thinking that Been, Ellen, and O'Regan (2019) call *supply skepticism*: the belief, promoted by local interest groups and some elected officials, that enabling additional market-rate housing supply will fail to reduce prices for existing homes. As Been, Ellen, and O'Regan (2019) note, supply-skeptical arguments are frequently deployed in anti-development campaign rhetoric, so it is difficult to know whether the arguments reflect sincerely held beliefs about the operation of the economy, or strategic language that development opponents know will resonate with prevalent folk-economic intuitions. Been, Ellen, and O'Regan (2019) identify four examples of economic reasoning that reject mainstream economic thinking on housing development and its effects. First, they characterize skeptics as claiming that housing is tied to land, so the normal rules of supply and demand do not apply (4). Second, the skeptics posit that housing markets are so segmented by price that adding supply in the high-price segment will not reduce rents in lower-price segments (5). Third, the skeptics make a "futility" argument (Hirschman 1991): that new development will induce additional housing demand, offsetting any price gains (6). Fourth and finally, the skeptics claim that adding supply—-especially of market-rate "luxury" housing–will locally increase prices through amenity effects, worsening affordability rather than solving it (7).

The elite version of Supply Skepticism openly rejects that classical economic theory applies to housing markets. However, average Americans do not have the same sophisticated economic schemas to apply to the operation of housing markets. Instead, they are likely to form their ideas around the elements of folk economics and zero-sum thinking. For example, opposition to for-profit housing development is likely to be associated with the belief that developers and land speculators' profits come at the expense of local residents, tenants, or communities—-not that communities see gains from these trades in the form of more abundant housing and lower rents. Similarly, lay people who do not "think like economists" may rely heavily on the Availability Heuristic (Tversky and Kahneman (1973)) when responding to the idea of increased housing supply. For example, when people see new market-rate housing, it may appear to be "luxury" housing and coincide with new amenities such as improved retail and restaurants or observed increases in local housing prices. The Availability Heuristic may lead to the inference that new housing was the cause of the higher prices. Even when asked about new housing supply's impact across entire markets, we expect that people are likely to think in terms of these highly local effects and the specific people served by specific housing projects, rather than regional markets. Zero-sum thinking may also lead people to see new "luxury" (i.e., market-rate) housing as coming at the expense of the local community and of more affordable housing, even though recent research indicates that construction of market-rate luxury housing opens up units in more affordable neighborhoods (Mast 2021).

Not only does the extant housing literature not examine the prevalence of these beliefs in the mass public, but it has not established the strength of the association between supply skepticism and support for additional local housing development. By framing housing policy attitudes primarily in terms of self-interest and ideology, the recent political science literature on the topic has neglected the potentially foundational role of economic knowledge and competence. One reason may be that political scientists take as given that voters adopt policy positions with incomplete knowledge of policies, and rely on information shortcuts and heuristics in almost all policy domains (Lupia 1994; Boudreau, Elmendorf, and MacKenzie 2015). However, the rules of supply and demand represent a set of basic facts that do not require encyclopedic knowledge and can be readily integrated into one's understanding of markets and public policy. With basic knowledge of classical economics, one can make predictions about the general relationship between additional housing supply and future housing prices. Voters who reject these basic economic principles are, we suspect, unlikely to make correct policy judgments, and may adopt housing policy attitudes counter to their self-interest as homeowners or as renters. If stated preferences over housing prices and stated beliefs about the effects of supply on price do not jointly lead to logically consistent policy attitudes, it suggests that not ideology but voter knowledge and competence is an obstacle to housing development.

3.1 Research Design

Our approach to our research question builds upon and emulates recent work in behavioral economics and economic psychology that uses survey data to capture how people think about basic economic questions (Andre et al. 2019, 2021; Stantcheva 2021), while also building on earlier work on economic reasoning and voter competence (Blendon et al. 1997; Caplan 2001, 2002). Deviating from dominant customs of economics scholarship, much of this recent work does not test formal models of the behavior of economic agent, instead aiming to capture the mental processes that individuals apply to major economic questions ranging from inflation to taxation. These studies have typically sought to elicit qualitative, verbal mental models of how markets function, and to understand how individuals assign responsibility around core economic questions. Frequently, they also compare how lay individuals with less economic training think through major questions differently than economists. For example, Andre et al. (2021) show that economists are more likely to think about inflation as a macroeconomic problem explained by monetary policy, and to think about inflation in those terms.

We bring a similar sort of approach to the study of supply skepticism. We have specific priors about the mental models that the public will apply when constructing models of housing markets, but these priors are rooted in knowledge of prior research on public opinion and voter psychology, not derived from formal models (e.g. Tversky and Kahneman 1973; Lupia 1994; Caplan 2001). Moreover, we examine the applied economic reasoning of our respondents. Presenting respondents a highly specific scenario allows us to measure how much average Americans integrate classical economic perspectives in their assessment of their local housing markets and their support for public policies related to housing.

Our priors are informed, in part, by preliminary results of Survey 1, which, in the style of Stantcheva (2021), invited respondents to offer open-ended comments about housing markets. The results of that exercise demonstrated that renters, especially, offered statements suggestive of zero-sum thinking–particularly with respect to landlords and "corporations" that they identified as the proximate cause of high rents. Unsolicited, barely any renters addressed prices in terms of market dynamics. In discussing the effects of housing development, homeowners were similarly more likely to talk about localized negative externalities (such as traffic congestion) than market-wide effects. (These results are consistent with work on "inflation narratives" showing that, compared to economists, average citizens are much more likely to think about inflation in terms of specific transactions than macroeconomic factors (Andre et al. 2021).

Prior work on general versus applied policy reasoning and attitude formation demonstrates that individuals embrace concepts and attitudes in the abstract, but revert either to self-interest or availability heuristics when asked about specifics (Jackman 1978; Citrin and Green 1990). For example, Jackman (1978) observed that educated, liberal Americans were more likely to endorse racial equality and civil rights in the abstract, but when pressed on details, such as imposing civil rights enforcement on businesses or desegregating their local schools, showed much less support. The logic of markets may work similarly. Marble and Nall (2021) show that about half of liberal homeowners embrace the idea of a federal guarantee of housing for all–a fairly abstract position. But when pressed for their support for specifics, their self-interest appears to play a more significant role, and only about half of homeowners who support the generalize principle of "housing for all" also support building more apartments in the area where they live. That slippage between the general and specific may be caused by activation of localized self-interest (Citrin and Green 1990) or because people will readily endorse a concept in the abstract, and will only reconsider once they have given the matter more thought in an applied setting. We expect that something similar may arise around classical economic reasoning in the context of housing: people may give "correct" answers to easy economic questions, but may be either unable or unwilling to apply the same reasoning to regional dynamics in housing markets.

Our empirical strategy is as follows across two surveys. In Survey 1 (fielded in March 2022) we start by asking the respondent to think about their city's future and whether they would prefer home prices and rents to be higher, lower, or the same as today, assuming no change in the economy or quality of life. We then present respondents with a set of scenarios describing hypothetical upzonings–measures to allow more density on lots previously limited to low residential density (usually under "R1" zoning). Such measures have been implemented by municipalities and state governments across the country. We ask respondents to predict both the effect these upzonings will have on future housing supply and what effect that change in regional housing stock will have on both home sale prices and rents. To distiguish skepticism about the effect of rezoning on quantity from skepticism about the effect of quantity on price, we also elicit predictions about the effect of an exogenous 10% increase in the metro-region's housing stock caused by the removal of development restrictions. At the end of the survey, we ask the respondent to predict the findings of Mast (2021)'s study about the effect of new development in higher-income neighborhoods on the region-wide availability of housing in lower-income neighborhoods. With this design, we're able to measure incongruities between respondents' stated preferences about housing prices, their knowledge about the price effects of added supply, and their understanding of the economic mechanism through which new expensive housing frees up more affordable housing.

In our second survey, we plan to collect data on our core outcome measure, which is individuals' self-reported beliefs about the effect of a 10% supply shock on regional housing prices under varied scenarios constructed to elicit different mental models that might deviate from the classical economics model. We then ask a series of questions about mechanisms, in two stages. In the first stage, we ask about the supply shock's impact on nine social and economic outcomes which–depending on one's mental model–may translate into price effects. In the second stage, we ask how shifts in those outcomes would, in general, be expected to increase or decrease home values and rents We then take the responses to these questions—-which collectively constitute the mental model of housing markets' response to supply shocks—-and use model-selection techniques to identify the mental mechanisms that are most associated with price predictions.

Survey 2 also collects responses, and assemble indexes, for a series of baseline factors that we expect to be associated with supply skepticism, including zero-sum thinking, self-reported exposure to observational evidence of new development occurring in places where home prices and rents are going up, and economic knowledge. Finally, we assess whether supply skepticism predicts opposition to pro-density zoning reforms among those who generally favor lower housing prices. If supply skepticism causes people to adopt positions that run counter to their stated preferences, then we can conclude that it is more important to the politics of housing than previously acknowledged. Beyond just housing, democratic accountability rests on the ability of voters to form policy preferences and judge whether the actions of elected officials are furthering those preferences. Our findings related to supply skepticism and other faulty mental models could explain why voters remain frustrated on so many key policy issues.

3.2 Using Conjoint Methods as a Robustness Check

The core quantity of interest in the paper is a measure of whether respondents believe that addition of housing supply results in lower housing prices. Respondents are given a vignette that describes a 10% increase in regional housing supply over the next five years. Respondents then answer a question about the likely effect of the policy on home values or rental prices for an average property.

Respondents on our first survey thought (on average) that the shock would cause prices and rents to increase. To check the robustness of this result, our second survey poses a similar 10% supply shock question while concurrently randomizing several features of the scenario and the price-elicitation question, as follows (Hainmueller, Hopkins, and Yamamoto 2014):

- Cause of Supply Shock: The cause of the 10% supply shock is described as resulting from 1) a productivity-improving change in construction technology ("tech" scenario), or a preemptive state policy to allow 2) more duplexes, triplexes, and fourplexes in neighborhoods of single-family homes ("plex" scenario), 3) more apartment and condo buildings near train and bus lines ("TOD scenario," or transit-oriented development), or 4) more suburban homes on farms and open space outside of cities ("greenfield" scenario). These causes should not much affect an economist's prediction about the effect of the shock on citywide prices, but, for a layperson operating with a different mental model, the scenarios may differ from one another in salient ways. For example, the "tech" scenario does not involve a policy change and as such may not trigger suspicions about special-interest giveways to greedy, market-manipulating developers. For a zero-sum thinker, though the increase in housing stock is the same as in other scenarios, there is no "malicious actor" lurking in the background and thus one person's gains must not necessarily involve another person's losses. Preemption of single-family zoning, which is heavily criticized, may lead some homeowners to evaluate housing supply's effects more negatively or to believe that developers will benefit and not pass on value to housing market consumers. Homeowners' price predictions may reflect their worries about local disamenities effects from "plex" development more than their expectations about region-wide price effects. Allowing more density around transit poses less threat to homeowners, but the perception of localized gentrification risk from high-end development in lower-income neighborhoods may translate into supply skepticism. Greenfield development may reduce housing prices—as it has in Sun Belt cities (Glaeser and Gyourko 2018). However, because it does not add to the housing stock within cities, city-dwelling tenants may not view it as efficacious because, by definition, they have been less habituated to it. Infill development, the stuff of the plex scenario and the TOD scenario, may trigger availability heuristics from city dwellers who have seen new buildings constructed in surrounding neighborhoods. As such, they might not engage in costly abstract thinking about supply and demand, but rather remember characteristics of development they've previously encountered and extrapolate from it.

- Elicitation type: We present questions about housing prices in one of three formats:
  - Simple causal effect elicitation. We first ask if the 10% housing supply increase will significantly increase, somewhat increase, have no effect, somewhat decrease, or significantly decrease prices. Respondents are then asked a follow-up question about how much more or less a given home with a posited counterfactual value would be worth, in five years, under the scenario. The counterfactual value is fed from our Zillow database and uses a random, researcher-specified inflation factor. Choice options are characterized in dollar value and percentage terms.
  - Complex causal effect elicitation. In this format, respondents are given the posited counterfactual value as part of the initial question. They are asked whether a home with that counterfactual value would be worth significantly more or less in five years under the scenario. We think this is harder than the "simple" elicitation format because it does not allow respondents to express a directional prediction without thinking in expressly counterfactual terms or calling to mind a house in their city with roughly the specified value. Except for the more extended wording, the overall structure of price elicitation is the same under the simple and complex methods.
  - Potential outcomes elicitation. Instead of asking for the expected ceteris paribus change in prices five years from now, respondents are asked first to predict price of a typical home or rental unit in five years. Then they're presented with the supply shock scenario, and we again elicit their prediction, this time assuming the supply shock. In the potential-outcomes elicitation format, respondents can enter any integer value as their prediction, whereas in the "simple" and "complex" formats, respondents are limited to values within the range of +/-30%.
- Inflation factor: We give respondents (in the "simple" and "complex" question formats) a realistic local value for housing prices or rents in their city, based on contemporary home price and rental data drawn from Zillow. To test for the possibility that the supply skepticism revealed by Study 1 was an artifact of the counterfactual prices in our survey instrument, we adjust the Zillow-inferred price or rent by an inflation factor drawn from {-20%, 0%, 20%, 40%}. Respondents are not told that the values selected to represent prices in five years were generated using this inflation adjustment.
- Rent Prices or Home Values: Individuals are asked about either rental prices or home values. These are typically highly correlated, but survey respondents may have different beliefs about the effect of home values and rental prices, and supply skepticism may be stronger for one or the other.

Our randomized question design differs from usual applications of the conjoint, since the primary estimand of interest is not the average marginal component effect (AMCE) (Hainmueller, Hopkins, and Yamamoto 2014). Instead, we are using the conjoint to assess how substantively modest perturbations to a core scenario—ia 10% supply shock that is constant across all profiles—is believed to change. These perturbations should matter little if respondents have coherent and consistent mental models of supply and demand. That is, beliefs about price elasticity should be invariant to question wording or the proximal cause of the supply shock. We do measure AMCEs, even though our power to do so with a one-shot survey question is limited. First, the AMCEs establish whether our findings are robust to question wording. Second, if the AMCEs do reveal substantial deviation under certain vignettes, this could be a clue to the mental models underlying supply skepticism. For most analyses, however, we pool over the different randomizations.

Responses to the supply shock scenario are standardized in two different ways. First, we assemble a coarse measure of strong supply skepticism. We code strong skepticism all responses that the housing supply shock will increase prices, and as weak skepticism responses that the supply shock will increase prices or have no effect. We also record the average predicted price effect in percentage terms, calculating this quantity for respondents given the potential outcomes prompt. We use the dichotomous measures of supply skepticism for our primary analyses, as they are robust to outliers.[1]

Because we are asking respondents to give us a single point prediction, our method of elicitation does not reveal uncertainty. We next ask respondents to offer a subjective indicator of their uncertainty around the issue. "How confident are you about the direction of the effect of this scenario on home values, that is, whether it would generally increase, decrease, or have no effect on home values? Not at all confident, not confident, somewhat confident, confident, or very confident." This at least gives us a qualitative self-report of respondents' confidence in their price predictions. To be sure, we would like to capture individuals' beliefs about the full probability distribution, but doing so would make our already-challenging survey much more cognitively taxing for respondents.

3.3 Measuring Important Dispositional Factors

After establishing the prevalence of supply skepticism, we undertake to assess the factors that covary with it. While we are interested in the role of attitudes and psychology around the political economy of housing, we are aware that self-reported beliefs about housing markets may reflect underlying mental models or heuristics that are not, in fact, specific to housing. Ex ante, we expect that some of these baseline beliefs and dispositions, such as zero-sum thinking or ignorance of basic supply-and-demand logic, will be correlated with supply skepticism. The results of these analyses are important. If supply skepticism happens to be highly correlated with low economic knowledge, then this suggests that generalized economic education may be a corrective. However, if respondents who otherwise give correct answers on brief economic test, or who reject zero-sum thinking, nevertheless endorse supply skepticism, this would suggest that the mental models that support supply skepticism are something other than a general economic knowledge problem.

We collect and assemble indexes (using the first component from principal component analysis) related to economic knowledge and zero-sum thinking. We separately collect items on partisanship and general political ideology.

Our economic knowledge scale is constructed from three questions about the effect of supply shocks on prices in other markets, which are asked in different sections of the survey: - If supply-chain problems cause automakers to produce fewer new cars, what happens to the price of used cars? - Imagine that a new, inexpensive fertilizer makes grain farms more productive. Farms treated with the fertilizer yield 50% more grain on average. Would widespread use of this fertilizer cause grain prices to increase, decrease, or stay the same? - Imagine that a new high-school program for training students to be plumbers causes a large increase in the number of plumbers in a city. Would wages for other residential plumbers in the city increase, decrease, or stay the same?

We also ask about the price effect of free trade agreements, but we do not include this in the index.[2] A free-trade agreement is a political act of national government, and candidates for national office frequently run on anti-trade or pro-trade platforms. We therefore expect responses to the free-trade question to reflect ideological commitments as well as economic knowledge.

Our measure of zero-sum thinking (ZST) is adapted from existing scales (Davidai and Ongis 2019; Johnson, Zhang, and Keil 2021). Because the widely used Belief in a Zero Sum Game (BZSG) scale (Różycka-Tran, Boski, and Wojciszke 2015) includes items with the possibility of cultural bias (for example, comparing life to a tennis game), as well as items that seemed to capture economic ideology rather than a generalized tendency towards zero-sum thinking (529) (Davidai and Ongis 2019), we omitted items that had a clear ideological direction. We also avoided items that may tap generic trust in government, which zero-sum thinkers may

[1] Quantitative predictions of price changes in the potential-outcomes elicitation format are unconstrained, whereas in the simple and complex formats, they are top-coded at "30% or more."

[2] "A free trade agreement is a pact between two or more nations to reduce barriers to imports and exports among them. Do free trade agreements make the price of products sold in the U.S. higher, lower or not make a difference?"

answer differently depending on whether the party they support is in power (Johnson, Zhang, and Keil 2021). We instead present four of our own items, constructed as pairwise items that ask people to identify which position is closest to their own. The pairwise items over which people were asked to choose were:

- "The art of politics is finding compromises that are good for everyone," or, "The art of politics is dominating the other side."
- "In life, when somebody gains, others usually have to lose," or, "In life, when somebody gains, others usually benefit too" (Scale item 3 from Różycka-Tran et al. (2019)).
- "When government policies help one group get ahead, other groups are usually held back," or, "When government policies help one group get ahead, other groups usually benefit too." (This is a policy-focused adaptation of Wilkins et al. (2015) ZST scale, Item 1.)
- "If someone gets richer it means that someone else gets poorer," or, "If someone gets richer it means they're satisfying other people's wants and needs." (This adapts Item 2 from the ZST scale in Różycka-Tran et al. (2019).)

While several of these items are likely to be correlated with left economic ideology, we expect that the first principal component of a scale constructed from these items will reveal an overall tendency to think in zero-sum terms. We expect that such zero-sum thinking will be highly correlated with supply skepticism. Zero-sum logic is commonly used by activist opponents of housing development (for example, the argument that market-rate housing makes building below-market-rate housing more difficult). Moreover, because market-rate development is usually done by developers, zero-sum thinkers may see land development rights as benefiting developers while delivering few advantages to the public at large.

In the second part of our paper, we seek to identify the mental models of different events in housing markets that covary with supply skepticism. In brief, we aim to understand how people think the supply shock in question is likely to affect certain outcomes in neighborhoods, and, second, how the changes brought about by a supply shock might affect housing prices in the region. We could attempt to elicit these mental models directly by asking people directly why they gave the price predictions they did (Andre et al. 2021). However, we know that survey respondents give inaccurate answers when they are asked to explain the reasons for their beliefs. For this reason, we partition our questions about mental models into two sections, so that respondents' answers about mechanisms are at least one step removed from their stated beliefs about supply and prices. In the first section, we ask individuals about the substantive implications of the supply shock scenario. In the second section, we ask individuals what they think each of the substantive implications will affect housing prices. Paired questions (on substantive outcomes and their associated market outcomes) are asked separately. We have modeled our mechanisms questions, in part, on the elite supply skepticism tenets summarized in Been, Ellen, and O'Regan (2019), and on the answers to some free-text questions about land use regulation and housing affordability that were posed on our first survey

We present nine pairs of items. In an early section of the survey, we ask about substantive outcomes associated with the presented scenario (Question A). Later in the survey, after respondents have answered several other sections of questions, we ask about the price-related outcome (Question B). In both sections, questions are randomized to obfuscate the question pairing, and to elicit answers to pricing mechanisms that will not represent motivated reasoning based on respondents' preferences around the posed supply-shock scenario.

Substantive Outcome	Price-Related Outcome	Concept tested	Notes
1A. This scenario would make more homes available to buy or rent in the region's more-expensive neighborhoods.	1B. When more homes become available to buy or rent in a region's more-expensive neighborhoods, this generally results in [higher/lower] home prices and rents in less-expensive neighborhoods.	Chain of moves and filtering (together with 2)	We expect supply skeptics to reject Proposition 2A (but not 1A) and Proposition 2B (but not 1B). This would be consist with the view that supply-and-demand forces operate within but not between market segments. By contrast, recent research finds that "chains of moves" unleashed by new housing in expensive neighborhoods free up housing in less affluent neighborhoods (Mast 2021).
2A. ... would make more homes available to buy or rent in the region's less-expensive neighborhoods	2B. When more homes become available to buy or rent in a region's less-expensive neighborhoods, this generally results in [higher/lower] home prices and rents in the same less-expensive neighborhoods.	Chain of moves and filtering (together with 1)	
3A. ... would result in more companies opening or expanding offices in the region.	3B. When more companies open or expand offices in a region, this generally results in ... [higher/lower] home prices and rents.	Agglomeration	We expect supply skeptics and optimists alike to agree with these propositions, though skeptics may be more likely to believe that new housing will attract in-migration of firms and workers.
4A. ... would result in more demolition of currently-affordable homes in the region.	4B. When there's more demolition of affordable homes in a region, this generally results in ... [higher/lower] rents for other affordable homes in the region.	Segmented markets / direct effect	These items capture a mechanism that we expect to manifest only in the supply-shock scenarios that focus on redevelopment (TOD and plex). Expectations about the 'direct effect' of a scenario on existing affordable homes will be more salient in laypeople's thinking about prices than the indirect effect of a larger housing stock on prices across all market segments.
5A ... would result in more corporations buying housing in the region.	5B. When corporations own more of the housing in a region, this generally results in ... [higher/lower] rents.	Scapegoating	We expect people who are high in zero-sum thinking will expect pro-housing state policy interventions to generate more corporate ownership of housing, and more corporate ownership to translate into higher rents.
6A. ... would reduce the overall quality of life in my neighborhood.	6B. When the overall quality of life in a neighborhood declines, this generally results in [higher/lower] home prices and rents in the neighborhood.	Neighborhood disamenities (aggregate)	We expect that almost all respondents will agree with 6B, since supply skeptics may still hold standard views of the demand side of the housing market. Answers to 6A will reveal whether people expect the different scenarios, which vary with respect to the geographic distribution of new housing (greenfields, transit corridors, existing residential neighborhoods), to have different impacts on neighborhood amenities.
7A. ... would result in more high-income people moving into lower-income neighborhoods.	7B. When more high-income people move into a lower-income neighborhood, this generally results in ... [higher/lower] prices and rents for other homes in the neighborhood.	Gentrification (people as amenity)	This gentrification story is standard in big-city politics. We expect that gentrification impacts (7A) will be highly correlated with price predictions among urban renters, consistent with a myopic focus on local rather than market-wide effects. We expect nearly all respondents to agree with Proposition 7B.
8A. ... would result in more expensive new housing being built next door to older, relatively affordable homes.	8B. When expensive new housing is built next door to older, relatively affordable homes, this generally ... [increases/decreases] the market value of the older homes.	Gentrification (building as amenity)	We expect nearly all respodents to agree with 8B. Agreement with 8A is likely to vary across scenarios (most in TOD, least in greenfield)
9A. ... would result in more new homes being built for people like me.	9B. When more new homes are built for people like me, this generally results in ... [higher/lower] prices and rents for people like me.	Segmented markets / personal story	This set of questions pertains to possible identitarian / zero-sum thinking about housing policy. Responses to this item would be consistent with recent findings on opposition to nearby buildings with expensive rents (Trounstine 2021).

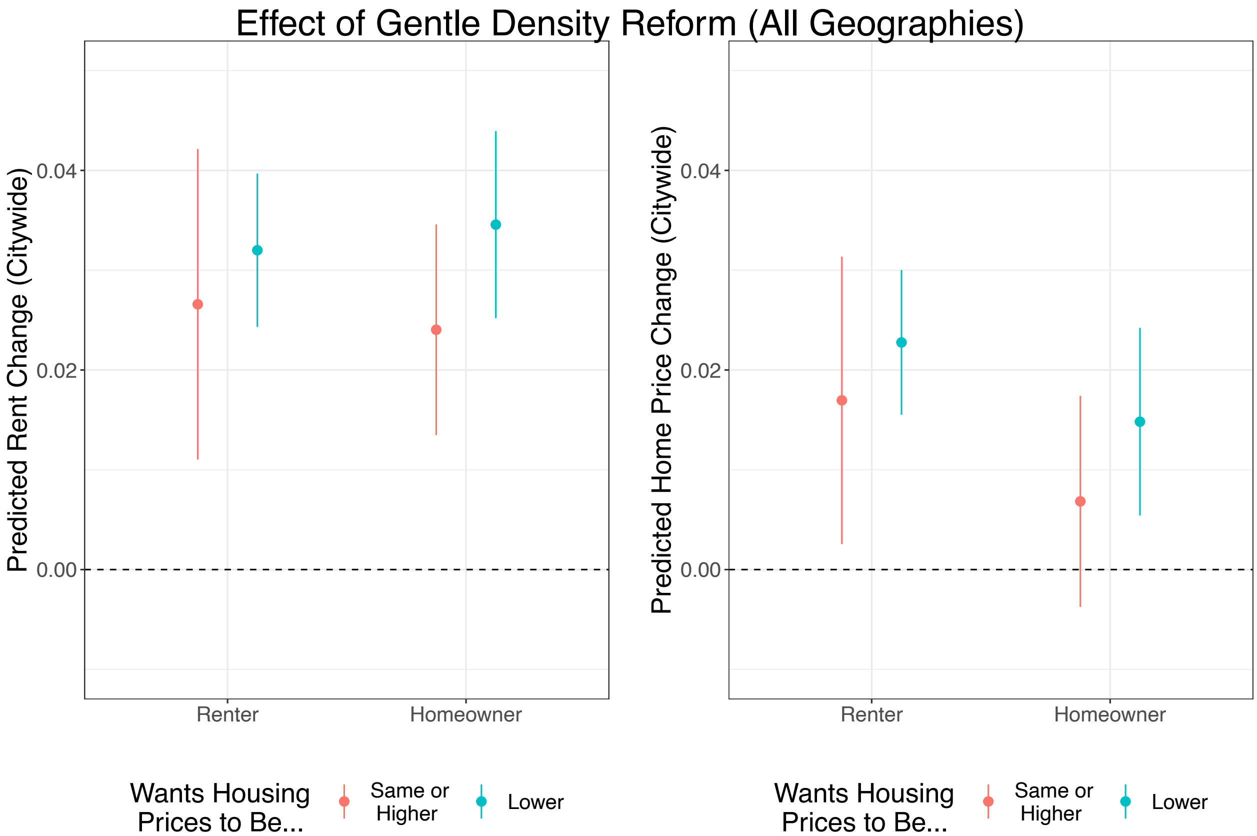
4 Previous Survey Results

In March 2022, we ran a survey on about 2,500 non-rural U.S. citizens, on a sample recruited by Bovitz/Forthright. We quota-sampled equal proportions of owners and renters and matched age, race and SES demographics to match the U.S. population overall. We elicited beliefs about housing from our panel in four different manners:

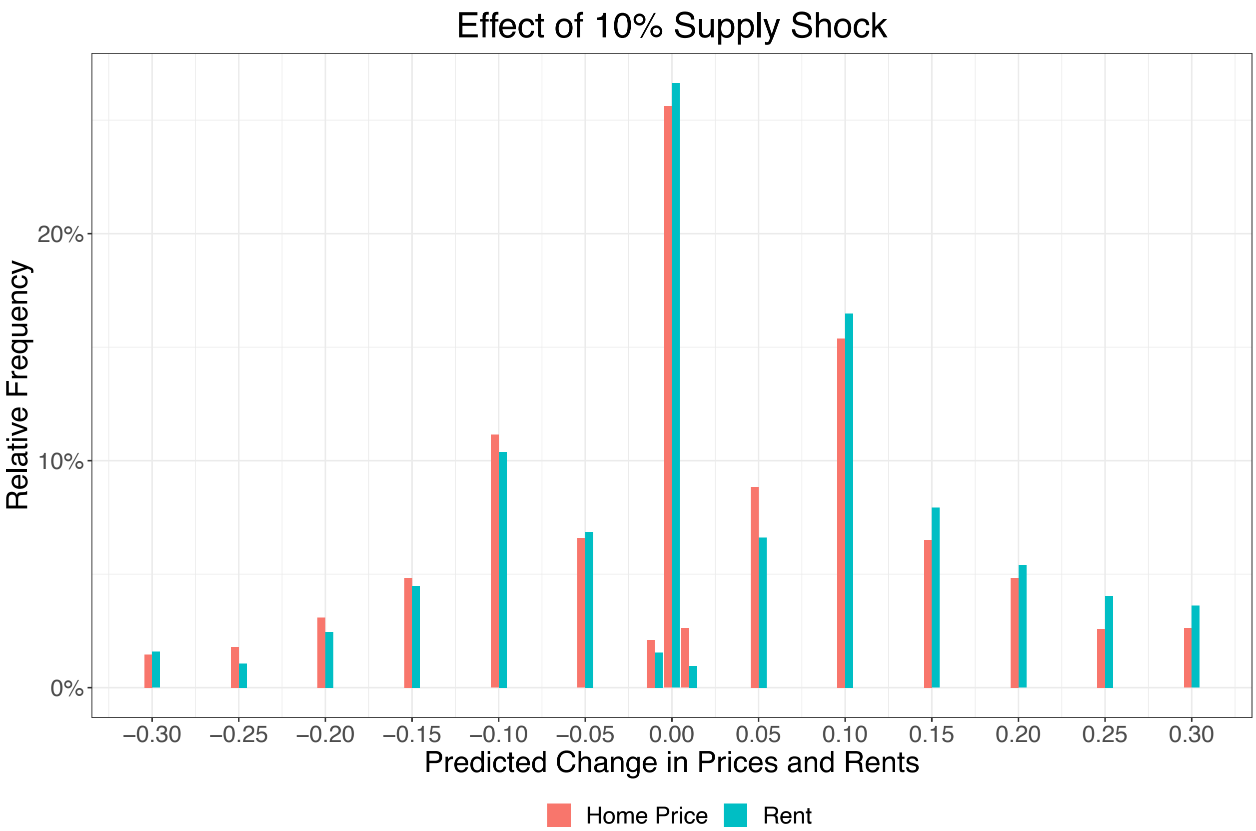
1. Free-text questions about land-use policy (Stantcheva 2021).
2. Survey experiment on quantity & price effects of "gentle density" rezoning.
3. Price effects of a hypothetical exogenous 10% supply shock.
4. Predict the finding of an academic study on filtering (Mast 2021).

The results left us with a puzzle that we hope to resolve in the proposed survey. Respondents, both homeowners and renters, overwhelmingly favored lower housing prices in their regions (over 60% compared to about 8% who wanted prices to rise). Further, respondents seemed able to give correct answers about the operation of supply and demand. About 80% of respondents correctly answered a hypothetical question regarding the relationship between supply chain issues in the automobile industry and their effects on the prices of used cars. Finally, a majority of respondents correctly predicted that a scenario in which the government legalized gentle-density reforms (for example, allowing small-unit multifamily home to be built in single-family detached neighborhoods), would lead to a larger housing stock.

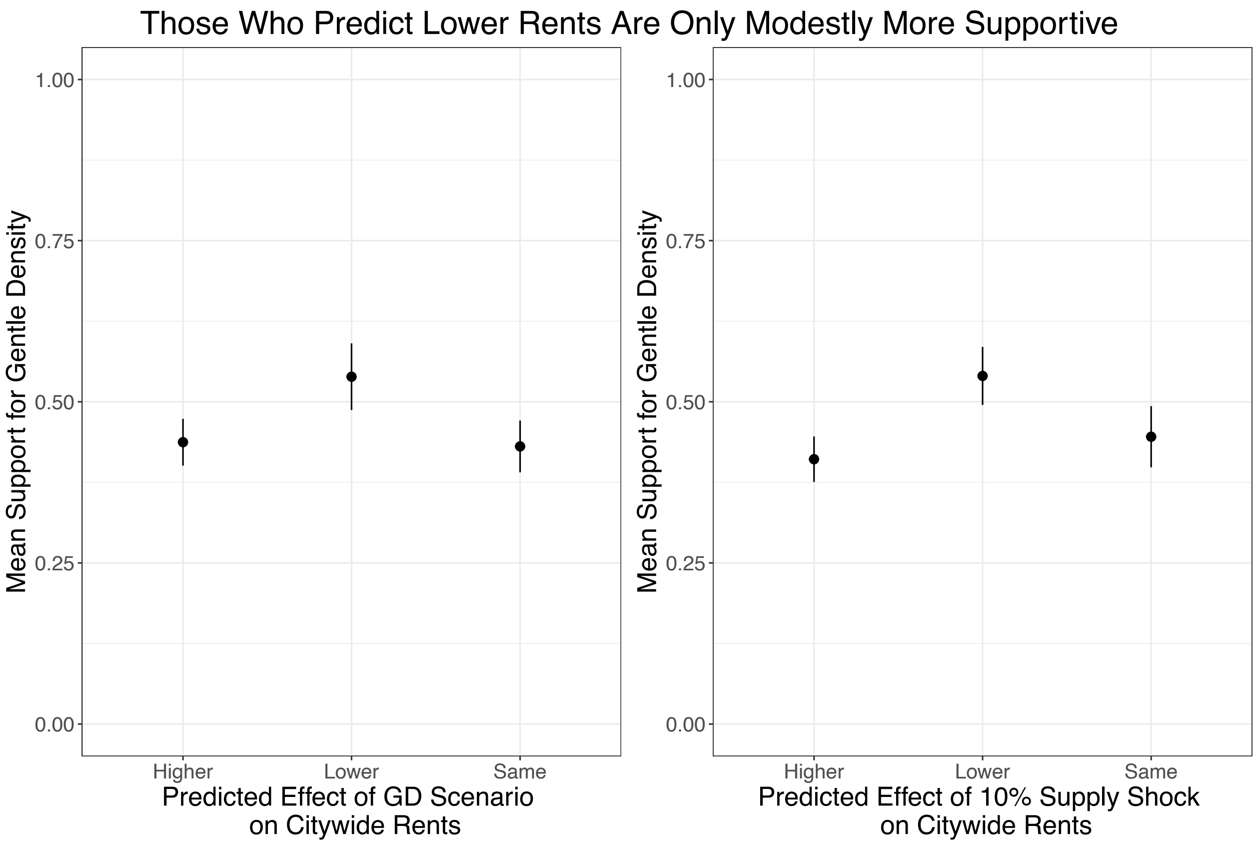
However, both homeowners and renters predicted that increased housing supply would lead to *higher home prices and rents* than in a counterfactual world where single-family neighborhoods were left as-is. Only homeowners who wanted stable or increased housing prices anticipated that the housing supply shock would lead to lower prices.



Respondents were also asked to predict the effect on prices of an exogenous 10% increase in the regional housing supply. The modal answer was that such a housing supply shock would have precisely zero effect, an implausible result. (A 10% housing stock increase over 5 years is about triple the average annualized growth rate for the US housing stock.) However, we also found that respondents anchored on a 10% *increase* in prices and slightly less so on a 10% decrease in prices. (Rental and home price predictions were largely the same.) These results indicate a fundamental incoherence between respondents' stated desire–lower housing prices–and their beliefs about policy interventions. If voters are unaware of how to achieve what they want or believe that policies meant to help them would actually hurt them, how then are they to effectively lobby elected officials for policy changes or hold elected officials accountable?



On this last point, we found that those who wanted prices to be lower and who also correctly predicted that increased housing supply would lead to lower prices were only modestly more likely to support gentle density zoning than those who predicted prices would remain the same or increase. Support for gentle-density reforms garnered just above above 50% of those polled among respondents who predicted increases in housing supply would lead to lower prices.



If we find people generally want lower-cost housing and some respondents correctly intuit that increases to regional supply will lower prices, why do they not endorse so-called "Yes in My Backyard" (YIMBY) policies? In our second survey, we interrogate the mental models that respondents apply to this question, considering how they think about prices as well as other considerations that rise to top-of-mind when they are asked to think about housing.

5 Import Simulated Data for Survey 2

5.1 Load Simulated Data

```
testing<-F # Toggle if you want to add test values (not currently in use)

col_names <- names(read_csv(here("data", "NEO - Supply Skepticism Experiment 2 - v3_July 8, 2022_22.
```

```
## Rows: 0 Columns: 314
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (314): StartDate, EndDate, Status, IPAddress, Progress, Duration (in sec...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
# temp <- read_csv(here("data", "NEO - Supply Skepticism Experiment 2 - v3_July 8, 2022_22.46.csv"),
# readr::spec(temp)

D <- read_csv(here("data", "NEO - Supply Skepticism Experiment 2 - v3_July 8, 2022_22.46.csv"),  col
  StartDate = col_datetime(format = ""),
```

```
EndDate = col_datetime(format = ""),
Status = col_double(),
IPAddress = col_character(),
Progress = col_double(),
`Duration (in seconds)` = col_double(),
Finished = col_double(),
RecordedDate = col_datetime(format = ""),
ResponseId = col_character(),
RecipientLastName = col_logical(),
RecipientFirstName = col_logical(),
RecipientEmail = col_logical(),
ExternalReference = col_logical(),
LocationLatitude = col_double(),
LocationLongitude = col_double(),
DistributionChannel = col_character(),
UserLanguage = col_character(),
`Q1.2_First Click` = col_double(),
`Q1.2_Last Click` = col_double(),
`Q1.2_Page Submit` = col_double(),
`Q1.2_Click Count` = col_double(),
Q2.1 = col_double(),
Q3.1_Browser = col_character(),
Q3.1_Version = col_character(),
`Q3.1_Operating System` = col_character(),
Q3.1_Resolution = col_character(),
Q3.2 = col_double(),
Q5.1 = col_double(),
Q5.2 = col_character(),
Q8.1 = col_double(),
Q8.2 = col_double(),
Q8.2_4_TEXT = col_character(),
Q8.3 = col_character(), # not parsed correctly by default (choose-all item)
Q8.4 = col_double(),
Q8.5 = col_double(),
Q8.5_4_TEXT = col_character(),
Q8.6 = col_logical(), # NB: columns not in use parsed to logical by default
Q8.7 = col_double(),
Q8.8 = col_logical(),
Q8.9 = col_logical(),
Q8.9_6_TEXT = col_logical(),
Q9.1 = col_double(),
`Q9.2_First Click` = col_double(),
`Q9.2_Last Click` = col_double(),
`Q9.2_Page Submit` = col_double(),
`Q9.2_Click Count` = col_double(),
Q9.3 = col_double(),
`Q9.4_First Click` = col_double(),
`Q9.4_Last Click` = col_double(),
`Q9.4_Page Submit` = col_double(),
`Q9.4_Click Count` = col_double(),
Q10.1 = col_number(), # not parsed correctly by default
`Q10.2_First Click` = col_double(),
`Q10.2_Last Click` = col_double(),
```

```
  `Q10.2_Page Submit` = col_double(),
  `Q10.2_Click Count` = col_double(),
  Q10.3 = col_number(), # not parsed correctly by default
  `Q10.4_First Click` = col_double(),
  `Q10.4_Last Click` = col_double(),
  `Q10.4_Page Submit` = col_double(),
  `Q10.4_Click Count` = col_double(),
  Q10.5 = col_number(), # not parsed correctly by default
  `Q10.6_First Click` = col_double(),
  `Q10.6_Last Click` = col_double(),
  `Q10.6_Page Submit` = col_double(),
  `Q10.6_Click Count` = col_double(),
  Q10.7 = col_number(), # not parsed correctly by default
  `Q10.8_First Click` = col_double(),
  `Q10.8_Last Click` = col_double(),
  `Q10.8_Page Submit` = col_double(),
  `Q10.8_Click Count` = col_double(),
  Q11.2 = col_double(),
  Q11.3 = col_double(),
  Q11.4 = col_double(),
  Q11.5 = col_double(),
  Q11.6 = col_double(),
  Q12.1 = col_double(),
  `Q12.2_First Click` = col_double(),
  `Q12.2_Last Click` = col_double(),
  `Q12.2_Page Submit` = col_double(),
  `Q12.2_Click Count` = col_double(),
  Q12.3 = col_double(),
  Q12.4 = col_double(),
  `Q12.5_First Click` = col_double(),
  `Q12.5_Last Click` = col_double(),
  `Q12.5_Page Submit` = col_double(),
  `Q12.5_Click Count` = col_double(),
  Q12.6 = col_logical(),
  `Q12.7_First Click` = col_double(),
  `Q12.7_Last Click` = col_double(),
  `Q12.7_Page Submit` = col_double(),
  `Q12.7_Click Count` = col_double(),
  Q12.8 = col_double(),
  `Q12.9_First Click` = col_double(),
  `Q12.9_Last Click` = col_double(),
  `Q12.9_Page Submit` = col_double(),
  `Q12.9_Click Count` = col_double(),
  Q13.1 = col_double(),
  `Q13.2_First Click` = col_double(),
  `Q13.2_Last Click` = col_double(),
  `Q13.2_Page Submit` = col_double(),
  `Q13.2_Click Count` = col_double(),
  Q13.3 = col_double(),
  Q13.4 = col_double(),
  `Q13.5_First Click` = col_double(),
  `Q13.5_Last Click` = col_double(),
  `Q13.5_Page Submit` = col_double(),
```

```
  `Q13.5_Click Count` = col_double(),
  Q13.6 = col_logical(),
  `Q13.7_First Click` = col_double(),
  `Q13.7_Last Click` = col_double(),
  `Q13.7_Page Submit` = col_double(),
  `Q13.7_Click Count` = col_double(),
  Q13.8 = col_double(),
  `Q13.9_First Click` = col_double(),
  `Q13.9_Last Click` = col_double(),
  `Q13.9_Page Submit` = col_double(),
  `Q13.9_Click Count` = col_double(),
  Q14.1 = col_number(), # not parsed correctly by default
  `Q14.2_First Click` = col_double(),
  `Q14.2_Last Click` = col_double(),
  `Q14.2_Page Submit` = col_double(),
  `Q14.2_Click Count` = col_double(),
  Q14.3 = col_character(),
  `Q14.4_First Click` = col_double(),
  `Q14.4_Last Click` = col_double(),
  `Q14.4_Page Submit` = col_double(),
  `Q14.4_Click Count` = col_double(),
  Q14.5 = col_double(),
  `Q14.6_First Click` = col_double(),
  `Q14.6_Last Click` = col_double(),
  `Q14.6_Page Submit` = col_double(),
  `Q14.6_Click Count` = col_double(),
  Q15.1 = col_double(),
  `Q15.2_First Click` = col_double(),
  `Q15.2_Last Click` = col_double(),
  `Q15.2_Page Submit` = col_double(),
  `Q15.2_Click Count` = col_double(),
  Q15.3 = col_double(),
  Q15.4 = col_double(),
  `Q15.5_First Click` = col_double(),
  `Q15.5_Last Click` = col_double(),
  `Q15.5_Page Submit` = col_double(),
  `Q15.5_Click Count` = col_double(),
  Q15.6 = col_logical(),
  `Q15.7_First Click` = col_double(),
  `Q15.7_Last Click` = col_double(),
  `Q15.7_Page Submit` = col_double(),
  `Q15.7_Click Count` = col_double(),
  Q15.8 = col_double(),
  `Q15.9_First Click` = col_double(),
  `Q15.9_Last Click` = col_double(),
  `Q15.9_Page Submit` = col_double(),
  `Q15.9_Click Count` = col_double(),
  Q16.1 = col_double(),
  `Q16.2_First Click` = col_double(),
  `Q16.2_Last Click` = col_double(),
  `Q16.2_Page Submit` = col_double(),
  `Q16.2_Click Count` = col_double(),
  Q16.3 = col_double(),
```

```
  Q16.4 = col_double(),
  `Q16.5_First Click` = col_double(),
  `Q16.5_Last Click` = col_double(),
  `Q16.5_Page Submit` = col_double(),
  `Q16.5_Click Count` = col_double(),
  Q16.6 = col_logical(),
  `Q16.7_First Click` = col_double(),
  `Q16.7_Last Click` = col_double(),
  `Q16.7_Page Submit` = col_double(),
  `Q16.7_Click Count` = col_double(),
  Q16.8 = col_double(),
  `Q16.9_First Click` = col_double(),
  `Q16.9_Last Click` = col_double(),
  `Q16.9_Page Submit` = col_double(),
  `Q16.9_Click Count` = col_double(),
  Q17.1 = col_number(), # not parsed correctly by default
  `Q17.2_First Click` = col_double(),
  `Q17.2_Last Click` = col_double(),
  `Q17.2_Page Submit` = col_double(),
  `Q17.2_Click Count` = col_double(),
  Q17.3 = col_logical(),
  `Q17.4_First Click` = col_double(),
  `Q17.4_Last Click` = col_double(),
  `Q17.4_Page Submit` = col_double(),
  `Q17.4_Click Count` = col_double(),
  Q17.5 = col_double(),
  `Q17.6_First Click` = col_double(),
  `Q17.6_Last Click` = col_double(),
  `Q17.6_Page Submit` = col_double(),
  `Q17.6_Click Count` = col_double(),
  Q18.1 = col_double(),
  Q18.2 = col_double(),
  Q19.1 = col_double(),
  Q19.2 = col_double(),
  Q20.2 = col_double(),
  Q20.3 = col_double(),
  Q20.4 = col_double(),
  Q20.5 = col_double(),
  Q20.6 = col_double(),
  Q20.7 = col_double(),
  Q20.8 = col_double(),
  Q20.9 = col_double(),
  Q20.10 = col_double(),
  Q20.11 = col_double(),
  Q22.1 = col_double(),
  Q22.2 = col_double(),
  Q24.1 = col_double(),
  Q24.2 = col_double(),
  Q24.3 = col_double(),
  Q24.4 = col_double(),
  Q25.1 = col_double(),
  Q25.2 = col_double(),
  Q25.3 = col_double(),
```

```
Q26.1 = col_double(),
Q27.2 = col_double(),
Q27.3 = col_double(),
Q27.4 = col_double(),
Q27.5 = col_double(),
Q27.6 = col_double(),
Q27.7 = col_double(),
Q27.8 = col_double(),
Q29.1 = col_double(),
Q29.2 = col_double(),
Q29.3 = col_double(),
Q29.4 = col_double(),
Q30.1 = col_double(),
Q30.2 = col_double(),
Q30.3 = col_double(),
Q30.4 = col_double(),
Q30.5 = col_double(),
Q30.6 = col_double(),
Q30.7 = col_logical(),
Q30.8 = col_character(), # not parsed correctly by default (choose-all item)
Q30.9 = col_double(),
Q30.10 = col_double(),
Q30.11 = col_double(),
Q30.12 = col_double(),
Q30.13 = col_double(),
Q30.14 = col_double(),
Q30.15 = col_double(),
Q30.16 = col_double(),
Q31.1 = col_double(),
Q31.2 = col_double(),
Q32.1 = col_character(),
PID = col_character(), # not parsed correctly by default
psid = col_character(), # not parsed correctly by default
RESPONDENT_ID = col_logical(),
order_hv_rent = col_double(),
test_API = col_logical(),
test_Q = col_logical(),
packrat = col_logical(),
econ_flow = col_double(),
response_order_forwhom = col_double(),
preemption_flow = col_double(),
which_price = col_character(),
scenario = col_character(),
inflation_factor = col_double(),
elicit_type = col_character(),
zip_or_city = col_character(),
want_price = col_character(),
random = col_character(), # does this need to be updated in survey?
rural_screen = col_logical(),
rent = col_number(),
rent_0.01 = col_number(),
rent_0.05 = col_number(),
rent_0.10 = col_number(),
```

```r
  rent_0.15 = col_number(),
  rent_0.20 = col_number(),
  rent_0.25 = col_number(),
  rent_0.30 = col_number(),
  City = col_character(),
  State = col_character(),
  hv = col_number(),
  hv_0.01 = col_number(),
  hv_0.05 = col_number(),
  hv_0.10 = col_number(),
  hv_0.15 = col_number(),
  hv_0.20 = col_number(),
  hv_0.25 = col_number(),
  hv_0.30 = col_number(),
  QCity_Q1.2 = col_logical(),
  QState_Q1.2 = col_logical(),
  where = col_character(),
  intro_embed = col_character(),
  event_embed_1 = col_character(),
  event_embed_2 = col_character(),
  event_embed_3 = col_character(),
  event_embed_4 = col_character(),
  event_embed_5 = col_character(),
  event_embed_6 = col_character(),
  event_embed_7 = col_number(),
  recap_embed_1 = col_character(),
  recap_embed_2 = col_character(),
  recap_embed_3 = col_character(),
  howmuch_embed_1 = col_character(),
  howmuch_embed_2 = col_character(),
  howmuch_embed_3 = col_character(),
  price_0.01 = col_number(),
  price_0.05 = col_number(),
  price_0.10 = col_number(),
  price_0.15 = col_number(),
  price_0.20 = col_number(),
  price_0.25 = col_number(),
  price_0.30 = col_number(),
  price = col_number(),
  wantprice_embed_1 = col_character(),
  wantprice_embed_2 = col_character(),
  wantprice_embed_3 = col_character(),
  AB_split = col_character(),
  mywhere = col_character(),
  subsidy_embed_1 = col_character(),
  SSsites_embed_1_cap = col_character(),
  SSsites_embed_1_lower = col_character(),
  SSsites_embed_2 = col_character()
))

# drop embedded data fields used only in question text, and other vestigal and unnecessary stuff

D <- D %>%
```

```r
  select(- (RecipientLastName:ExternalReference), # Qualtrics unused field
         - UserLanguage, # Qualtrics unused field
         - test_API, # for testing
         - test_Q, # for testing
         - zip_or_city, # not randomized in this version of survey
         - want_price, # not randomized in this version of survey
         - packrat, # stripped questions
         - starts_with("price"), # used if test_Q == TRUE
         - Q8.6, # used if packrat == TRUE
         - Q8.8, # used if packrat == TRUE
         - Q8.9, # used if packrat == TRUE
         - Q30.7 # used if packrat == TRUE
         )
```

5.2 Clean & Recode

```r
# Intro demographics section of survey
D<-D%>%
  mutate(
    age.cat=recode(Q8.1,'1'='18-29', '2'='30-44',
                        '3'='45-64', '4'='65 plus'),
    male=as.numeric(Q8.2=='1')
  )

D$race.eth<-NA
D$race.eth[D$Q8.3=="1"]<-"White"
D$race.eth[D$Q8.3=="2"]<-"Black"
D$race.eth[D$Q8.3=="4"]<-"Asian"
## Order is important here; any Hispanic supersedes race.
D$race.eth[grep("3", D$Q8.3)]<-"Hispanic"
D$race.eth[D$Q8.3%in%c("5", "6")]<-"Multi/Other"
D$race.eth[is.na(D$race.eth)]<-"Multi/Other"

# commented out the demographic fields not currently in use
D<-D%>%
  mutate(
    has.ba=as.numeric(Q8.4=='4'),
    ownhome=as.numeric(Q8.5=='1'),
#    employed.ft=as.numeric(Q8.6=='1'),
    want.price=recode(Q8.7, '1'='Higher', '2'='Same', '3'='Lower'),
#    has.kids=as.numeric(D$Q8.8=='1'),
#    married=as.numeric(D$Q8.9=='2')
    income = Q30.15, # not recoded, 11 point scale, `1` < $30,000, `11` > $150,000
    housing.costs = Q30.16, # not recoded, 14 point scale, `1` < $250/month, `14` > $20k/month
    cost.burden = housing.costs/income # very coarse measure of cost burden, dividing income on 11 p
    )

# Typical housing type as reported by respondent.
D<-D%>%
  mutate(
    hous.typ.rent = recode(Q9.1, '1'='Small_Apt', '2'='Large_Apt', '3'='Small_Townhome', '4'='Large_
    hous.typ.own = recode(Q9.3, '1'='Small_Condo', '2'='Large_Condo', '3'='Small_Townhome', '4'='Lar
  )
```

```
# Create index of economic knowledge. Though $know.trade is a knowledge question we exclude it from

D<-D%>%
  mutate(
    know.trade=as.numeric(Q22.1=='2'),
    know.ss.used=as.numeric(Q30.6=='1'),
    know.ss.grain=as.numeric(Q30.14=='2'),
    know.ss.wages=as.numeric(Q22.2=='2')
  )

know.ss.pc<-D%>%
  select(starts_with("know.ss"))%>%
  drop_na() %>%
  prcomp()
pc.x<-as.data.frame(know.ss.pc$x)
names(pc.x)<-paste0("know.ss.", names(pc.x))

# assign ResponseId to know.PC.x and join to D
rep_id <- D %>%
  filter(if_all(starts_with("know.ss"), ~ !is.na(.x))) %>%
  dplyr::pull(ResponseId)
pc.x <- pc.x %>% mutate(ResponseId = rep_id)

D <- left_join(D, pc.x, by="ResponseId")

D$know.ss.tot<-rowMeans(select(D, names(know.ss.pc$center)))


# Create index of zero-sum thinking.
D<-D%>%
  mutate(
    zst.politics=as.numeric(Q29.1=='2'),
    zst.life=as.numeric(Q29.2=='1'),
    zst.policy=as.numeric(Q29.3=='1'),
    zst.wealth=as.numeric(Q29.4=='1')
  )

zst.pc<-D%>%
  select(starts_with("zst"))%>%
  drop_na() %>%
  prcomp()
pc.x<-as.data.frame(zst.pc$x)
names(pc.x)<-paste0("zst.", names(pc.x))
rep_id <- D %>%
  filter(if_all(starts_with("zst"), ~ !is.na(.x))) %>%
  dplyr::pull(ResponseId)
pc.x <- pc.x %>% mutate(ResponseId = rep_id)
D <- left_join(D, pc.x, by="ResponseId")

D$zst.tot<-rowMeans(select(D, starts_with("zst")))

# exposure to observed correlation between price & development (higher values signifify greater agre
D<-D%>% mutate(obs.price.dev=6-as.numeric(Q30.1))
```

```r
## Engagement with local politics.
D<-D%>%
  mutate(
    engage.votelocal=as.numeric(Q30.3=='1'),
    engage.candidates=as.numeric(Q30.5),
#    locgov.careissues=as.numeric(Q30.7=='1'), # packrat
    engage.petition=as.numeric(grepl("1", Q30.8)),
    engage.nbhdmtg=as.numeric(grepl("2", Q30.8)),
    engage.hearing=as.numeric(grepl("3", Q30.8)),
    engage.contact=as.numeric(grepl("4", Q30.8)),
    engage.count=engage.petition+engage.nbhdmtg+engage.hearing+engage.contact
    )

engage.pc<-D%>%
  select(engage.count, engage.votelocal, engage.candidates)%>%
  drop_na() %>%
  prcomp()
#Assign the principal components to the dataset.
pc.x<-as.data.frame(engage.pc$x)
names(pc.x)<-paste0("engage.", names(pc.x))
rep_id <- D %>%
  filter(if_all(c(engage.count, engage.votelocal, engage.candidates),
                ~ !is.na(.x))) %>%
  dplyr::pull(ResponseId)
pc.x <- pc.x %>% mutate(ResponseId = rep_id)
D <- left_join(D, pc.x, by="ResponseId")
D$engage.tot<-rowMeans(select(D, c(engage.count, engage.votelocal, engage.candidates)))

# partisanship, ideology, national politics
D <- D %>%
  mutate(
    repub = as.numeric(Q30.11), # 1 = Strong, 2 = Not so strong
    dem = as.numeric(recode(Q30.10, '1'='7', '2'='6')),
    ind = as.numeric(recode(Q30.12, '1'='5', '2'='3', '3'='4')),
    pid7 = coalesce(repub, dem, ind)
  ) %>%
  select(-repub, -dem, -ind) %>%
  mutate(
    libcon=as.numeric(recode(Q30.2, '1'='-1', '2'='0', '3'='1', '4'=NULL)),
    voted20=as.numeric(Q30.3),
    pid3.nolean=recode(Q30.9, '1'='dem', '2'='rep', '3'='io', '4'='io')
    )

D$pid3.wlean<-D$pid3.nolean
D$pid3.wlean[D$Q30.12=='1']<-'dem'
D$pid3.wlean[D$Q30.12=='2']<-'rep'

# other demographics.

# Respondent description of own neighborhood
D <- D %>%
  mutate(
    nabe.live=recode(Q30.13,
```

```
                    '1'='city_dense',
                    '2'='city_sparse',
                    '3'='burb_dense',
                    '4'='burb_sparse',
                    '5'='small_town',
                    '6'='rural_farm',
                    '7'='rural_notfarm',
                    )
  )


# Support for public policies. Variable naming convention: housing policies begin with 'hous'; cross

D <- D %>%
  mutate(
    hous.TOD=6-as.numeric(Q31.1), # generic TOD development in metro region
    hous.sprawl=6-as.numeric(Q31.2), # generic greenfield development in metro region
    hous.sprawl.preempt=6-as.numeric(Q11.2), # state preemption for greenfield development
    hous.GD.preempt=6-as.numeric(Q11.3), # state preemption for gentle density (plex) development
    hous.TOD.preempt=6-as.numeric(Q11.4), # state preemption for TOD development
    hous.SFH.preempt=6-as.numeric(Q11.5), # state preemption for big SFH development
    hous.no.preempt=6-as.numeric(Q11.6)#, # no state preemption for housing development
    # pc.rent=6-as.numeric(Q24.1), # cap rents
    # pc.phone=6-as.numeric(Q24.2), # cap smartphone prices
    # pc.proptax=6-as.numeric(Q24.3), # cap property taxes
    # pc.car=6-as.numeric(Q24.4), # cap car prices
    # cs.hous=6-as.numeric(Q25.1), # cross-subsidy, housing
    # cs.phone=6-as.numeric(Q25.2), # cross-subsidy, smartphones
    # cs.car=6-as.numeric(Q25.3), # cross-subsidy, cars
    # cs.hous.low=case_when(subsidy_embed_1 == "lower-income" ~ cs.hous),
    # cs.phone.low=case_when(subsidy_embed_1 == "lower-income" ~ cs.phone),
    # cs.car.low=case_when(subsidy_embed_1 == "lower-income" ~ cs.car),
    # cs.hous.mid=case_when(subsidy_embed_1 == "middle-income" ~ cs.hous),
    # cs.phone.mid=case_when(subsidy_embed_1 == "middle-income" ~ cs.phone),
    # cs.car.mid=case_when(subsidy_embed_1 == "middle-income" ~ cs.car),
    # right.return=6-as.numeric(Q26.1), # tenant right-of-return (SB330)
    )

# Create indices of support for price controls and cross-subsidy requirements, excluding housing and

# cs.mid.pc<-D%>%
#   select(cs.phone.mid, cs.car.mid)%>%
#   drop_na() %>%
#   prcomp()
# #Assign the principal components to the dataset.
# pc.x<-as.data.frame(cs.mid.pc$x)
# names(pc.x)<-paste0("cs.mid.", names(pc.x))
# rep_id <- D %>%
#   filter(if_all(c(cs.phone.mid, cs.car.mid),
#                 ~ !is.na(.x))) %>%
#   dplyr::pull(ResponseId)
# pc.x <- pc.x %>% mutate(ResponseId = rep_id)
# D <- left_join(D, pc.x, by="ResponseId")
```

```r
# D$cs.mid.tot<-rowMeans(select(D, c(cs.phone.mid, cs.car.mid)))
#
# cs.low.pc<-D%>%
#   select(cs.phone.low, cs.car.low)%>%
#   drop_na() %>%
#   prcomp()
#
# #Assign the principal components to the dataset.
# pc.x<-as.data.frame(cs.low.pc$x)
# names(pc.x)<-paste0("cs.low.", names(pc.x))
# rep_id <- D %>%
#   filter(if_all(c(cs.phone.low, cs.car.low),
#                 ~ !is.na(.x))) %>%
#   dplyr::pull(ResponseId)
# pc.x <- pc.x %>% mutate(ResponseId = rep_id)
# D <- left_join(D, pc.x, by="ResponseId")
# D$cs.low.tot<-rowMeans(select(D, c(cs.phone.low, cs.car.low)))
#
# pc.pc<-D%>%
#   select(pc.phone, pc.car)%>%
#   drop_na() %>%
#   prcomp()
# #Assign the principal components to the dataset.
# pc.x<-as.data.frame(pc.pc$x)
# names(pc.x)<-paste0("pc.", names(pc.x))
# rep_id <- D %>%
#   filter(if_all(c(pc.phone, pc.car),
#                 ~ !is.na(.x))) %>%
#   dplyr::pull(ResponseId)
# pc.x <- pc.x %>% mutate(ResponseId = rep_id)
# D <- left_join(D, pc.x, by="ResponseId")
# D$pc.tot<-rowMeans(select(D, c(pc.phone, pc.car)))

# General housing market beliefs (mechanism - step 2). Coded so that 1 = positive effect on price/re
D <- D %>%
  mutate(
    agglom.price = as.numeric(recode(Q27.2, '1'='1', '2'='-1', '3'='0')), # more businesses
    demo.price = as.numeric(recode(Q27.3, '1'='1', '2'='-1', '3'='0')), # more demo of affordable ho
    corp.price = as.numeric(recode(Q27.4, '1'='1', '2'='-1', '3'='0')), # more corporate ownership
    qolworse.price = as.numeric(recode(Q27.5, '1'='-1', '2'='1', '3'='0')), # less quality of life
    gentry.price = as.numeric(recode(Q27.6, '1'='1', '2'='-1', '3'='0')), # more high-income people
    nextdoor.price = as.numeric(recode(Q27.7, '1'='-1', '2'='1', '3'='0')), # expensive new housing
    forme.price = as.numeric(recode(Q27.8, '1'='1', '2'='-1', '3'='0')) # more housing for people li
  )

# code here onward assumes correct parsing of column types

# Predicted Effects of $scenario - home value & rent
 D <- D %>%
  mutate( # this is simple & complex format only
    shock.rento = 6 - coalesce(Q12.1, Q13.1),
    shock.rentc.up = coalesce(Q12.3, Q13.3),
    shock.rentc.up = recode(shock.rentc.up, '1'=0.01, '2'=0.05, '3'=0.10, '4'=0.15, '5'=0.20, '6'=0.
```

```r
    shock.rentc.down = coalesce(Q12.4, Q13.4),
    shock.rentc.down = recode(shock.rentc.down, '1'=-0.01, '2'=-0.05, '3'=-0.10, '4'=-0.15, '5'=-0.2
    shock.rentc = case_when(shock.rento %in% c(4,5) ~ shock.rentc.up,
                            shock.rento %in% c(1,2) ~ shock.rentc.down,
                            shock.rento == 3 ~ 0),
    shock.hvo = 6 - coalesce(Q15.1, Q16.1),
    shock.hvc.up = coalesce(Q15.3, Q16.3),
    shock.hvc.up = recode(shock.hvc.up, '1'=0.01, '2'=0.05, '3'=0.10, '4'=0.15, '5'=0.20, '6'=0.25,
    shock.hvc.down = coalesce(Q15.4, Q16.4),
    shock.hvc.down = recode(shock.hvc.down, '1'=-0.01, '2'=-0.05, '3'=-0.10, '4'=-0.15, '5'=-0.20, '
    shock.hvc = case_when(shock.hvo %in% c(4,5) ~ shock.hvc.up,
                            shock.hvo %in% c(1,2) ~ shock.hvc.down,
                            shock.hvo == 3 ~ 0),
    )

 # Add potential-outcome format questions.
 D <- D %>%
  mutate(
    po.shock.rentnow = as.numeric(Q10.1), # rent predictions
    po.shock.rent5yr.Y0 = as.numeric(Q10.3),
    po.shock.rent5yr.Y1 = as.numeric(Q14.1),
    po.shock.rentc = (po.shock.rent5yr.Y1 - po.shock.rent5yr.Y0) / po.shock.rent5yr.Y0,
    shock.rentc = coalesce(shock.rentc, po.shock.rentc),
    po.shock.hvnow = as.numeric(Q10.5),  # hv predictions
    po.shock.hv5yr.Y0 = as.numeric(Q10.7),
    po.shock.hv5yr.Y1 = as.numeric(Q17.1),
    po.shock.hvc = (po.shock.hv5yr.Y1 - po.shock.hv5yr.Y0) / po.shock.hv5yr.Y0,
    shock.hvc = coalesce(shock.hvc, po.shock.hvc),
  )

# Add dummy skepticism variables (wk = weak, str = strong) for analysis that is robust to outliers.
D <- D %>%
  mutate(
    shock.rentskep.str = as.numeric(shock.rentc > 0),
    shock.rentskep.wk = as.numeric(shock.rentc >= 0),
    shock.hvskep.str = as.numeric(shock.hvc > 0),
    shock.hvskep.wk = as.numeric(shock.hvc >= 0),
    shock.poolskep.str = coalesce(shock.rentskep.str, shock.hvskep.str),
    shock.poolskep.wk = coalesce(shock.rentskep.wk, shock.hvskep.wk),
  )

# Add directional confidence, anxiety Qs
 D <- D %>%
  mutate(
    shock.hv.angst = 5 - Q18.1,
    shock.rent.angst = 5 - Q18.2,
    shock.hv.conf = 6 - coalesce(Q15.8, Q16.8, Q17.5),
    shock.rent.conf = 6 - coalesce(Q12.8, Q13.8, Q14.5),
  )

# Add mechanism (substantive outcome) Qs
  D <- D %>%
    mutate(
```

```
      shock.chain.low = 6 - Q20.2, # chain of moves, less expensive neighborhoods
      shock.chain.high = 6 - Q20.3, # chain of moves, more expensive neighborhoods
      shock.agglom = 6 - Q20.4, # more businesses
      shock.demo = 6 - Q20.5, # more demo of affordable homes
      shock.corp = 6 - Q20.6, # more corporate ownership of homes
      shock.qolworse = 6 - Q20.8, # worse quality of life in my neighborhood
      shock.gentry = 6 - Q20.9, # more high income people in low-income nabes
      shock.nextdoor = 6 - Q20.10, # more spendy new homes by cheaper older ones
      shock.forme = 6 - Q20.11, # more new housing for people like me
    )

# Add survey time ($time.predict and $time.total. I've included time spent answering the "how confid

D <- D %>%
  mutate(
    time.predict = case_when(
      elicit_type=="simple" & which_price=="rent" ~
        `Q12.2_Page Submit` +
        `Q12.5_Page Submit` +
        `Q12.9_Page Submit`,
      elicit_type=="simple" & which_price=="hv" ~
        `Q15.2_Page Submit` +
        `Q15.5_Page Submit` +
        `Q15.9_Page Submit`,
      elicit_type=="complex" & which_price=="rent" ~
        `Q13.2_Page Submit` +
        `Q13.5_Page Submit` +
        `Q13.9_Page Submit`,
      elicit_type=="complex" & which_price=="hv" ~
        `Q16.2_Page Submit` +
        `Q16.5_Page Submit` +
        `Q16.9_Page Submit`,
      elicit_type=="po" & which_price=="rent" ~
        `Q10.2_Page Submit` +
        `Q10.4_Page Submit` +
        `Q14.2_Page Submit` +
        `Q14.6_Page Submit`,
      elicit_type=="po" & which_price=="hv" ~
        `Q10.6_Page Submit` +
        `Q10.8_Page Submit` +
        `Q17.2_Page Submit` +
        `Q17.6_Page Submit`,
    ),
    time.total = `Duration (in seconds)`
  )

# Add indicator for gov't vs. technology nature of the supply shock.

D <- D %>%
  mutate(
    shock.class = fct_collapse(
      as_factor(scenario),
      Tech = "tech", StateLaw = c("tod", "greenfield", "plex")
```

```
    ))
```

5.3 Identify "Speeder" Respondents

```
D %>%
  filter(Finished == "1") %>%
  rename(duration_in_seconds = `Duration (in seconds)`) %>%
  mutate(
    seconds = as.numeric(duration_in_seconds),
    minutes = factor(case_when(
      seconds < 5*60 ~ "Less than 5 min",
      seconds >= 5*60 & seconds < 7*60 ~ "5-7 min",
      seconds >= 7*60 & seconds < 9*60 ~ "7-9 min",
      seconds >= 9*60 & seconds < 11*60 ~ "9-11 min",
      seconds >= 11*60 & seconds < 15*60 ~ "11-15 min",
      seconds >= 15*60 & seconds < 20*60 ~ "15-20 min",
      seconds >= 20*60 ~ "More than 20 min"
    ), levels = c("Less than 5 min","5-7 min","7-9 min","9-11 min","11-15 min","15-20 min","More tha
  ) %>%
  group_by(minutes) %>%
  summarize(n = n())
```

```
## # A tibble: 4 x 2
##   minutes              n
##   <fct>            <int>
## 1 Less than 5 min    377
## 2 11-15 min            1
## 3 15-20 min            4
## 4 More than 20 min     1
```

6 Survey 2 Pre-Analysis Plan

This draft PAP highlights the main results we intend to report from Survey 2.

6.1 Robustness Checks of Survey 1 Results

Our first goal is to determine whether the supply skepticism documented in our first survey may have been an artifact of the specific rezoning scenario, question wording, or the counterfactual prices and rents piped into the questions.

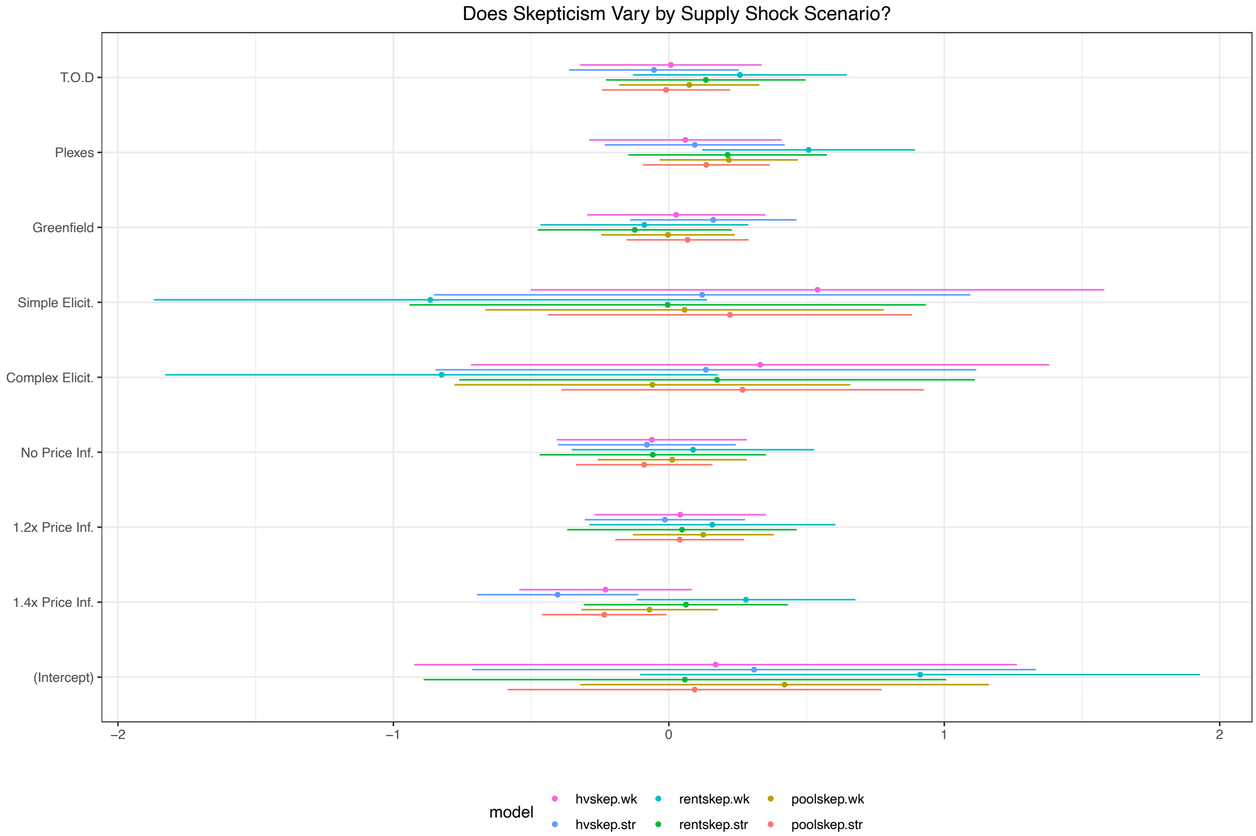
6.1.1 Conjoint Analysis

We tackle the robustness question first by depicting AMCE-style estimates of the effect of each randomized-attribute level on the probability of a "skeptical" response, (i.e. that increased supply will not lead to decreased prices), to the supply-shock scenario in survey two.

We may observe greater supply skepticism with respect to certain scenarios. For example, if people are thinking in terms of local amenity and disamenity effects rather than regional market effects, the "plex" scenario (which threatens to alter existing single-family neighborhoods) may elicit more downward-effect predictions than the other scenarios. However, this was the scenario posed on Survey 1, where we found ample evidence of supply skepticism.

```
D_mod <- D %>% mutate(
  inflation_factor = as_factor(inflation_factor),
```

```
  scenario = fct_relevel(as_factor(scenario), "tech"), # set reference level
  elicit_type = fct_relevel(as_factor(elicit_type), "po") # set reference level
)


mods.conjoint <- tidy.mods.conjoint <- list() # list to hold fitted models

yvar <- c("shock.poolskep.str", "shock.poolskep.wk", "shock.rentskep.str", "shock.rentskep.wk", "sho
terms <- "~ scenario + elicit_type + inflation_factor"
lr.mod <- linear_reg() # declare model. No need for clustered SEs because each conjoint-style attrib

for(i in 1:length(yvar)){
 mods.conjoint[[i]]<-
 fit(lr.mod, formula=as.formula(paste0(yvar[i], terms)), data = D_mod)
}

names(mods.conjoint) <- c("poolskep.str", "poolskep.wk", "rentskep.str", "rentskep.wk", "hvskep.str"

tidy.mods.conjoint <- map(mods.conjoint, ~ tidy(.))

model_labels <- c(
    "rentskep.str" = "Rent(+)",
    "rentskep.wk" = "Rent(+/=)",
    "hvskep.str" = "Home Prices(+)",
    "hvskep.wk" = "Home Prices(+/=)",
    "poolskep.str" = "All(+)",
    "poolskep.wk" = "All(+/=)"
  )

dwplot(mods.conjoint, show_intercept = TRUE)  %>%
  relabel_predictors(.,scenariotod="T.O.D",
                     scenarioplex="Plexes",
                     scenariogreenfield="Greenfield",
                     elicit_typesimple="Simple Elicit.",
                     elicit_typecomplex="Complex Elicit.",
                     inflation_factor1="No Price Inf.",
                     inflation_factor1.2="1.2x Price Inf.",
                     inflation_factor1.4="1.4x Price Inf.") +
  labs(title = "Does Skepticism Vary by Supply Shock Scenario?") +
  theme_bw()+
  theme(plot.title = element_text(hjust = 0.5), legend.position = "bottom") # +
```



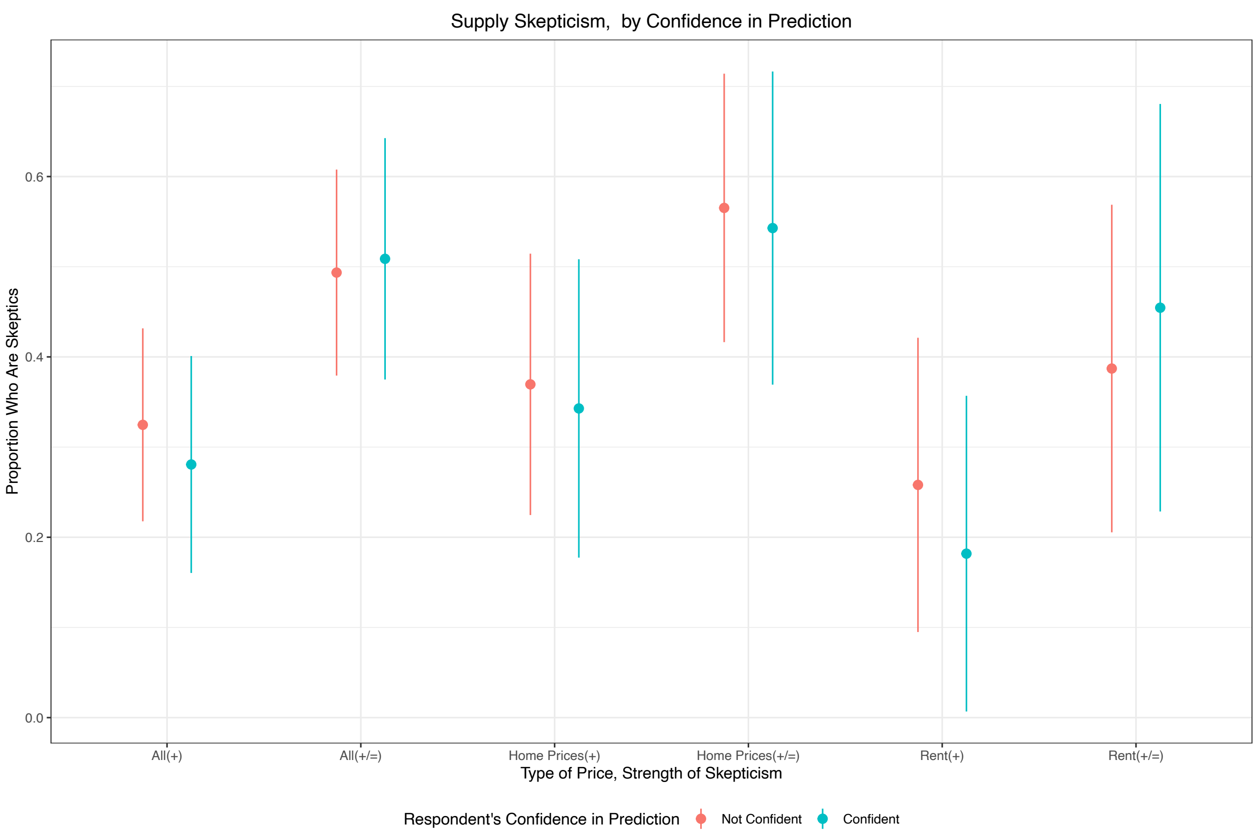

```
# facet_wrap(. ~ model, labeller=as_labeller(model_labels))
```

6.1.2 Supply Skepticism and Self-Reported Confidence

As an additional check, we disaggregate responses according to self-reported confidence of price predictions. If the supply skepticism we observed was mainly a manifestation of noisy guessing by survey respondents, we would expect to find a large difference in the probability of a skeptical response as between people who report high and low levels of confidence in the direction of their prediction.

```
D_mod <- D %>% mutate(
  want = fct_collapse(as_factor(want.price), NotLower = c("Higher", "Same"), Lower = "Lower"),
  rent.conf = as.numeric(shock.rent.conf > median(
    c(D$shock.rent.conf, D$shock.hv.conf), na.rm = TRUE)),
  hv.conf = as.numeric(shock.hv.conf > median(
    c(D$shock.rent.conf, D$shock.hv.conf), na.rm = TRUE)),
  confidence = coalesce(rent.conf, hv.conf), # modify this line if future survey elicits both rent a
  know.ss = as.numeric(know.ss.PC1 > median(D$know.ss.PC1, na.rm = TRUE)),
  lay.empirics = as.numeric(obs.price.dev > median(D$obs.price.dev, na.rm = TRUE)),
  zst = as.numeric(zst.PC1 > median(D$zst.PC1, na.rm = TRUE)),
)

D_mod %>%
  filter(!is.na(confidence)) %>%
  pivot_longer(shock.rentskep.str:shock.poolskep.wk,
               names_to = "DV",
               values_to = "response") %>%
  nest(data = -c(DV, confidence)) %>%
  mutate(model = map(data, ~ lm_robust(response ~ 1, data = .)),
```

```
        tidied = map(model, tidy)) %>%
  unnest(tidied) %>%
  mutate(xlabel = case_when(
    DV == "shock.rentskep.str" ~ "Rent(+)",
    DV == "shock.rentskep.wk" ~ "Rent(+/=)",
    DV == "shock.hvskep.str" ~ "Home Prices(+)",
    DV == "shock.hvskep.wk" ~ "Home Prices(+/=)",
    DV == "shock.poolskep.str" ~ "All(+)",
    DV == "shock.poolskep.wk" ~ "All(+/=)"
  )) %>%
  ggplot(aes(x=xlabel, y=estimate, group=confidence)) +
  geom_pointrange(aes(ymin=conf.low,ymax=conf.high, color=factor(confidence)),
                  position=position_dodge(width=.5)) +
  ylab("Proportion Who Are Skeptics") +
  xlab("Type of Price, Strength of Skepticism") +
  labs(title = "Supply Skepticism,  by Confidence in Prediction") + theme_bw() +
  scale_color_discrete("Respondent's Confidence in Prediction", labels=c("Not Confident","Confident"
  theme(plot.title = element_text(hjust = 0.5), legend.position = "bottom")
```



6.2 Dispositional Factors and Exposure as Moderators of Supply Skepticism

We next examine how supply skepticism covaries with zero-sum thinking, economic knowledge, and self-reported exposure to the co-occurrence of high prices and housing development.

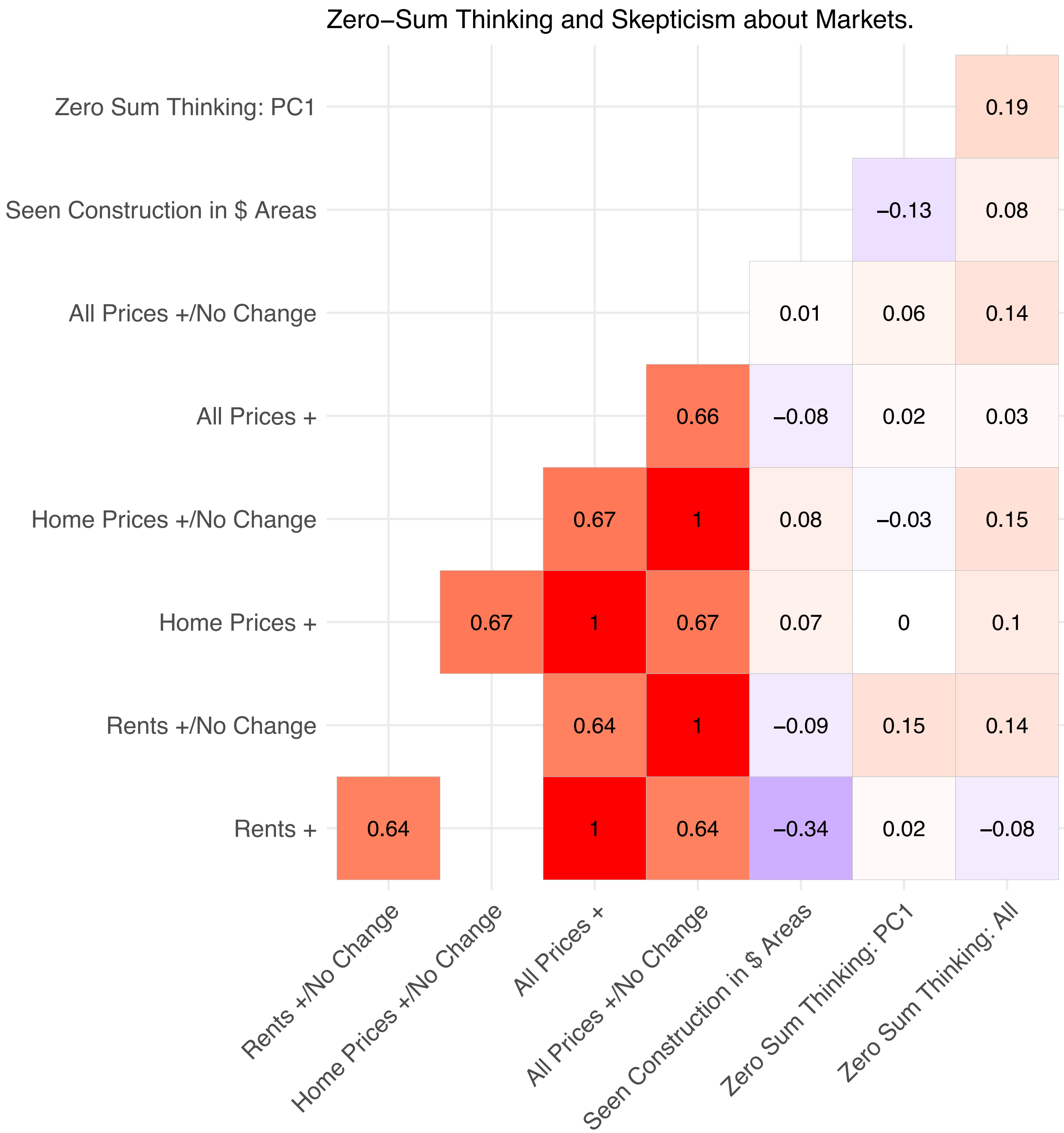
We present results first in the form of correlation-matrix heatmaps.

We posit that the degree to which a respondent is a "zero-sum thinker" correlates with their skepticism that various housing supply increases will have an ultimate effect on prices. Zero-sum thinkers tend to see policy as producing winners and losers. They feel that if zoning changes benefit developers or other parts of the real estate sector by removing hurdles to new construction, this must mean that renters, existing residents must be losing. As such, they will question the ultimate impact on prices various supply shocks have on regional housing markets and be more skeptical about "Economics 101" mental models which would predict a drop in price following an increase in supply.

We also predict that exposure to new housing being built in more expensive areas of a respondent's metro will correlate with more skepticism about the effect that increased supply has in lowering housing prices. Exposure to such construction, we posit, activates the Availability Heuristic (Tversky and Kahneman 1973) which puts such development at top of mind. As such, respondents will prefer to generalize from that experience rather than engage in costly thinking through abstract mental models. A disposition to zero-sum thinking will further exacerbate this reliance on recent experience as it would seem to validate the idea that new development only exacerbates existing inequality.

6.2.1 Zero-Sum Thinking, Exposure, and Supply Skepticism

```
library(ggcorrplot)
# correlation of supply skepticism with zero sum thinking & reported exposure to correlational evide

D%>%
  select(contains("skep."), obs.price.dev, zst.PC1, zst.tot) %>%
  rename("Rents +"="shock.rentskep.str",
         "Rents +/No Change"="shock.rentskep.wk",
         "Home Prices +"="shock.hvskep.str",
         "Home Prices +/No Change"="shock.hvskep.wk",
         "All Prices +"="shock.poolskep.str",
         "All Prices +/No Change"="shock.poolskep.wk",
         "Seen Construction in $ Areas"="obs.price.dev",
         "Zero Sum Thinking: PC1"="zst.PC1",
         "Zero Sum Thinking: All"="zst.tot") %>%
  cor(use="pairwise.complete.obs") %>%
  ggcorrplot(type="lower", lab=T, title="Zero-Sum Thinking and Skepticism about Markets.") +
  theme(legend.position="none")
```

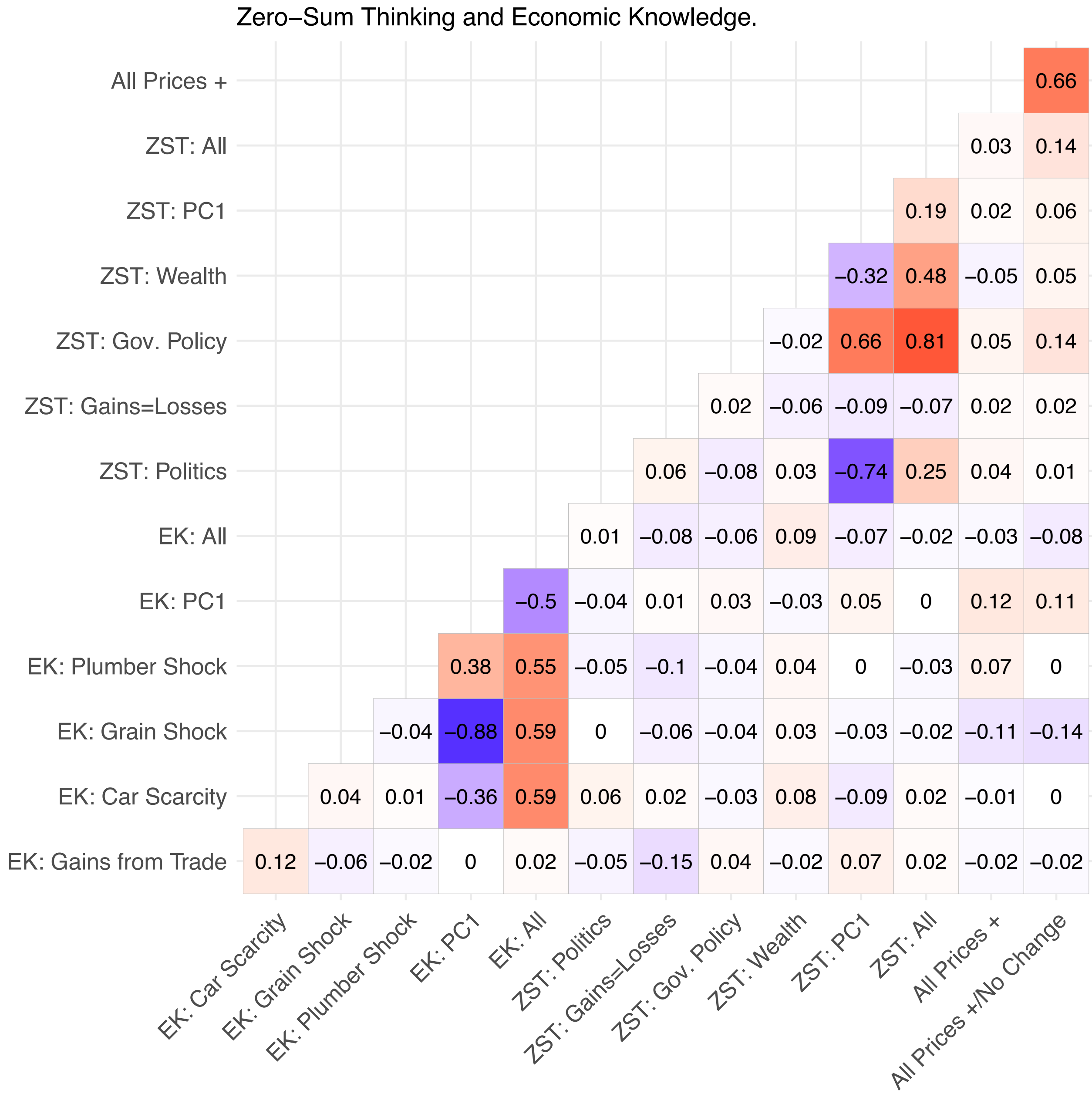


6.2.2 Zero-Sum Thinking, Economic Knowledge, and Supply Skepticism

We also expect zero-sum thinking to be negatively correlated with economic knowledge, which in turn will be negatively correlated with supply skepticism.

```
D%>%
  select(starts_with("know"), starts_with("zst"), know.ss.PC1, know.ss.tot, zst.PC1, zst.tot, shock.
  dplyr::select(-c(know.ss.PC2, know.ss.PC3, zst.PC2, zst.PC3, zst.PC4)) %>%
  rename("EK: Gains from Trade"="know.trade",
         "EK: Car Scarcity" = "know.ss.used",
         "EK: Grain Shock"="know.ss.grain",
         "EK: Plumber Shock"="know.ss.wages",
```

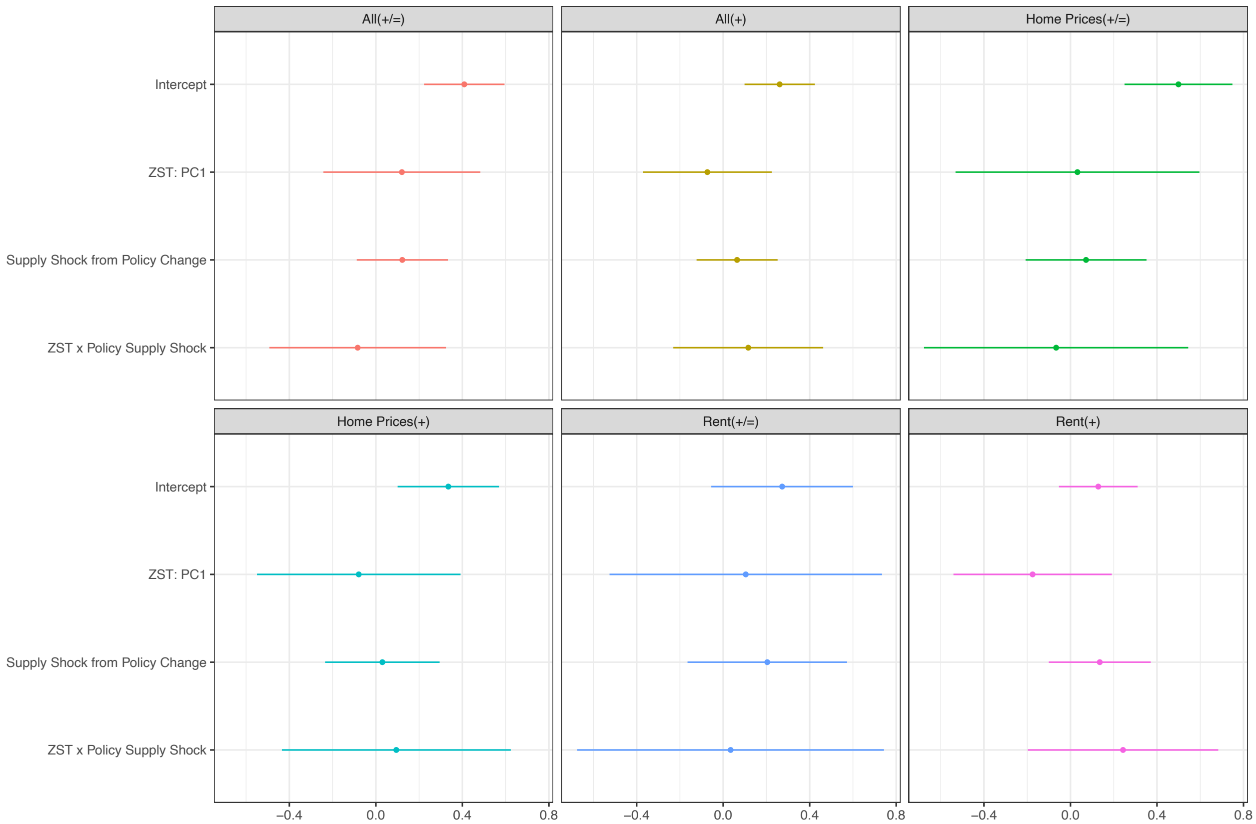
```
        "EK: PC1"="know.ss.PC1",
        "ZST: PC1"="zst.PC1",
        "ZST: All"="zst.tot",
        "ZST: Politics"="zst.politics",
        "ZST: Gains=Losses"="zst.life",
        "ZST: Gov. Policy"="zst.policy",
        "ZST: Wealth"="zst.wealth",
        "All Prices +"="shock.poolskep.str",
        "All Prices +/No Change"="shock.poolskep.wk",
        "EK: All"="know.ss.tot"
        ) %>%
cor(use="pairwise.complete.obs") %>%
ggcorrplot(type="lower", lab=T, title="Zero-Sum Thinking and Economic Knowledge.") +
theme(legend.position="none")
```



6.2.3 Model-Based Results

We model supply skepticism in its "strong" and "weak" forms as a function of the first-dimension principal component of our four-question zero-sum thinker question battery, a dummy variable indicating whether supply shock was a technological advance or a change in policy, as well as the interaction of those two variables. We expect to see positive and statistically significant coefficients for the zero-sum thinking variable as well as the interaction between that variable and the dummy variable indicating a policy-related supply shock.

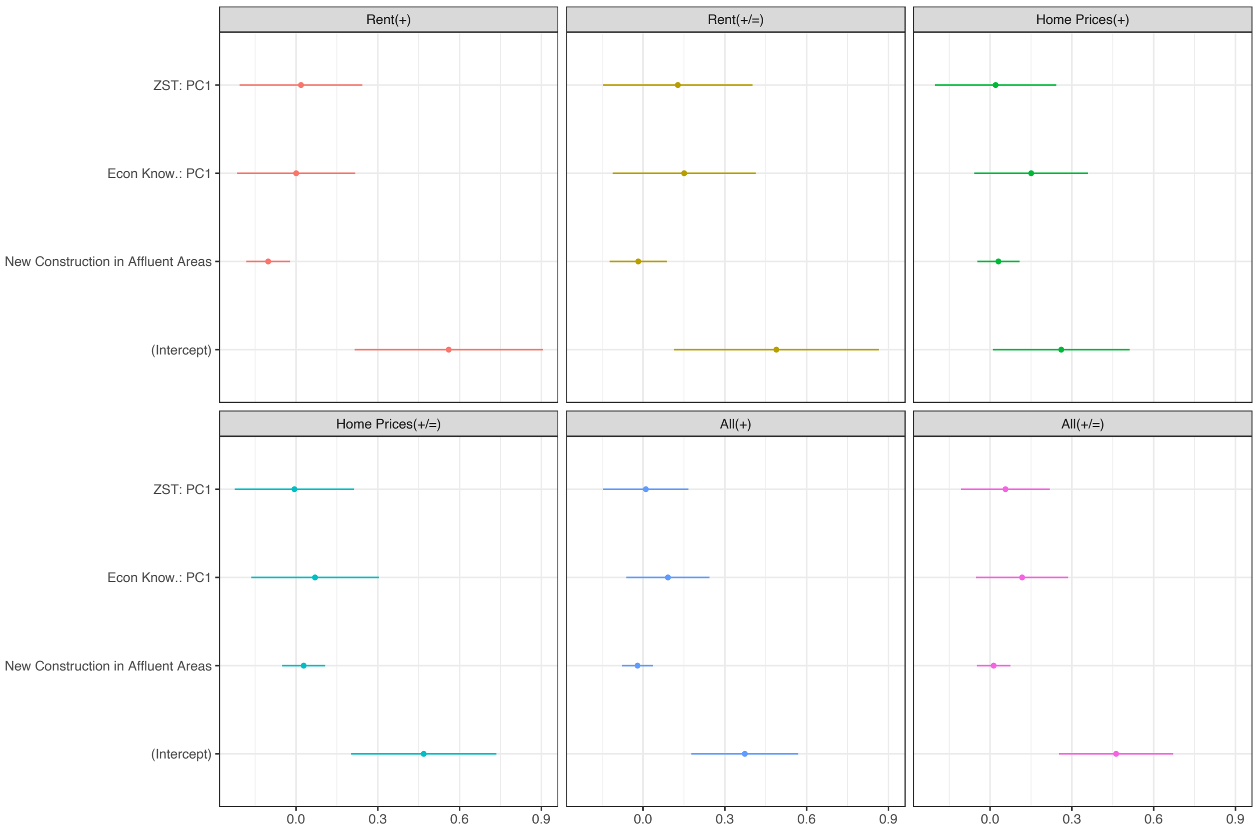
```
# Model of zero-sum thinking interacted with type of supply shock. Expectation is the ZSTers will be

results <- D_mod %>% mutate(gov_shock=ifelse(shock.class=="Tech",0,1)) %>%
  pivot_longer(shock.rentskep.str:shock.poolskep.wk,
                       names_to = "DV",
                       values_to = "response") %>%
  nest(data = -c(DV)) %>%
  mutate(
    model = map(data, ~ lm_robust(response ~
                                    zst.PC1 +
                                    gov_shock +
                                    zst.PC1:gov_shock,
                                  data = .)),
    tidied = map(model, tidy))

model_names <- c(
 "Model 1"="Rent(+)",
    "Model 2" = "Rent(+/=)",
    "Model 3" = "Home Prices(+)",
    "Model 4" = "Home Prices(+/=)",
    "Model 5" = "All(+)",
    "Model 6" = "All(+/=)"
)

dwplot(results$model,show_intercept = TRUE)  +
  # relabel_predictors(zst.PC1="ZST: PC1",
  #                    gov_shock="Supply Shock from Policy Change") +
  scale_y_discrete(labels=c("ZST x Policy Supply Shock","Supply Shock from Policy Change","ZST: PC1"
  theme_bw()+
  theme(plot.title = element_text(hjust = 0.5), legend.position = "none") + facet_wrap(. ~ model,
                                                                                              labeller = as
```



We also posit that respondents with higher degrees of economic knowledge will be less supply skeptical, controlling for their level of zero-sum thinking and their self-reported exposure to new construction in affluent areas of their region.

```
# Model with multiple predictors (ZST, econ knowledge, exposure). Discuss how to present/plot result

results <- D_mod %>%
  pivot_longer(shock.rentskep.str:shock.poolskep.wk,
                     names_to = "DV",
                     values_to = "response") %>%
  nest(data = -c(DV)) %>%
  mutate(
    model = map(data, ~ lm_robust(response ~
                                    zst.PC1 +
                                    know.ss.PC1 +
                                    obs.price.dev,
                                  data = .)),
    tidied = map(model, tidy))

model_names <- c(
 "Model 1"="Rent(+)",
    "Model 2" = "Rent(+/=)",
    "Model 3" = "Home Prices(+)",
    "Model 4" = "Home Prices(+/=)",
    "Model 5" = "All(+)",
    "Model 6" = "All(+/=)"
)
```

```r
dwplot(results$model,show_intercept = TRUE)  %>%
   relabel_predictors(zst.PC1="ZST: PC1",
                      know.ss.PC1="Econ Know.: PC1",
                      obs.price.dev="New Construction in Affluent Areas") +
  theme_bw()+
  theme(plot.title = element_text(hjust = 0.5), legend.position = "none") + facet_wrap(. ~ model,
                                                                                           labeller = as
```



6.3 Mental Models of the Housing Market

We first estimate the share of the population that agrees with each mental-model proposition. Then we used several agnostic model building techniques to investigate the extent to which the mental-model attributes are themselves predictive of respondents' price and rent predictions.

We subset the data using a median split on zero-sum thinking, as we expect that respondents who are high in zero-sum thinking will differ in predictable ways from other respondents. We hypothesize that they are:

- more likely to think that government-triggered supply shocks will increase corporate-ownership of housing, and that corporate ownership will increase rents.
- less likely to agree that a positive supply shock will increase the availability, and lower the price, of relatively affordable housing.
- more likely to think that the plex scenario will reduce the quality of life in their neighborhood.
- more apt to predict that policy-triggered supply shocks will result in gentrification, both in terms of higher-income people moving to previously low-income neighborhoods, (Scenario 7), and expensive market-rate housing being built, (Scenario 8.)

6.3.1 Descriptive Results

The following is a representative figure which, for simplicity of exposition, does not show every two-part mental model described above. The left-hand column depicts the split between zero-sum thinkers and non zero-sum thinkers in their support for each mental model outlined in the table in Section 2.3 for each supply-shock scenario. The right-hand column depicts the split between zero-sum and non-zero sum thinkers in their predictions of the first-stage (substantive) outcome on housing prices, pooled across all supply-shock scenarios.

```
D_mod <- D %>%
  mutate(
  zst = as.numeric(zst.PC1 > median(D$zst.PC1, na.rm = TRUE))
  )

# generate means and CIs for plots: share of pop that agrees or strongly agrees with each posited "s

# mental model stage 1 plots (substantive outcome). First assemble results with SE for plots.
D_plots_1 <- D_mod %>%
  filter(!is.na(zst)) %>%
  pivot_longer(shock.chain.low:shock.forme,
                     names_to = "DV",
                     values_to = "response") %>%
  nest(data = -c(DV, zst, scenario)) %>%
  mutate(
    model = map(data, ~ lm(response>3 ~ 1, data = .)),#  lm rather than lm_robust b/c no pooling ove
    tidied = map(model, tidy),
    response.freq = map(data, ~.x %>%
                          group_by(response) %>%
                          summarize(n = n())
                          )
  ) %>%
  unnest(tidied, response.freq)

plots_1 <- D_plots_1 %>%
  filter(!is.na(response)) %>%
  mutate(zst = fct_recode(factor(zst), `lo.ZST` = "0", `hi.ZST` = "1")) %>%
  nest(data = -c(DV)) %>%
  mutate(
    title = case_when(
      DV=="shock.chain.low" ~ "Availability of homes (less expensive)",
      DV=="shock.chain.high" ~ "Availability of homes (more expensive)",
      DV=="shock.agglom" ~ "Business agglomeration",
      DV=="shock.demo" ~ "Demolition of affordable homes",
      DV=="shock.corp" ~ "Corporate ownership of housing",
      DV=="shock.qolworse" ~ "Quality of life (worse)",
      DV=="shock.gentry" ~ "Gentrification",
      DV=="shock.nextdoor" ~ "Expensive new housing nextdoor to affordable homes",
      DV=="shock.forme" ~ "New housing for people like me"
      ),
    plot = map2(.x = data, .y = title, ~ ggplot(.x,
        aes(x = factor(zst),
        y=n,
        fill=as.factor(response))) +
  facet_wrap(~ scenario, switch="both", ncol = 1) +
  geom_col(position = "fill", width = 0.75) +
```

```
  scale_fill_manual("Posited mechanism",
                    breaks = c("5", "4", "3", "2", "1"),
                    values = c("darkblue", "lightblue", "lightgrey", "pink", "red"),
                    labels = c("Strongly agree", "Somewhat agree", "Neither",
                               "Somewhat disagree", "Strongly disagree")) +
  labs(title=paste0(.y),
       x = "",
       y = "") +
  coord_cartesian(ylim = c(0, 1)) +
  geom_errorbar(
    aes(ymax = estimate + 1.96*std.error, ymin = estimate - 1.96*std.error),
    width = 0.1) +
  theme(#strip.background = element_blank(),
        #strip.placement = "outside",
        panel.spacing = unit(0.2, "lines"),
        plot.title = element_text(size = 10),
        strip.text = element_text(angle = 90, size = 8), # angle switch didn't work
        axis.text.x= element_text(size = 6) # not working to adjust tick size
        ) +
  coord_flip(ylim = c(0, 1))))
```

```
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
```

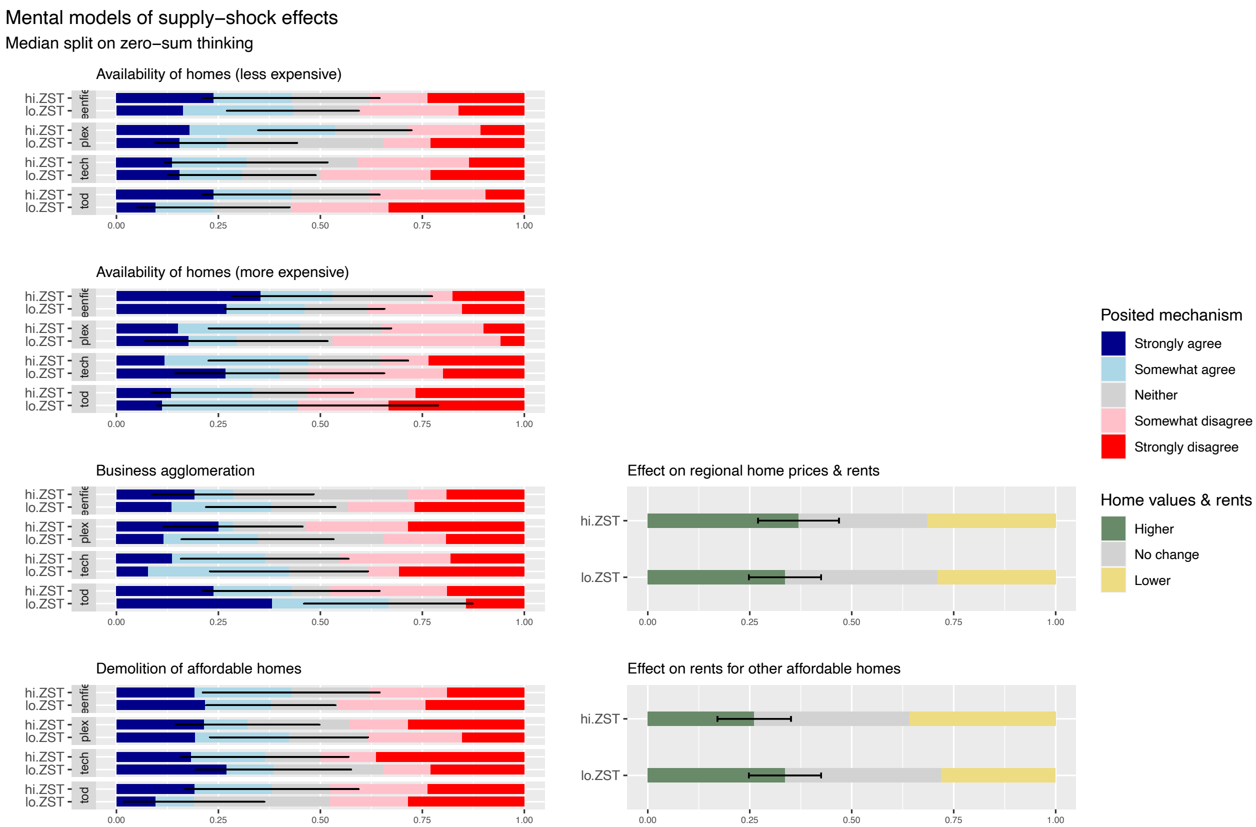
```
# plots_1$plot[[1]]

# mental model stage 2 plots (price)
D_plots_2 <- D_mod %>%
  filter(!is.na(zst)) %>%
  pivot_longer(agglom.price:forme.price,
                       names_to = "DV",
                       values_to = "response") %>%
  nest(data = -c(DV, zst)) %>%
  mutate(
    model = map(data, ~ lm(response==1 ~ 1, data = .)),#  lm rather than lm_robust b/c no pooling or
    tidied = map(model, tidy),
    response.freq = map(data, ~.x %>%
                              group_by(response) %>%
                              summarize(n = n())
                              )
  ) %>%
  unnest(tidied, response.freq)

plots_2 <- D_plots_2 %>%
  filter(!is.na(response)) %>%
  mutate(zst = fct_recode(factor(zst), `lo.ZST` = "0", `hi.ZST` = "1")) %>%
  nest(data = -c(DV)) %>%
```

```
  mutate(
    title = case_when(
      DV=="agglom.price" ~ "Effect on regional home prices & rents",
      DV=="demo.price" ~ "Effect on rents for other affordable homes",
      DV=="corp.price" ~ "Effect on rents",
      DV=="qolworse.price" ~ "Effect on home prices & rents in neighborhood",
      DV=="gentry.price" ~ "Effect on home prices & rents in neighborhood",
      DV=="nextdoor.price" ~ "Effect on market value of older home nextdoor",
      DV=="forme.price" ~ "Effect on home prices & rents for people like me..."
      ),
    plot = map2(.x = data, .y = title, ~ ggplot(.x,
        aes(x = factor(zst),
        y=n,
        fill=as.factor(response))) +
  geom_col(position = "fill", width = 0.25) +
  scale_fill_manual("Home values & rents",
                    breaks = c("1", "0", "-1"),
                    values = c("darkseagreen4", "lightgrey", "lightgoldenrod2"),
                    labels = c("Higher", "No change", "Lower")) +
  labs(title=paste0(.y),
       x = "",
       y = "") +
  coord_cartesian(ylim = c(0, 1)) +
  geom_errorbar(
    aes(ymax = estimate + 1.96*std.error, ymin = estimate - 1.96*std.error),
    width = 0.1) +
  theme(#strip.background = element_blank(),
        #strip.placement = "outside",
        panel.spacing = unit(0.2, "lines"),
        plot.title = element_text(size = 10),
        strip.text = element_text(angle = 90, size = 8),
        axis.text.x= element_text(size = 6) # not working to adjust tick size
        ) +
  coord_flip(ylim = c(0, 1))))
```

```
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
## Coordinate system already present. Adding new coordinate system, which will replace the existing
```

```
# grid.arrange(grobs = plots_1$plot, ncol = 1) # default layout doesn't work at all

names(plots_1$plot) <- unique(D_plots_1$DV)
names(plots_2$plot) <- unique(D_plots_2$DV)

# following layout guidance from https://patchwork.data-imaginist.com/articles/guides/layout.html
layout <- 'A#
B#
CD
EF'
```

```r
wrap_plots(A = plots_1$plot[["shock.chain.low"]],
           B = plots_1$plot[["shock.chain.high"]],
           C = plots_1$plot[["shock.agglom"]],
           D = plots_2$plot[["agglom.price"]],
           E = plots_1$plot[["shock.demo"]],
           F = plots_2$plot[["demo.price"]],
           design = layout) +
  plot_layout(guides = 'collect') +
  plot_annotation(
    title = 'Mental models of supply-shock effects',
    subtitle = "Median split on zero-sum thinking"
  )
```



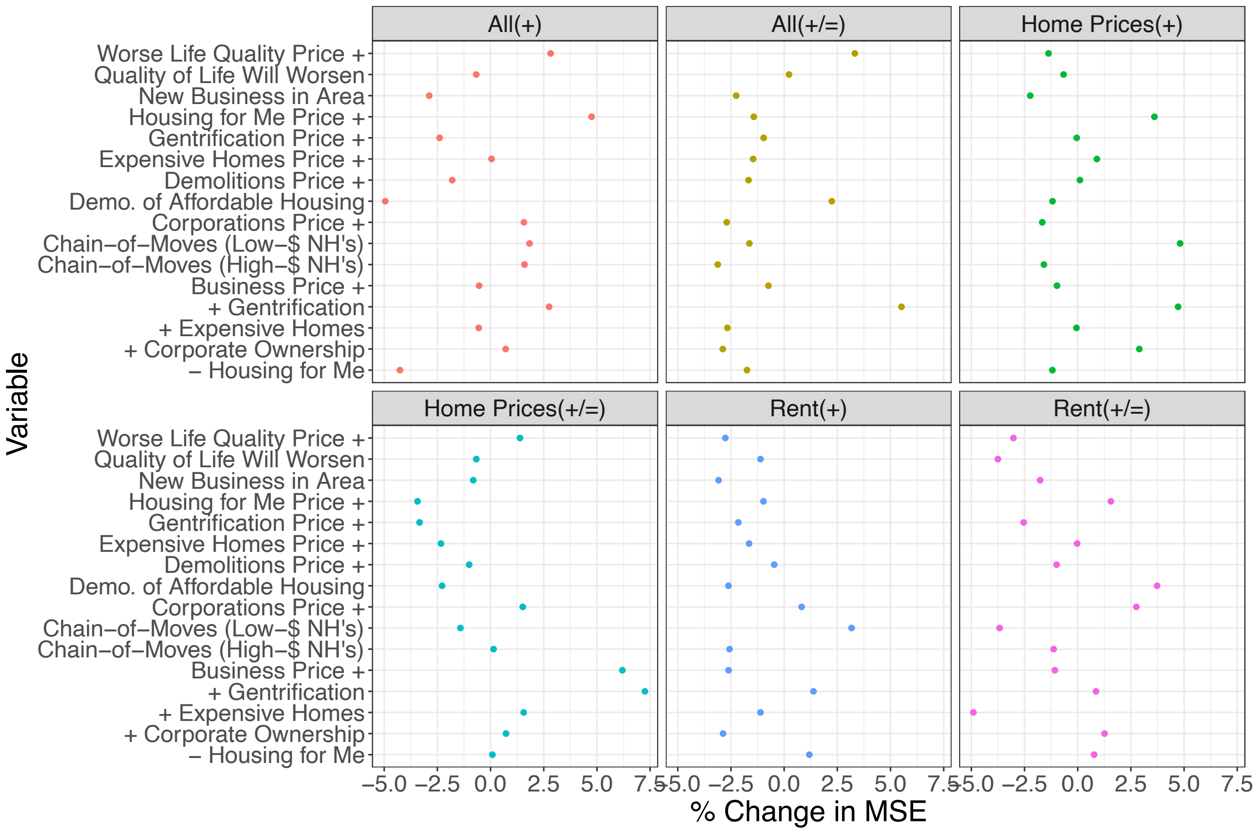
6.3.2 Model-Based Results

We utilize a three-pronged approach–measuring the relative "importance" of each mental model in our survey: random forests, OLS with standardized betas and a LASSO regression. We do not have a hypothesis as to which variables will have the greatest influence over supply skepticism, but instead are treating this as an exploratory exercise.

The random forest model produces a statistic measuring the relative "importance" of each variable by the percent change in model mean squared error it contributes, on average, across all the models produced by this method (Grömping 2009). Thus, variables with higher values contribute most to correct classification out of sample.

```r
#Report variable-importance results from linear and RF models of price prediction as function of sut

#DVs:
```

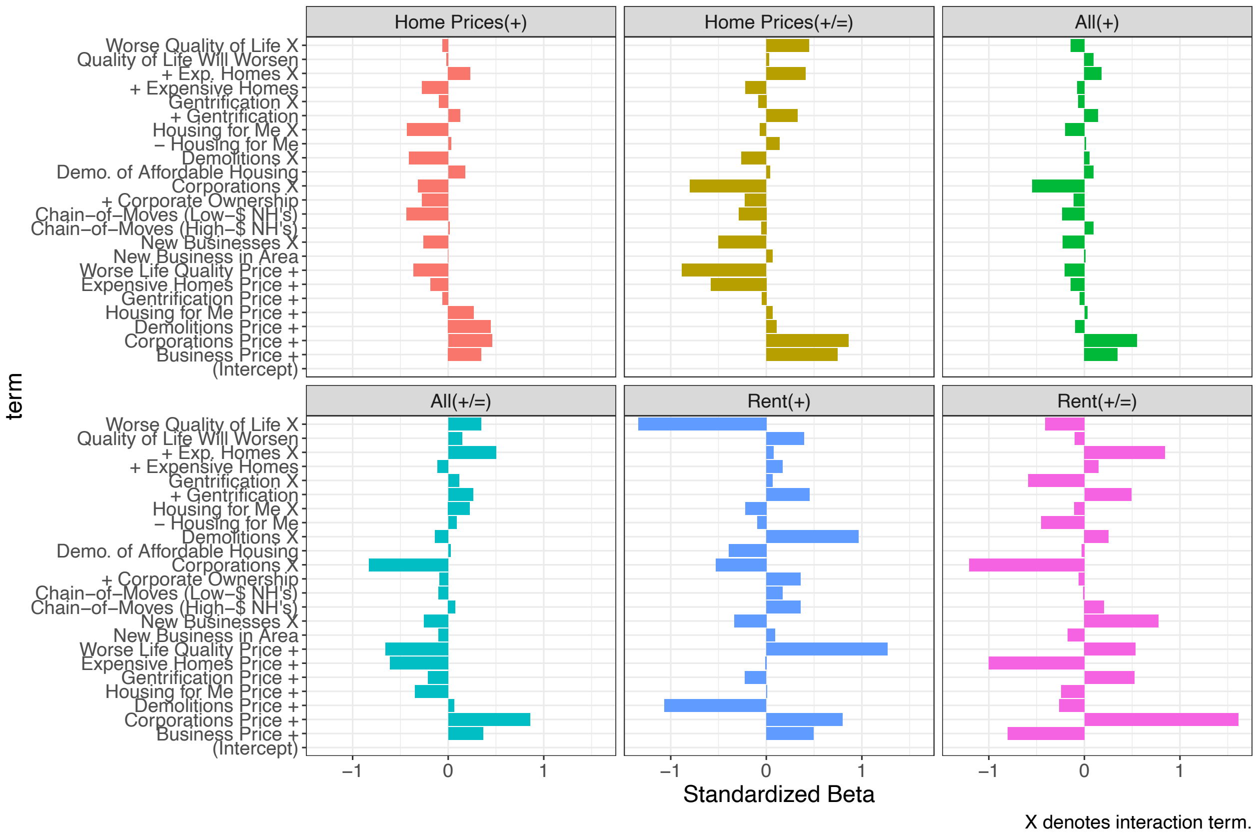
```r
dvs <- c("shock.rentskep.str","shock.rentskep.wk","shock.hvskep.str","shock.hvskep.wk","shock.poolsk

rhs <- "shock.chain.low + shock.chain.high + shock.agglom +
                     shock.demo + shock.corp + shock.qolworse + shock.gentry + shock.nextdoor +
                     shock.forme + agglom.price + demo.price + corp.price + qolworse.price + gentry.

##RF model.

models <- NULL

for (i in dvs){
  formula <- as.formula(paste0(i, " ~ ",rhs))
  x <- D %>% randomForest(formula , importance=T,data=.,na.action = na.omit) %>%  importance()
  rf_out <- tibble("var"=rownames(x), "IncMSE"=x[,1], "model"=i)
  models <- bind_rows(models, rf_out)
}

models %>% mutate(model=case_when(
    model=="shock.rentskep.str" ~ "Rent(+)",
    model=="shock.rentskep.wk" ~ "Rent(+/=)",
    model=="shock.hvskep.str" ~ "Home Prices(+)",
    model=="shock.hvskep.wk" ~ "Home Prices(+/=)",
    model=="shock.poolskep.str" ~ "All(+)",
    model=="shock.poolskep.wk"  ~ "All(+/=)",
    TRUE ~ model),
    var = case_when(
      var=="agglom.price" ~ "Business Price +",
      var=="demo.price" ~ "Demolitions Price +",
      var=="corp.price" ~ "Corporations Price +",
      var=="qolworse.price" ~ "Worse Life Quality Price +",
      var=="gentry.price" ~ "Gentrification Price +",
      var=="nextdoor.price" ~ "Expensive Homes Price +",
      var=="forme.price" ~ "Housing for Me Price +",
         var=="shock.chain.low" ~ "Chain-of-Moves (Low-$ NH's)",
         var=="shock.chain.high" ~ "Chain-of-Moves (High-$ NH's)",
         var=="shock.agglom" ~ "New Business in Area",
         var=="shock.demo" ~ "Demo. of Affordable Housing",
         var=="shock.corp" ~ "+ Corporate Ownership",
         var=="shock.qolworse" ~ "Quality of Life Will Worsen",
         var=="shock.gentry" ~ "+ Gentrification",
         var=="shock.nextdoor" ~ "+ Expensive Homes",
         var=="shock.forme" ~ "- Housing for Me",

      )) %>%
      ggplot(aes(x=IncMSE, y=var, color=model,group=model)) + geom_point(position=position_dodge(.9)
  scale_y_discrete("Variable") +
  scale_x_continuous("% Change in MSE") +
  theme_bw() +
  theme(legend.position = "none", text=element_text(size=20)) +
  facet_wrap(.~model)
```



We next measure the relative importance of each mental model (both the substantive effects of each upzoning scenario and the effect of each substantive change on housing on prices), using a least-squares regression with standardized betas. We also include an interaction term for each corollary effect and its effect on prices where applicable. For instance, if a respondent believes upzoning will both lead to more demolition of current affordable housing and that said demolition will cause prices to increase, the interaction term would be $1 \times 1 = 1$. For these regressions, the variables with the values farthest from zero have the greatest "influence" over the dependent variable–either correlating with increased or decreased supply skepticism.

```
##Use Standardized Betas for the linear model.
library(lm.beta)

dvs <- c("shock.rentskep.str","shock.rentskep.wk","shock.hvskep.str","shock.hvskep.wk","shock.poolsk

rhs <- "shock.chain.low + shock.chain.high + shock.agglom*agglom.price +shock.demo*demo.price + shoc

outputs <- NULL
for (i in dvs){
  formula <- as.formula(paste0(i, " ~ ", rhs))

  outputs[[i]] <- D %>% lm(formula, data=.) %>% lm.beta() %>% tidy() %>%
    dplyr::select(-c(estimate, std.error))

}

model_names <- c(
    "shock.rentskep.str"="Rent(+)",
    "shock.rentskep.wk" = "Rent(+/=)",
    "shock.hvskep.str" = "Home Prices(+)",
```

```
    "shock.hvskep.wk"  = "Home Prices(+/=)",
    "shock.poolskep.str" = "All(+)",
    "shock.poolskep.wk" = "All(+/=)"
)

labels=c("shock.forme:forme.price"="Housing for Me X",
         "shock.nextdoor:nextdoor.price"="+ Exp. Homes X",
         "shock.gentry:gentry.price"="Gentrification X",
         "shock.qolworse:qolworse.price"= "Worse Quality of Life X",
         "shock.corp:corp.price"="Corporations X",
         "shock.demo:demo.price"="Demolitions X",
         "shock.agglom:agglom.price"="New Businesses X",
         "forme.price"="Housing for Me Price +",
         "shock.forme"="- Housing for Me",
         "nextdoor.price"="Expensive Homes Price +",
         "shock.nextdoor"="+ Expensive Homes",
        "gentry.price"="Gentrification Price +",
        "shock.gentry"="+ Gentrification",
        "qolworse.price"="Worse Life Quality Price +",
        "shock.qolworse"="Quality of Life Will Worsen",
        "corp.price"="Corporations Price +",
        "shock.corp"="+ Corporate Ownership",
        "demo.price"="Demolitions Price +",
        "shock.demo"="Demo. of Affordable Housing",
        "agglom.price"="Business Price +",
        "shock.agglom"="New Business in Area",
        "shock.chain.high"="Chain-of-Moves (High-$ NH's)",
        "shock.chain.low"="Chain-of-Moves (Low-$ NH's)")

ggplot(bind_rows(outputs, .id="model") %>% filter(term!="(Intercept"), aes(x=std_estimate, y=term, g
  scale_y_discrete(labels=labels) + geom_bar(stat="identity",position="dodge") +
  scale_x_continuous("Standardized Beta") +
  facet_wrap(model~.,labeller = as_labeller(model_names)) +theme_bw()+ theme(legend.position = "none
```



Finally, we implement a LASSO regression to identify the mental models that are most clearly associated with supply skepticism. While our explanatory variables occupy differing scales, we can compare each intermediate mechanism as well as each predicted effect on price by comparing coefficients. Further, the LASSO method of penalized regression sets non-influential variables to zero (Roth 2004), which allows for a quick visual inspection to determine which mental models dominate respondents' thinking about housing markets.

Finally, we implement a LASSO regression. While our explanatory variables occupy differing scales, we can compare each intermediate mechanism as well as each predicted effect on price by comparing coefficients. Further, the LASSO method of penalized regression sets non-influential variables to zero (Roth 2004), which allows for a quick visual inspection to determine which mental models dominate respondents' thinking about housing markets. While the traditional LASSO method does not allow for interaction variables, we are exploring recent extensions of this method and invite any suggestions or ideas.

```
library(glmnet)
```

```
## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack

## Loaded glmnet 4.1-4

##
## Attaching package: 'glmnet'

## The following object is masked from 'package:gtools':
##
```

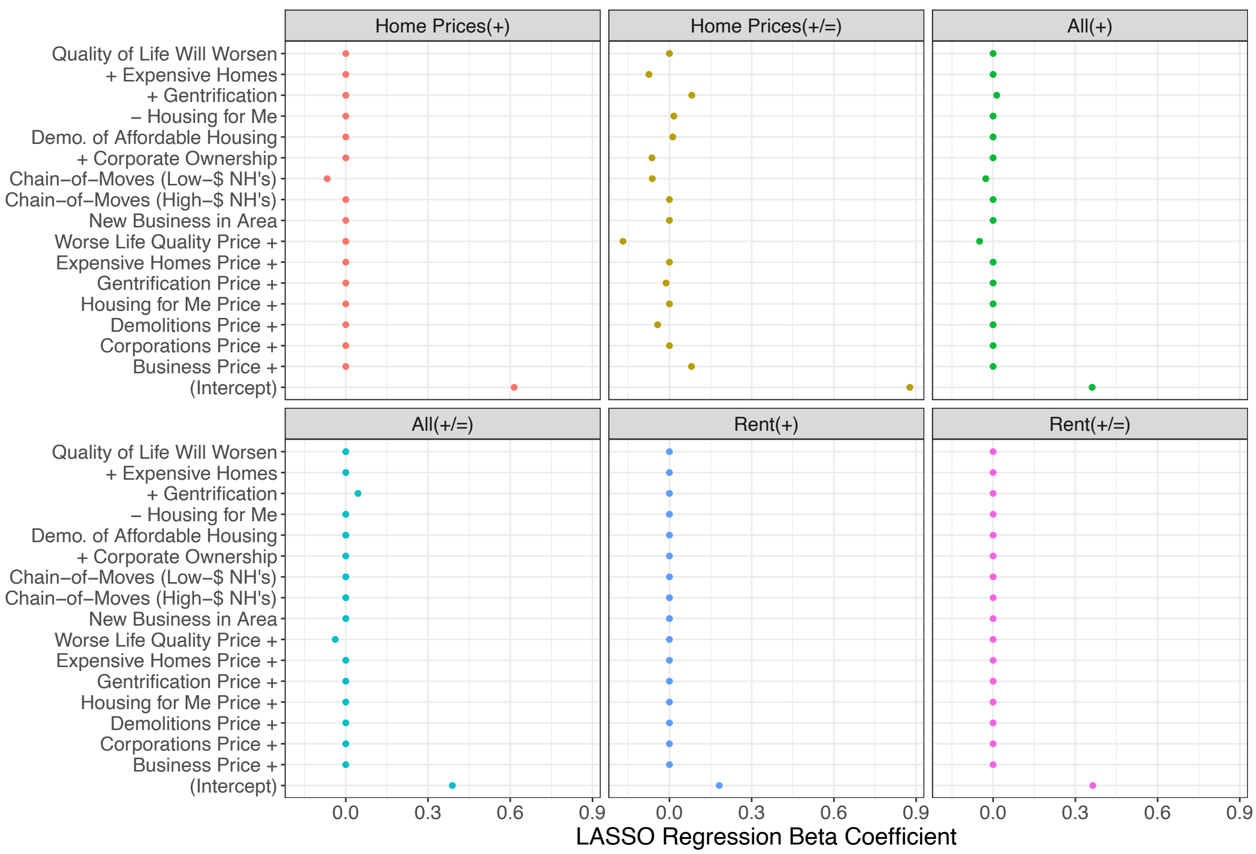
```
##     na.replace
```

```
dvs <- c("shock.rentskep.str","shock.rentskep.wk","shock.hvskep.str","shock.hvskep.wk","shock.poolsk

model_names <- c(
    "shock.rentskep.str"="Rent(+)",
    "shock.rentskep.wk" = "Rent(+/=)",
    "shock.hvskep.str" = "Home Prices(+)",
    "shock.hvskep.wk"  = "Home Prices(+/=)",
    "shock.poolskep.str" = "All(+)",
    "shock.poolskep.wk" = "All(+/=)"
)


labels=c("shock.forme:forme.price"="Housing for Me X",
         "shock.nextdoor:nextdoor.price"="+ Exp. Homes X",
         "shock.gentry:gentry.price"="Gentrification X",
         "shock.qolworse:qolworse.price"= "Worse Quality of Life X",
         "shock.corp:corp.price"="Corporations X",
         "shock.demo:demo.price"="Demolitions X",
         "shock.agglom:agglom.price"="New Businesses X",
         "forme.price"="Housing for Me Price +",
         "shock.forme"="- Housing for Me",
         "nextdoor.price"="Expensive Homes Price +",
         "shock.nextdoor"="+ Expensive Homes",
        "gentry.price"="Gentrification Price +",
        "shock.gentry"="+ Gentrification",
        "qolworse.price"="Worse Life Quality Price +",
        "shock.qolworse"="Quality of Life Will Worsen",
        "corp.price"="Corporations Price +",
        "shock.corp"="+ Corporate Ownership",
        "demo.price"="Demolitions Price +",
        "shock.demo"="Demo. of Affordable Housing",
        "agglom.price"="Business Price +",
        "shock.agglom"="New Business in Area",
        "shock.chain.high"="Chain-of-Moves (High-$ NH's)",
        "shock.chain.low"="Chain-of-Moves (Low-$ NH's)")


all_coefs <- NULL

for (i in dvs){

  lass_data <- D %>% dplyr::select(i, shock.chain.low,shock.chain.high, shock.agglom,
                       shock.demo, shock.corp, shock.qolworse ,shock.gentry ,shock.nextdoor,
                       shock.forme ,agglom.price ,demo.price ,corp.price ,qolworse.price ,gentry.price

  y <- lass_data %>% dplyr::select(i) %>% pull()

  x <- lass_data %>% dplyr::select(shock.chain.low,shock.chain.high, shock.agglom,
                       shock.demo, shock.corp, shock.qolworse ,shock.gentry ,shock.nextdoor,
                       shock.forme ,agglom.price ,demo.price ,corp.price ,qolworse.price ,gentry.price

  cv_model <- cv.glmnet(x,y,alpha=1)
```

```
  best_lambda <- cv_model$lambda.min

  coefs <- glmnet(x,y,alpha=1, lambda=best_lambda) %>% coef()

  coef_df <- tibble("vars"=rownames(coefs), beta=coefs[,1], dv=i)

  all_coefs <- bind_rows(all_coefs, coef_df)
}
```

```
## Note: Using an external vector in selections is ambiguous.
## i Use `all_of(i)` instead of `i` to silence this message.
## i See <https://tidyselect.r-lib.org/reference/faq-external-vector.html>.
## This message is displayed once per session.
```

```
ggplot(all_coefs %>% filter(!is.na(dv)), aes(x=beta, y=vars, group=dv, color=dv)) + geom_point() +
  scale_y_discrete("",labels=labels) +
  theme_bw() +
  scale_x_continuous("LASSO Regression Beta Coefficient") +
  facet_wrap(dv~.,labeller = as_labeller(model_names)) +theme_bw()+ theme(legend.position = "none",
```



6.4 Political Support for State Zoning Reforms

Finally, what is the relationship between supply skepticism and support for policy reforms to enable more housing development? Though our design does not allow us to manipulate a respondent's degree of supply skepticism, we hope to motivate further work in a causal-inference framework by documenting whether support for upzoning is explained to a significant degree by the interaction between the respondent's desire for lower housing prices and the respondent's belief about the effect of a similar supply shock on prices and rents.

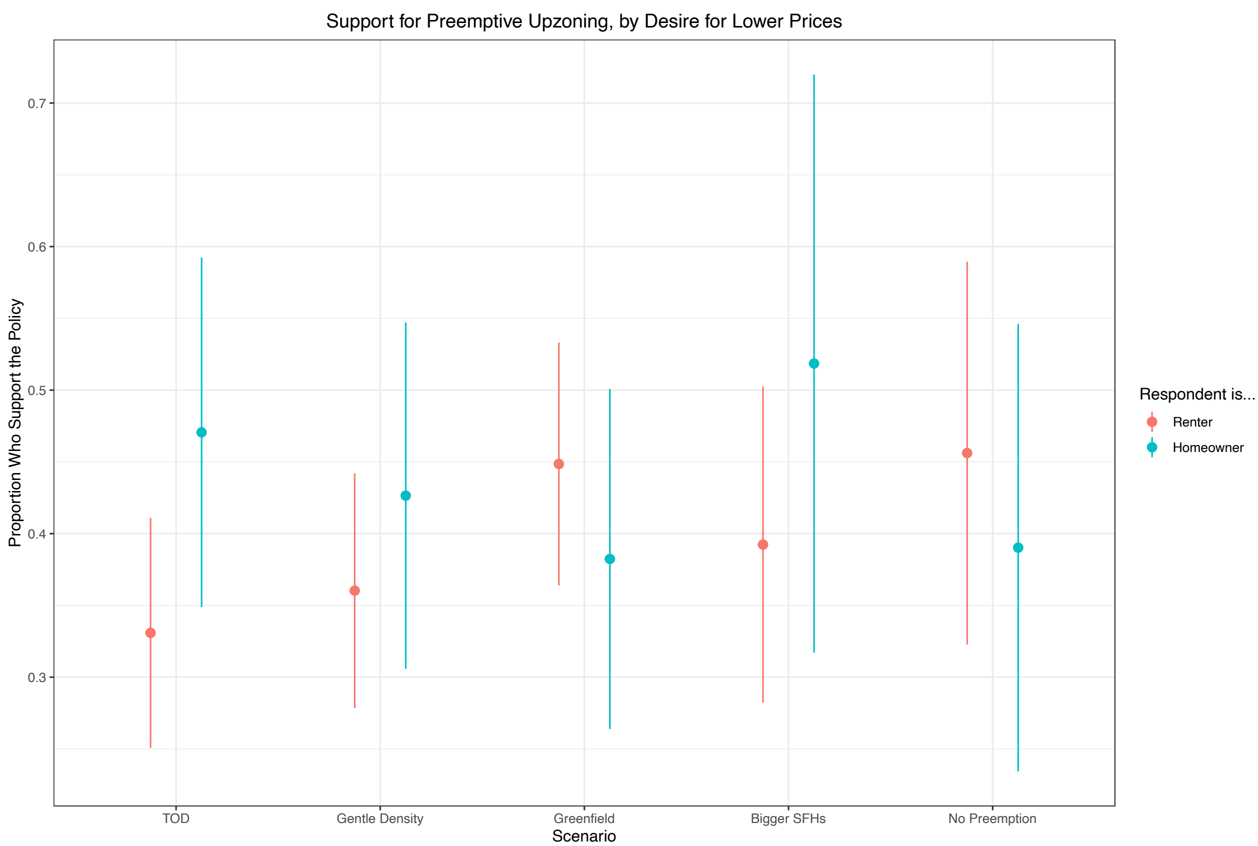
We also include in the model self-reported anxiety about "tail risk" from the rezoning scenario. For homeowners, this is the self-reported perceived risk of a large decrease in one's home value. For renters, it is the opposite–the risk of a large increase in one's monthly rent.

As a prelude to the models, we will report support for upzoning and state-preemption scenarios separately for renters and homeowners, and among those who support and oppose lower housing prices for their city.

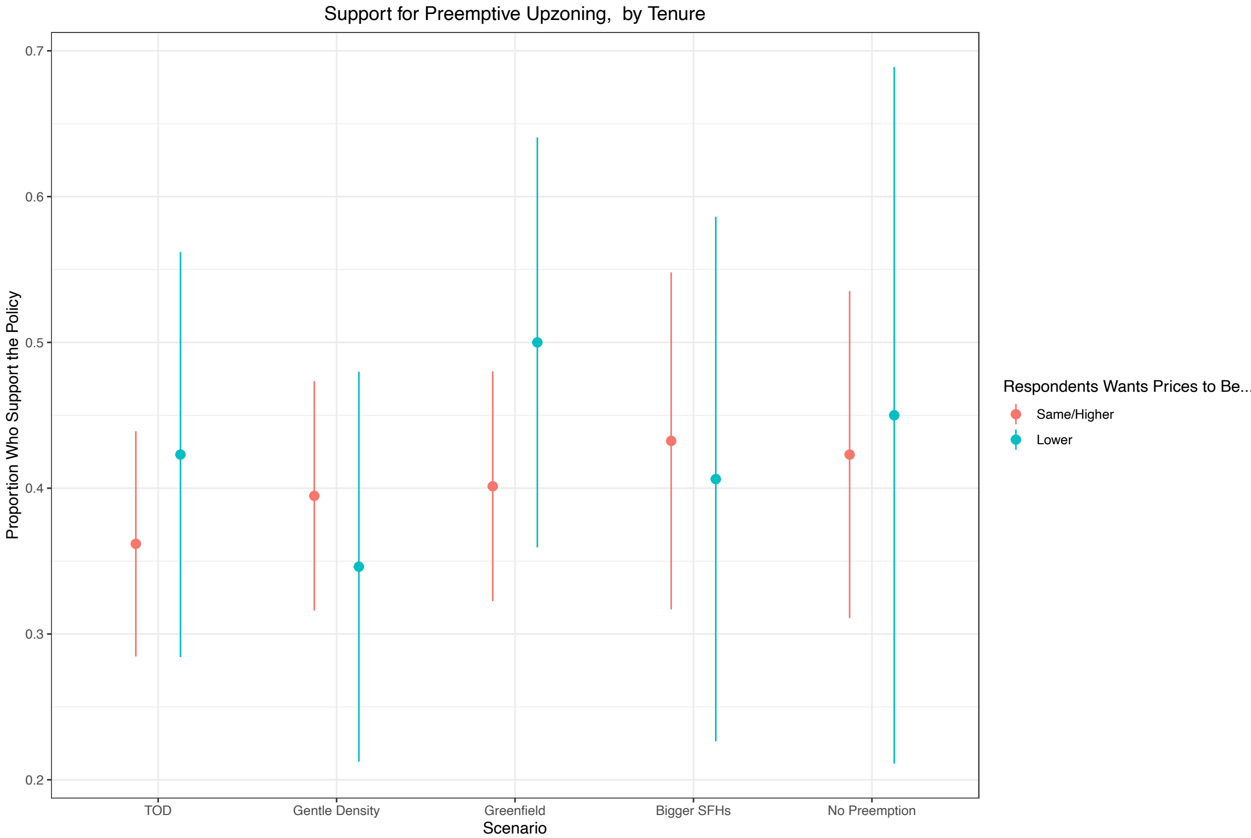
6.4.1 Support for Preemption, By Tenure and By Desire for Lower Housing Prices

```
# could add the

D_mod <- D %>% mutate(
  want = fct_collapse(as_factor(want.price), NotLower = c("Higher", "Same"), Lower = "Lower"),
  ownscenario.preempt = case_when(scenario == "tod" ~ hous.TOD.preempt,
                                  scenario == "plex" ~ hous.GD.preempt,
                                  scenario == "greenfield" ~ hous.sprawl.preempt)
)

support.ownhome <- D_mod %>%
  filter(!is.na(ownhome)) %>%
  pivot_longer(c(hous.TOD.preempt, hous.sprawl.preempt, hous.GD.preempt, hous.SFH.preempt, hous.no.p
                     names_to = "scenario.support",
                     values_to = "response") %>%
  nest(data = -c(scenario.support, ownhome)) %>%
  mutate(model = map(data, ~ lm_robust(response>3 ~ 1, data = .)),
         tidied = map(model, tidy)) %>%
  unnest(tidied) %>%
  mutate(xlabel = case_when(
    scenario.support == "hous.TOD.preempt" ~ "TOD",
    scenario.support == "hous.sprawl.preempt" ~ "Greenfield",
    scenario.support == "hous.GD.preempt" ~ "Gentle Density",
    scenario.support == "hous.SFH.preempt" ~ "Bigger SFHs",
    scenario.support == "hous.no.preempt" ~ "No Preemption",
  )) %>%
  ggplot(aes(x=xlabel, y=estimate, group=ownhome)) +
  scale_x_discrete(limits = c("TOD","Gentle Density", "Greenfield", "Bigger SFHs","No Preemption"))
  geom_pointrange(aes(ymin=conf.low,ymax=conf.high, color=factor(ownhome)),
                  position=position_dodge(width=.5)) +
  ylab("Proportion Who Support the Policy") +
  xlab("Scenario") +
  labs(title = "Support for Preemptive Upzoning,  by Tenure") +
  scale_color_discrete("Respondents Wants Prices to Be...", labels=c("Same/Higher","Lower")) +
  theme_bw()+
  theme(plot.title = element_text(hjust = 0.5))

support.want <- D_mod %>%
  filter(!is.na(want)) %>%
  pivot_longer(c(hous.TOD.preempt, hous.sprawl.preempt, hous.GD.preempt, hous.SFH.preempt, hous.no.p
                     names_to = "scenario.support",
                     values_to = "response") %>%
  nest(data = -c(scenario.support, want)) %>%
  mutate(model = map(data, ~ lm_robust(response>3 ~ 1, data = .)),
         tidied = map(model, tidy)) %>%
```

```
  unnest(tidied) %>%
  mutate(xlabel = case_when(
    scenario.support == "hous.TOD.preempt" ~ "TOD",
    scenario.support == "hous.sprawl.preempt" ~ "Greenfield",
    scenario.support == "hous.GD.preempt" ~ "Gentle Density",
    scenario.support == "hous.SFH.preempt" ~ "Bigger SFHs",
    scenario.support == "hous.no.preempt" ~ "No Preemption",
  )) %>%
  ggplot(aes(x=xlabel, y=estimate, group=want)) +
  scale_x_discrete(limits = c("TOD","Gentle Density", "Greenfield", "Bigger SFHs","No Preemption"))
  geom_pointrange(aes(ymin=conf.low,ymax=conf.high, color=factor(want)),
                  position=position_dodge(width=.5)) +
  ylab("Proportion Who Support the Policy") +
  xlab("Scenario") +
  labs(title = "Support for Preemptive Upzoning, by Desire for Lower Prices") +
  theme_bw()+
  scale_color_discrete("Respondent is...", labels=c("Renter","Homeowner"))+
  theme(plot.title = element_text(hjust = 0.5))
support.want
```



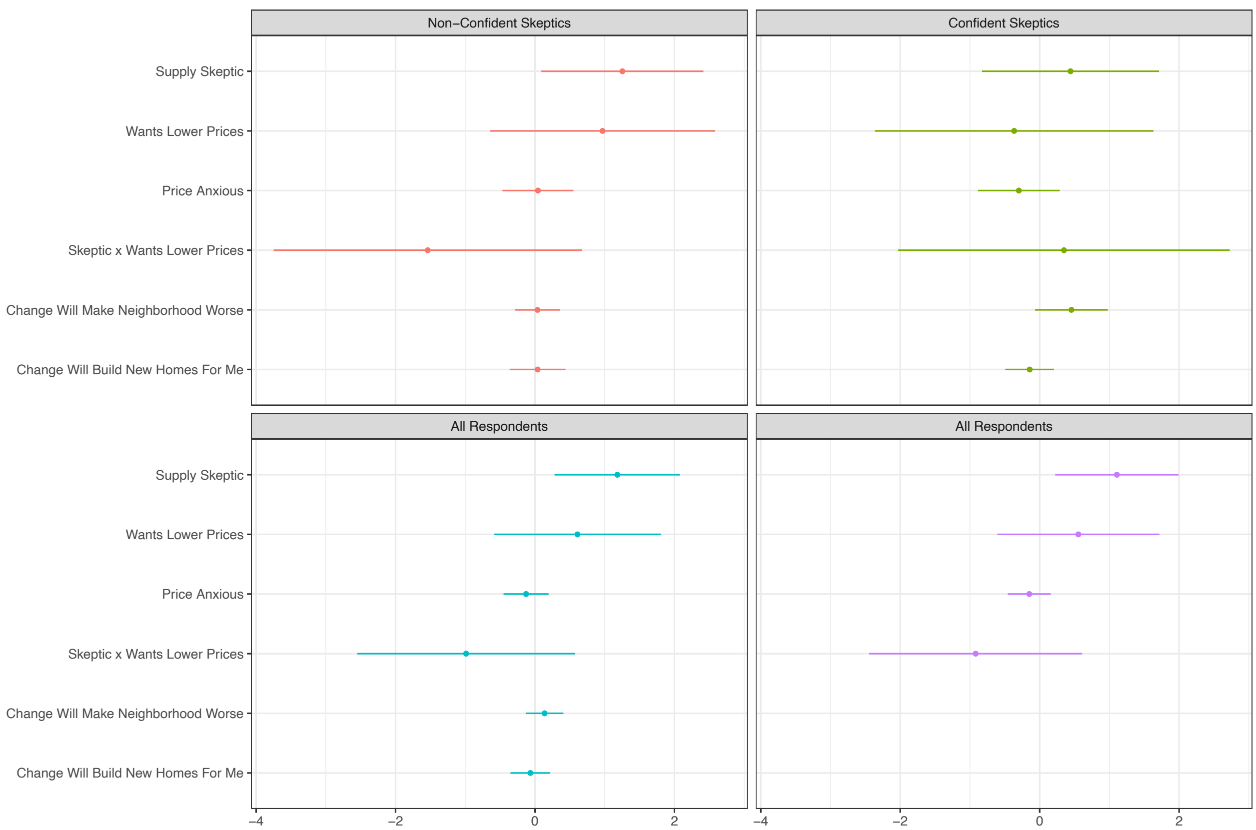

```
support.ownhome
```



We next model support for various upzoning policies as a function of whether the respondent is supply skeptical and their desires about regional housing prices. We predict that supply skeptics will not support upzonings even if they desire lower housing costs or fear increases in their own costs, (for renters.) We also predict that respondent's who are confident in their supply skepticism will be less supportive of upzoning than those who are not.

```
#nested variants of the basic model (start with just price prediction, want, want:price prediction,
#SO Model the above with sample split on confidence

D_mod <- D %>% mutate(
  want = fct_collapse(as_factor(want.price), NotLower = c("Higher", "Same"), Lower = "Lower"),
  ownscenario.preempt = case_when(scenario == "tod" ~ hous.TOD.preempt,
                                  scenario == "plex" ~ hous.GD.preempt,
                                  scenario == "greenfield" ~ hous.sprawl.preempt),
  want.lower = ifelse(want.price=="Lower",1,0),
  shock.angst = coalesce(shock.hv.angst, shock.rent.angst),
    rent.conf = as.numeric(shock.rent.conf > median(
    c(D$shock.rent.conf, D$shock.hv.conf), na.rm = TRUE)),
  hv.conf = as.numeric(shock.hv.conf > median(
    c(D$shock.rent.conf, D$shock.hv.conf), na.rm = TRUE)),
  confidence = coalesce(rent.conf, hv.conf)
)

mod_1 <- D_mod %>%
  lm_robust(ownscenario.preempt ~ shock.poolskep.wk + want.lower+ shock.poolskep.wk*want.lower + sho

mod_2 <- D_mod %>%
  lm_robust(ownscenario.preempt ~ shock.poolskep.wk + want.lower+ shock.poolskep.wk*want.lower + sho
```

```
mod_3_hi_conf <- D_mod %>% filter(confidence==1) %>%
  lm_robust(ownscenario.preempt ~ shock.poolskep.wk + want.lower+ shock.poolskep.wk*want.lower + sho

mod_3_low_conf <- D_mod %>% filter(confidence==0) %>%
  lm_robust(ownscenario.preempt ~ shock.poolskep.wk + want.lower+ shock.poolskep.wk*want.lower + sho


dwplot(list(mod_1,mod_2, mod_3_hi_conf,mod_3_low_conf)) +
  scale_y_discrete(labels=c("shock.poolskep.wk"="Supply Skeptic",
                    "want.lower"="Wants Lower Prices",
                    "shock.angst"="Price Anxious",
                    "shock.qolworse"="Change Will Make Neighborhood Worse",
                    "shock.forme"="Change Will Build New Homes For Me",
                    "shock.poolskep.wk:want.lower"="Skeptic x Wants Lower Prices")) +
  theme_bw()+
  theme(plot.title = element_text(hjust = 0.5), legend.position = "none") + facet_wrap(.~model,
                                                                                        labeller=as_l
                                                                                          "Model 1"="
                                                                                          "Model 2"="
                                                                                          "Model 3"="
                                                                                          "Model 4"="
                                                                                        )))
```

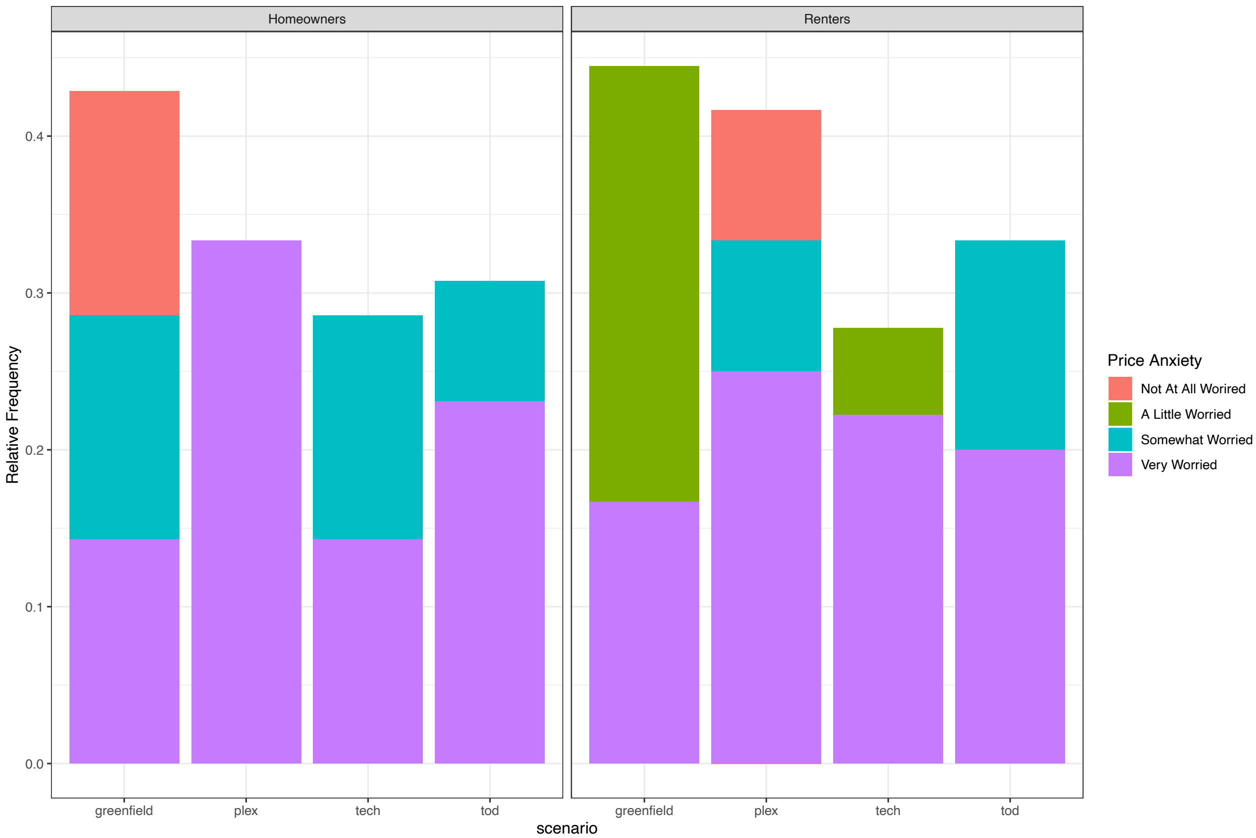


6.4.2 Support for State Zoning Preemption as a Function of Tenure and Scenario

We next show price anxiety as a function of both the respondent's housing tenure and the upzoning scenario they viewed. We predict that the technological change scenario will provoke the least amount of anxiety that rents will increase (for renters), or home prices will decrease (for homeowners). Similarly, the greenfield development scenario will provoke less anxiety than either change initiated by government policy.

```
D_mod <- D %>% mutate(
  want = fct_collapse(as_factor(want.price), NotLower = c("Higher", "Same"), Lower = "Lower"),
  ownscenario.preempt = case_when(scenario == "tod" ~ hous.TOD.preempt,
                                  scenario == "plex" ~ hous.GD.preempt,
                                  scenario == "greenfield" ~ hous.sprawl.preempt),
  shock.angst = coalesce(shock.hv.angst, shock.rent.angst)
)

# Initial plot: distribution of anxiety by scenario. @Stan, grouping by tenure didn't work here. Any
D_mod %>% dplyr::select(shock.hv.angst, shock.rent.angst, scenario) %>%
  pivot_longer(c(shock.hv.angst, shock.rent.angst),
                     names_to = "tenure",
                     values_to = "response") %>%
  filter(!is.na(response)) %>%
  group_by(tenure, scenario,response) %>%
  summarise(n=n()) %>%
  group_by(tenure, scenario) %>%
  mutate(pct_total=n/sum(n)) %>%
  ggplot(aes(x = scenario, y=pct_total,fill = as.factor(response), group=tenure)) +
  geom_bar(stat="identity",position = "dodge") +
  facet_grid(.~tenure, labeller=as_labeller(c("shock.hv.angst"="Homeowners","shock.rent.angst"="Rent
  scale_fill_discrete("Price Anxiety", labels=c("1"="Not At All Worired","2"="A Little Worried","3"=
  theme_bw()+
  ylab("Relative Frequency")
```

```
## `summarise()` has grouped output by 'tenure', 'scenario'. You can override
## using the `.groups` argument.
```



Finally, we model support for government-initiated upzonings as a function of the respondent's supply skepticism and desire for lower prices. Additionally, we model support for these upzonings as a function of a respondent's belief that the supply shock scenario will create additional lower-income affordable housing units. In both, we include controls for a respondent's price anxiety, their belief that the supply shock will make their quality of life worse and their belief that the supply shock will result in more housing for people like them.

```
# Regression 1.0 Question is whether people who are skeptics are meaningfully less supportive of sta
D_mod %>%
  filter(!is.na(want)) %>%
  nest(data = -ownhome) %>%
  mutate(
    model = map(data, ~ lm_robust(ownscenario.preempt ~
                                   shock.poolskep.wk +
                                   want +
                                   shock.poolskep.wk:want +
                                   shock.angst,
                                 data = .)),
    tidied = map(model, tidy))
```

```
## # A tibble: 2 x 4
##   ownhome data                 model      tidied
##     <dbl> <list>               <list>     <list>
## 1       1 <tibble [52 x 392]>  <lm_robst> <df [5 x 9]>
## 2       0 <tibble [152 x 392]> <lm_robst> <df [5 x 9]>
```

```
# Regression 1.1. This adds qol and housing-for-me to the predictors.
skeps <-D_mod %>%
  filter(!is.na(want)) %>%
```

	Renters	Homeowners
(Intercept)	3.732	1.837
	(1.111)	(0.926)
Skeptic	1.162	1.592
	(0.590)	(0.782)
Wants Lower Prices	0.720	0.906
	(0.699)	(1.007)
Homes for Me	−0.131	0.024
	(0.172)	(0.273)
Worse Quality of Life	−0.108	0.324
	(0.186)	(0.181)
Price Anxiety	−0.175	−0.192
	(0.232)	(0.288)
Skeptic x Wants Lower Prices	−1.579	−1.358
	(1.292)	(1.217)
Num.Obs.	33	32
R2	0.155	0.173
AIC	129.0	125.4
BIC	141.0	137.1
RMSE	1.34	1.34

```
  nest(data = -ownhome) %>%
  mutate(
    model = map(data, ~ lm_robust(ownscenario.preempt ~
                                    shock.poolskep.wk +
                                    want +
                                    shock.poolskep.wk:want +
                                    shock.forme +
                                    shock.qolworse +
                                    shock.angst,

                                  data = .)),
    tidied = map(model, tidy))

names(skeps$model) <- c("Renters","Homeowners")

modelsummary(skeps$model, coef_rename = c("shock.poolskep.wk"="Skeptic",
                                          "wantLower"="Wants Lower Prices",
                                          "shock.forme"="Homes for Me",
                                          "shock.qolworse"="Worse Quality of Life",
                                          "shock.angst"="Price Anxiety",
                                          "shock.poolskep.wk:wantLower"="Skeptic x Wants Lower Price
```

```
# Regression 2.0 This uses chain-of-moves prediction (lower-income) as the measure of skepticism / c
D_mod %>%
  filter(!is.na(want)) %>%
  nest(data = -ownhome) %>%
  mutate(
    model = map(data, ~ lm_robust(ownscenario.preempt ~
                                    shock.chain.low +
                                    want +
                                    shock.chain.low:want +
```

```
                                    shock.angst,
                                  data = .)),
    tidied = map(model, tidy))
```

```
## # A tibble: 2 x 4
##   ownhome data                 model      tidied
##     <dbl> <list>               <list>     <list>
## 1       1 <tibble [52 x 392]>  <lm_robst> <df [5 x 9]>
## 2       0 <tibble [152 x 392]> <lm_robst> <df [5 x 9]>
```

```
# Regression 2.1 Same as 2.0 but with the additional predictors.
chain_of_moves <- D_mod %>%
  filter(!is.na(want)) %>%
  nest(data = -ownhome) %>%
  mutate(
    model = map(data, ~ lm_robust(ownscenario.preempt ~
                                    shock.chain.low +
                                    want +
                                    shock.chain.low:want +
                                    shock.forme +
                                    shock.qolworse +
                                    shock.angst,
                                  data = .)),
    tidied = map(model, tidy))

names(chain_of_moves$model) <- c("Renters","Homeowners")

modelsummary(chain_of_moves$model, coef_rename = c("shock.poolskep.wk"="Skeptic",
                                          "wantLower"="Wants Lower Prices",
                                          "shock.forme"="Homes for Me",
                                          "shock.qolworse"="Worse Quality of Life",
                                          "shock.angst"="Price Anxiety",
                                          "shock.poolskep.wk:wantLower"="Skeptic x Wants Lower Price
```

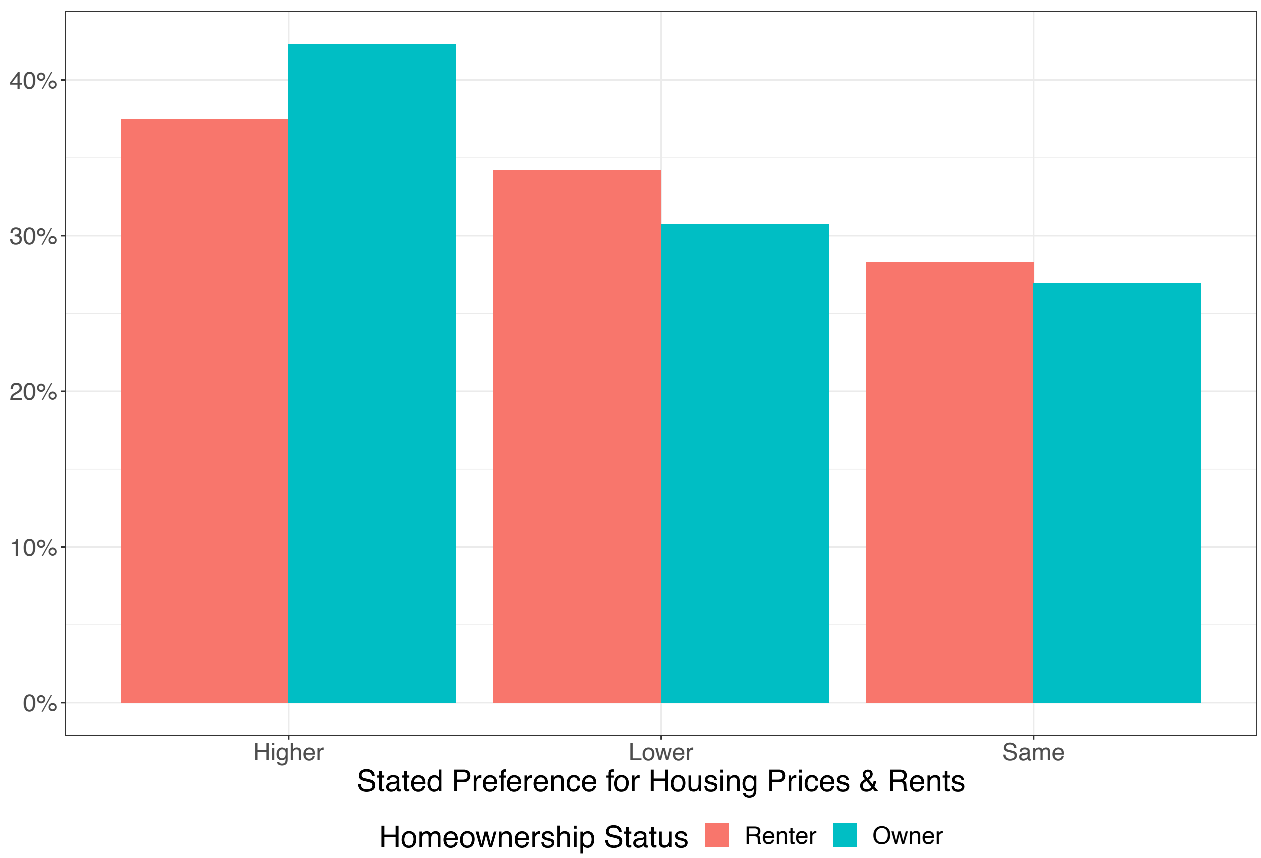
7 Supplemental Information

7.1 Descriptive Statistics

```
# @Stan, we should modify this histogram so that it results are subset by $ownhome. The code I wrote
D %>% filter(!is.na(want.price) & !is.na(ownhome)) %>% group_by(ownhome, want.price) %>%
  summarise(count = n()) %>% mutate(freq= count/sum(count)) %>%
  ggplot(aes(x=want.price, y=freq, group=ownhome,fill=factor(ownhome))) +
  geom_bar(stat="identity", position="dodge")+theme_bw() +
 scale_y_continuous("",labels=scales::percent) +
 scale_x_discrete("Stated Preference for Housing Prices & Rents") +
  scale_fill_discrete("Homeownership Status", labels=c("Renter","Owner")) +
 theme(text=element_text(size=20), legend.position = "bottom")
```

```
## `summarise()` has grouped output by 'ownhome'. You can override using the
## `.groups` argument.
```

	Renters	Homeowners
(Intercept)	3.322	3.382
	(1.031)	(1.203)
shock.chain.low	0.231	−0.122
	(0.192)	(0.241)
Wants Lower Prices	0.336	1.109
	(1.340)	(1.213)
Homes for Me	0.098	0.042
	(0.171)	(0.240)
Worse Quality of Life	−0.108	0.199
	(0.178)	(0.173)
Price Anxiety	−0.281	−0.212
	(0.199)	(0.242)
shock.chain.low:wantLower	−0.047	−0.212
	(0.419)	(0.348)
Num.Obs.	45	45
R2	0.107	0.120
AIC	174.0	174.0
BIC	188.4	188.5
RMSE	1.40	1.40




```
# D %>%
#   filter(!is.na(want.price)) %>%
#   group_by(ownhome) %>%
#   count(want.price) %>%
```

```
#  mutate(percent = n/sum(n)) %>%
#  ggplot(aes(x = want.price), y = percent, fill = ownhome) +
#  geom_bar(stat="identity", position="dodge")
```

7.2 Market skepticism and substantive effect mental models

We expect that skepticism about housing market mechanisms will not be limited to prices. Rather, this skepticism will also correlate with skepticism about other fundamental concepts of housing economics such as filtering (Mast 2021). It will also correlate with zero-sum thinking about who ultimately benefits from new housing stock–separate from the price effects. The ongoing housing debate has been characterized by arguments that increases in housing supply will induce corporations to take more ownership of regional housing stock, will exacerbate gentrification, or will result in overall worse quality of life. We expect that individuals with a general tendency toward zero-sum thinking (as measured by our abbreviated scale) will be more likely to perceive locally adverse effects of development and unfair advantage for developers and gentrifiers.

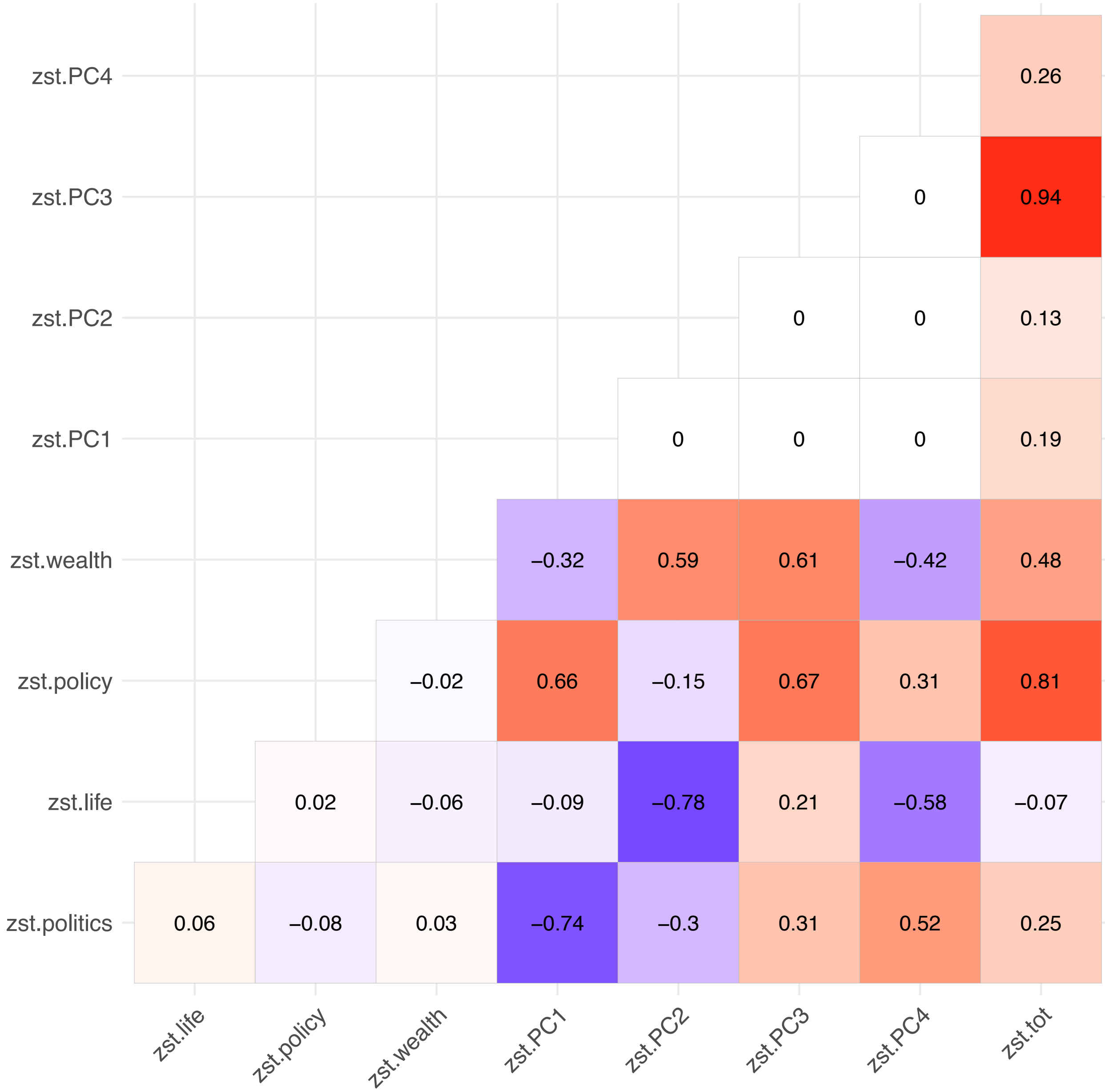
```
D%>%
  select(contains("skep."), shock.chain.low, shock.chain.high, shock.agglom, shock.demo, shock.corp,
  rename("Rents +"="shock.rentskep.str",
         "Rents +/No Change"="shock.rentskep.wk",
         "Home Prices +"="shock.hvskep.str",
         "Home Prices +/No Change"="shock.hvskep.wk",
         "All Prices +"="shock.poolskep.str",
         "All Prices +/No Change"="shock.poolskep.wk",
         "Zero Sum Thinking: PC1"="zst.PC1",
         "Zero Sum Thinking: All"="zst.tot",
         "Chain-of-Moves (Low-$ NH's)"="shock.chain.low",
         "Chain-of-Moves (High-$ NH's)"="shock.chain.high",
         "New Business in Area"="shock.agglom",
         "Demo. of Affordable Housing"="shock.demo",
         "+ Corporate Ownership"="shock.corp",
         "Quality of Life Will Worsen"="shock.qolworse",
         "+ Gentrification"="shock.gentry",
         "+ Expensive Homes"="shock.nextdoor",
         "- HousFinally, we plan to interrogate several other correlations between our item response
ing for Me"="shock.forme") %>%
  cor(use="pairwise.complete.obs") %>%
  ggcorrplot(type="lower", lab=T, title="Market Skepticism and Mental Models.") +
  theme(legend.position="none")
```

tions are preregistered below. *SO: We can cut these. If we don't have a hypothesis about

7.2.1 Zero Sum Thinkers Will Have Less Economic Knowledge

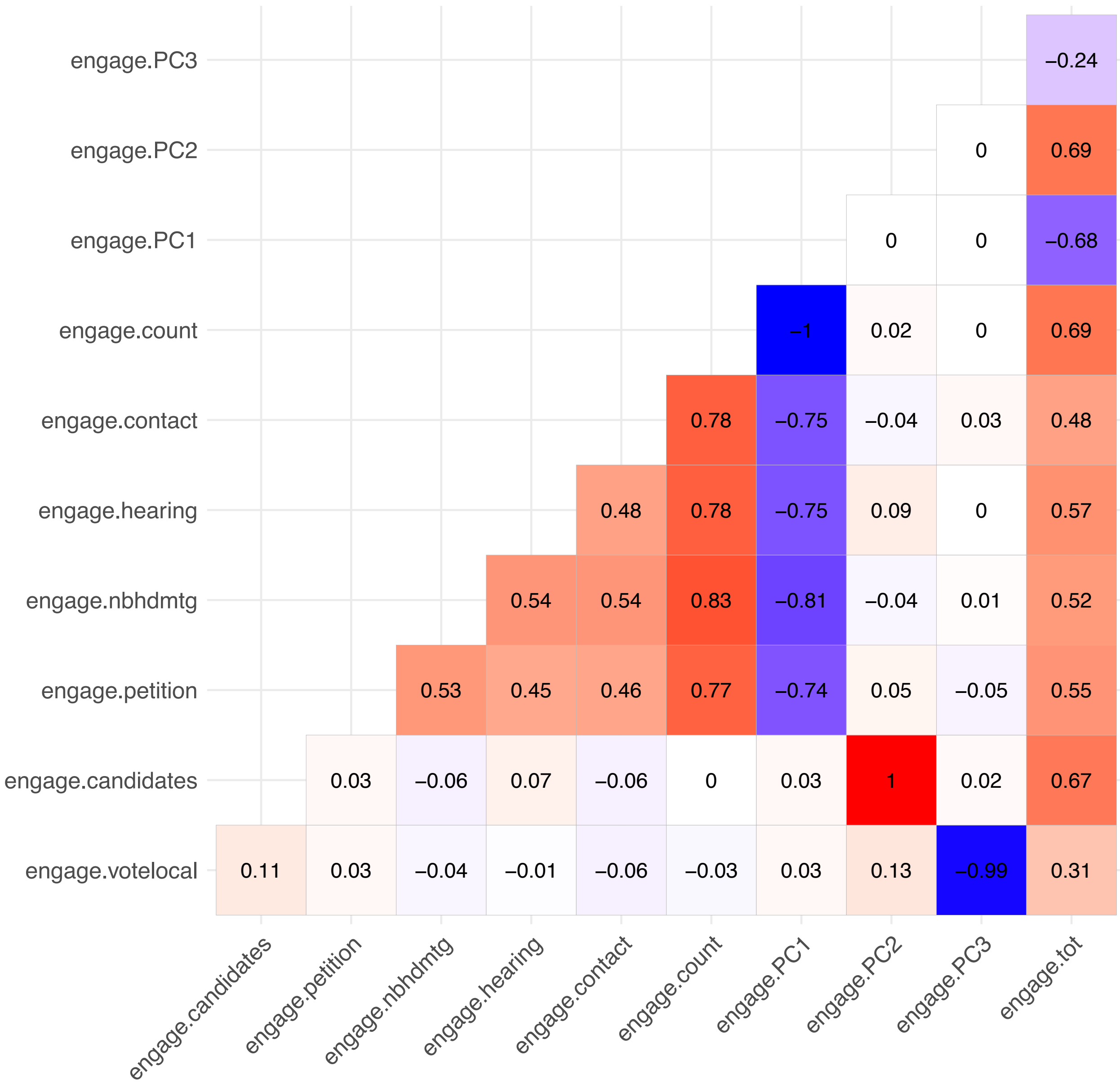
7.2.2 Zero sum thinking items

```
D%>%
  select(starts_with("zst")) %>%
  cor(use="pairwise.complete.obs") %>%
  ggcorrplot(type="lower", lab=T) +
  theme(legend.position="none")
```



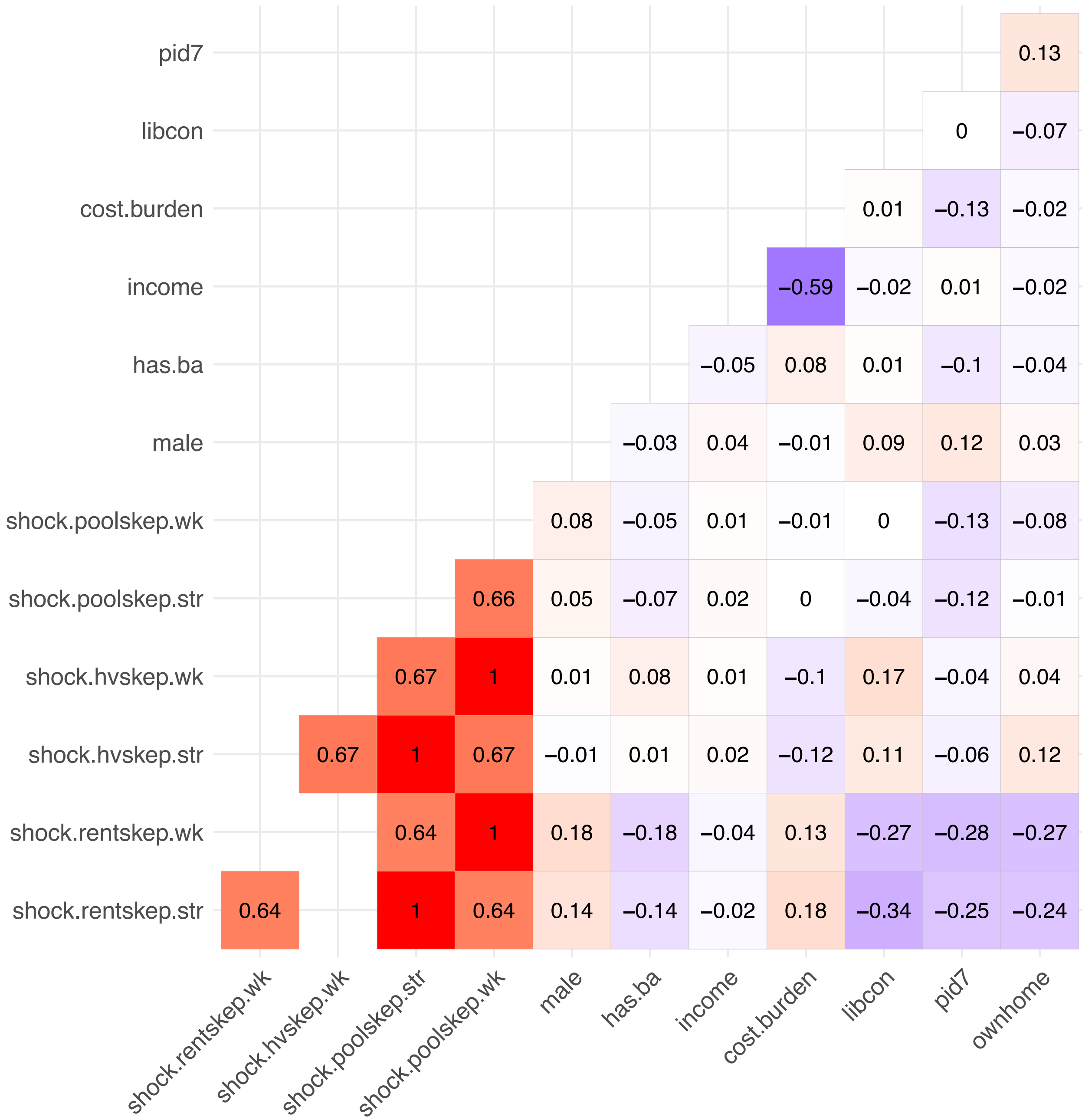
7.2.3 Local political engagement items

```
D%>%
  select(starts_with("engage")) %>%
  cor(use="pairwise.complete.obs") %>%
  ggcorrplot(type="lower", lab=T) +
  theme(legend.position="none")
```



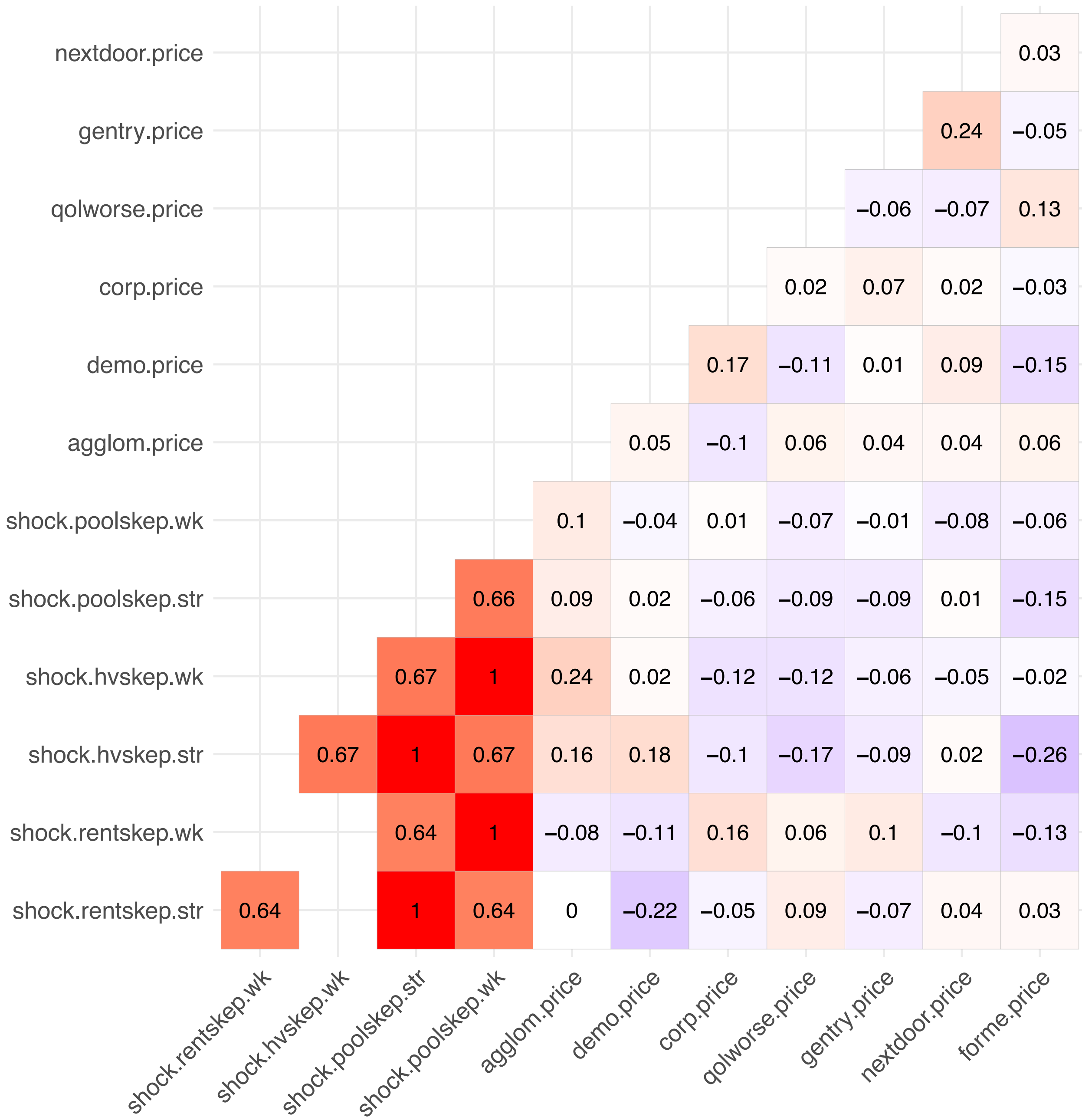
7.2.4 Supply skepticism and demographics

```
# correlation of supply skepticism with zero sum thinking & demographics
D%>%
  select(contains("skep."), race.eth, male, age.cat, has.ba, income, cost.burden, libcon, pid7, ownh
  sapply(., as.numeric) %>%
  cor(use="pairwise.complete.obs") %>%
  ggcorrplot(type="lower", lab=T) +
  theme(legend.position="none")
```



7.2.5 Supply skepticism and price effect mental models

```
D%>%
  select(contains("skep."), ends_with(".price"), -want.price) %>%
  sapply(., as.numeric) %>%
  cor(use="pairwise.complete.obs") %>%
  ggcorrplot(type="lower", lab=T) +
  theme(legend.position="none")
```

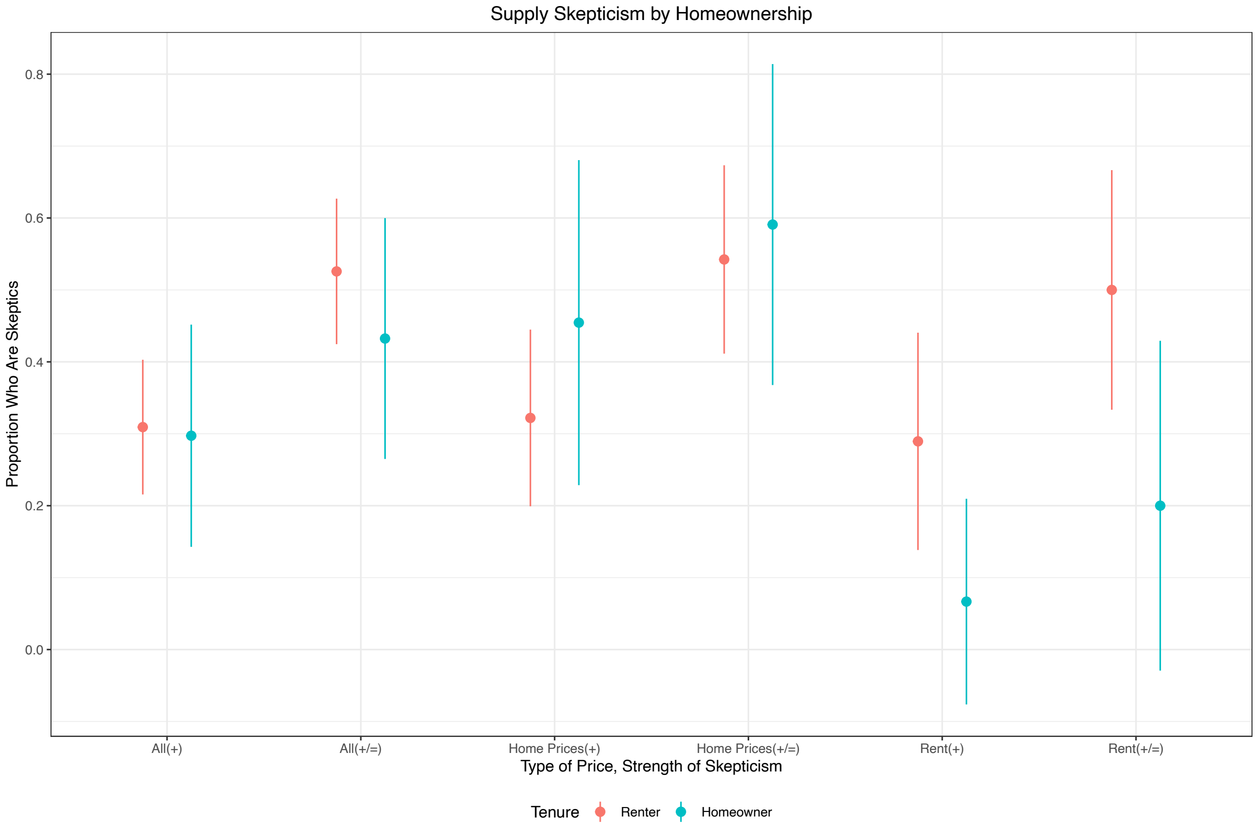


7.2.6 Supply skepticism by target subgroup

We interrogate the following set of hypotheses using OLS regressions preregistered below. In each case, a statistically significant coefficient indicates a "supply-skeptical" subpopulation. Further, differences between subpopulations can be measured by the divergence between each coefficient for each dependent variable representing a different form of supply skepticism.

We expect homeowners to be stronger supply skeptics than renters. Homeowners have more material compulsion to doubt market mechanisms (Fischel 2001) and may engage in post-hoc rationalization. Renters, on the other hand, stand to benefit most from added supply bringing down prices in their metro areas. Though Hankinson (2018) documents instances where renters become as averse to new housing as homeowners when they perceive new development as threatening, renters are responding more to tail-risk in local housing markets rather than region-wide changes as described in our scenarios. Thus, renters should exhibit less supply-skepticism than homeowners. We also expect both groups to exhibit more supply skepticism concerning prices in the tenure status that mirrors theirs–i.e. homeowners will exhibit more supply skepticism about home prices and renters will exhibit more supply skepticism towards rents.

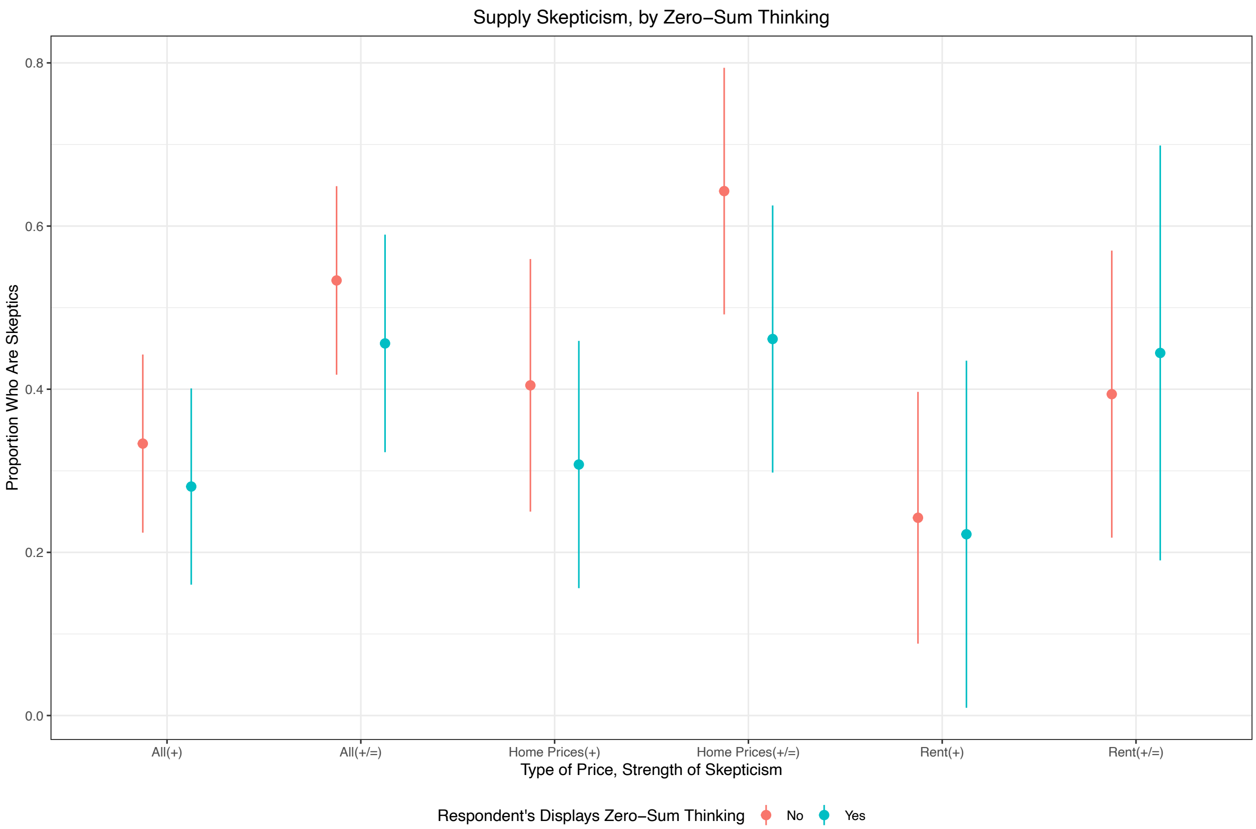
```r
# Targets subsets are owners vs. renters, and people who do/do not want prices to be lower

# This is similar to slide 13 in rosen_hanlon_handouts.pdf, but CIs should be robust to account for

D_mod <- D %>% mutate(
  want = fct_collapse(as_factor(want.price), NotLower = c("Higher", "Same"), Lower = "Lower"),
  rent.conf = as.numeric(shock.rent.conf > median(
    c(D$shock.rent.conf, D$shock.hv.conf), na.rm = TRUE)),
  hv.conf = as.numeric(shock.hv.conf > median(
    c(D$shock.rent.conf, D$shock.hv.conf), na.rm = TRUE)),
  confidence = coalesce(rent.conf, hv.conf), # modify this line if future survey elicits both rent a
  know.ss = as.numeric(know.ss.PC1 > median(D$know.ss.PC1, na.rm = TRUE)),
  lay.empirics = as.numeric(obs.price.dev > median(D$obs.price.dev, na.rm = TRUE)),
  zst = as.numeric(zst.PC1 > median(D$zst.PC1, na.rm = TRUE)),
)

# Owner vs. Renter
D_mod %>%
  filter(!is.na(ownhome)) %>%
  pivot_longer(shock.rentskep.str:shock.poolskep.wk,
                     names_to = "DV",
                     values_to = "response") %>%
  nest(data = -c(DV, ownhome)) %>%
  mutate(model = map(data, ~ lm_robust(response ~ 1, data = .)),
         tidied = map(model, tidy)) %>%
  unnest(tidied) %>%
  mutate(xlabel = case_when(
    DV == "shock.rentskep.str" ~ "Rent(+)",
    DV == "shock.rentskep.wk" ~ "Rent(+/=)",
    DV == "shock.hvskep.str" ~ "Home Prices(+)",
    DV == "shock.hvskep.wk" ~ "Home Prices(+/=)",
    DV == "shock.poolskep.str" ~ "All(+)",
    DV == "shock.poolskep.wk" ~ "All(+/=)"
  )) %>%
  ggplot(aes(x=xlabel, y=estimate, group=ownhome)) +
  geom_pointrange(aes(ymin=conf.low,ymax=conf.high, color=factor(ownhome)),
                position=position_dodge(width=.5)) +
  ylab("Proportion Who Are Skeptics") +
  xlab("Type of Price, Strength of Skepticism") +
  labs(title = "Supply Skepticism by Homeownership") + theme_bw() +
  scale_color_discrete("Tenure", labels=c("Renter","Homeowner")) +
  theme(plot.title = element_text(hjust = 0.5), legend.position = "bottom")
```



We hypothesize that respondents who display higher levels of zero sum thinking will be more skeptical about the effects that new housing supply has on lowering prices. Supply skepticism and zero-sum thinking will be correlated as zero-sum thinkers believe that policy can make all people better off, but rather always produces losers.

```
# By zero-sum thinking
D_mod %>%
  filter(!is.na(zst)) %>%
  pivot_longer(shock.rentskep.str:shock.poolskep.wk,
                     names_to = "DV",
                     values_to = "response") %>%
  nest(data = -c(DV, zst)) %>%
  mutate(model = map(data, ~ lm_robust(response ~ 1, data = .)),
         tidied = map(model, tidy)) %>%
  unnest(tidied) %>%
  mutate(xlabel = case_when(
    DV == "shock.rentskep.str" ~ "Rent(+)",
    DV == "shock.rentskep.wk" ~ "Rent(+/=)",
    DV == "shock.hvskep.str" ~ "Home Prices(+)",
    DV == "shock.hvskep.wk" ~ "Home Prices(+/=)",
    DV == "shock.poolskep.str" ~ "All(+)",
    DV == "shock.poolskep.wk" ~ "All(+/=)"
  )) %>%
  ggplot(aes(x=xlabel, y=estimate, group=zst)) +
  geom_pointrange(aes(ymin=conf.low,ymax=conf.high, color=factor(zst)),
                  position=position_dodge(width=.5)) +
  ylab("Proportion Who Are Skeptics") +
  xlab("Type of Price, Strength of Skepticism") +
```

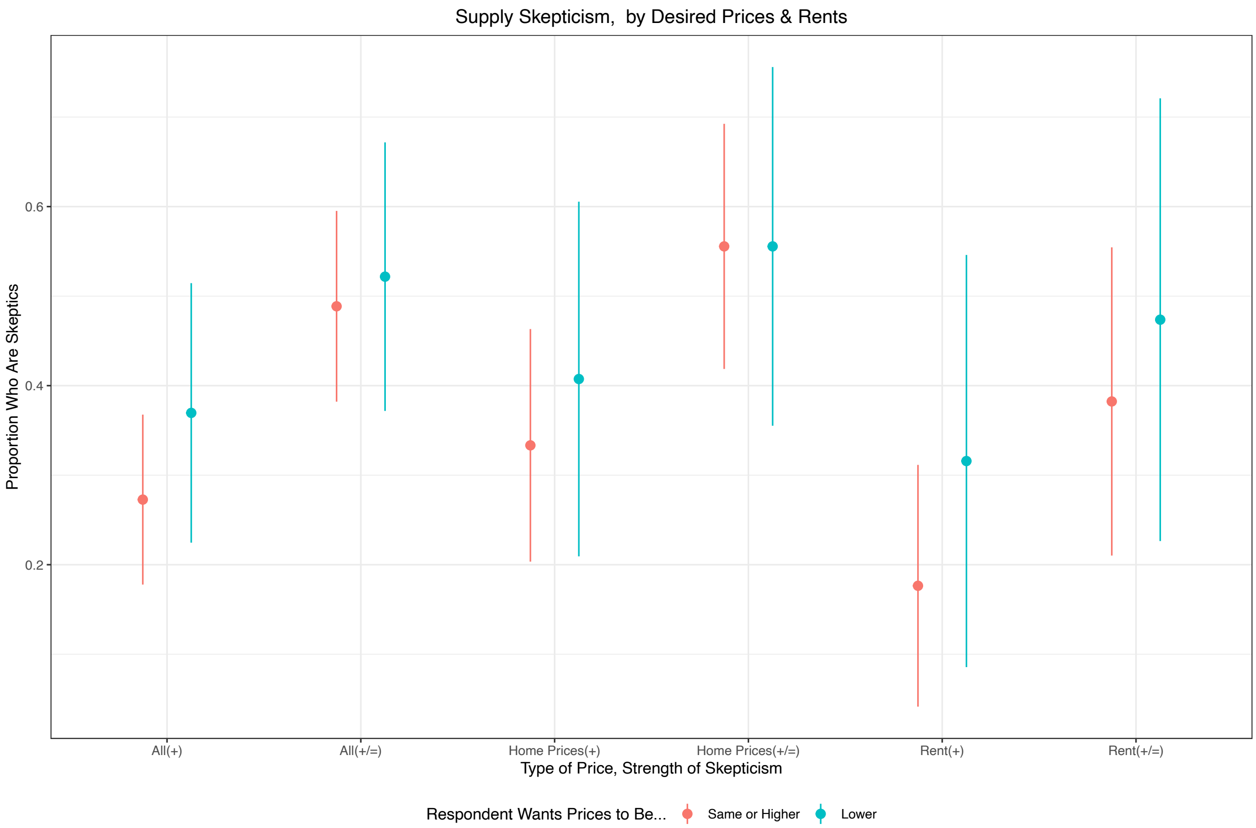
```r
  labs(title = "Supply Skepticism, by Zero-Sum Thinking") + theme_bw() +
  scale_color_discrete("Respondent's Displays Zero-Sum Thinking", labels=c("No","Yes")) +
  theme(plot.title = element_text(hjust = 0.5), legend.position = "bottom")
```



We are agnostic about outcomes, but plan to explore differences in supply skepticism in the following subsamples: - Those who wish for housing costs in their region to decrease vs. those who wish for them to increase. - Those who are exhibit more confidence in their prediction about the effects of supply shocks. - Those who demonstrate knowledge about the effects of supply shocks in other areas aside from housing. - Those who demonstrate knowledge about the effects of trade liberalization. - Those who have been exposed to new housing construction in expensive areas of their region.

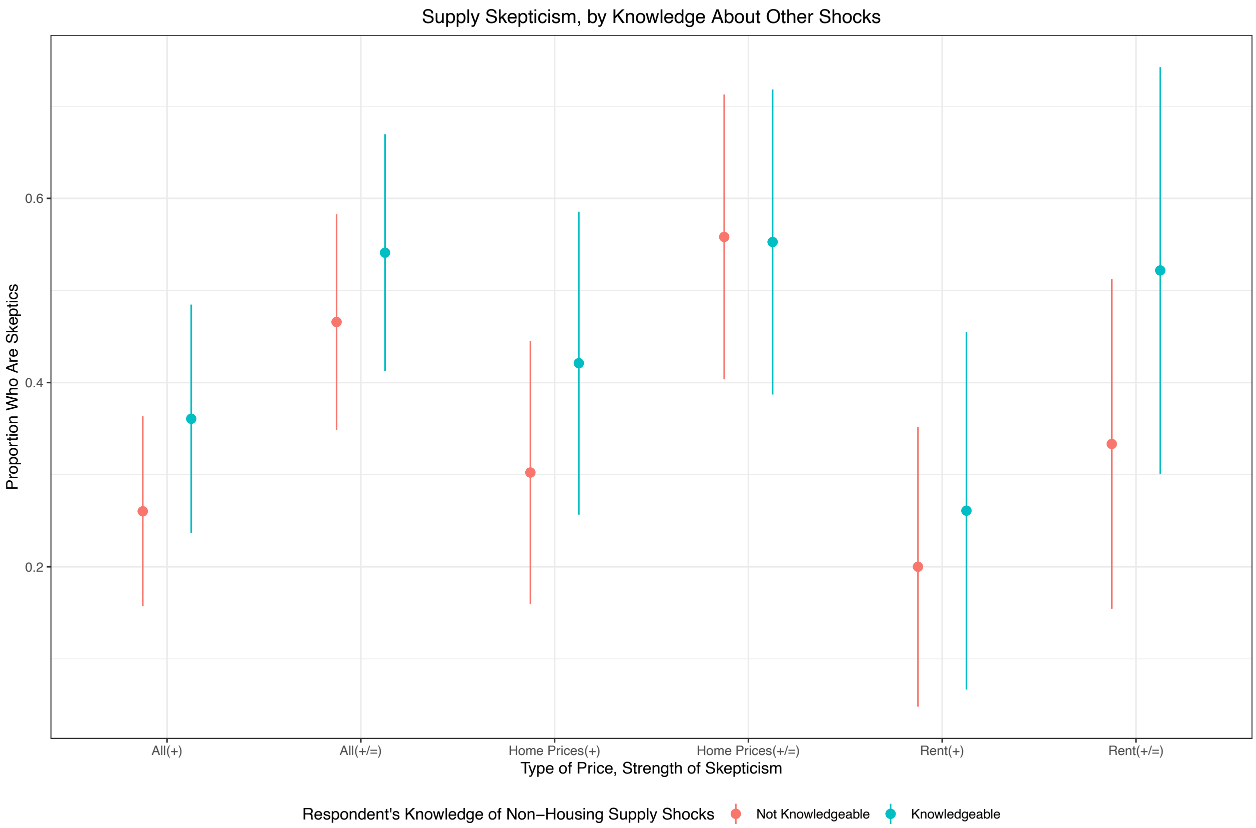
```r
# Want Lower vs. Not Lower
D_mod %>%
  filter(!is.na(want)) %>%
  pivot_longer(shock.rentskep.str:shock.poolskep.wk,
                      names_to = "DV",
                      values_to = "response") %>%
  nest(data = -c(DV, want)) %>%
  mutate(model = map(data, ~ lm_robust(response ~ 1, data = .)),
         tidied = map(model, tidy)) %>%
  unnest(tidied) %>%
  mutate(xlabel = case_when(
    DV == "shock.rentskep.str" ~ "Rent(+)",
    DV == "shock.rentskep.wk" ~ "Rent(+/=)",
    DV == "shock.hvskep.str" ~ "Home Prices(+)",
    DV == "shock.hvskep.wk" ~ "Home Prices(+/=)",
    DV == "shock.poolskep.str" ~ "All(+)",
    DV == "shock.poolskep.wk" ~ "All(+/=)"
```

```
  )) %>%
  ggplot(aes(x=xlabel, y=estimate, group=want)) +
  geom_pointrange(aes(ymin=conf.low,ymax=conf.high, color=factor(want)),
                  position=position_dodge(width=.5)) +
  ylab("Proportion Who Are Skeptics") +
  xlab("Type of Price, Strength of Skepticism") +
  labs(title = "Supply Skepticism,  by Desired Prices & Rents") + theme_bw() +
  scale_color_discrete("Respondent Wants Prices to Be...", labels=c("Same or Higher","Lower")) +
  theme(plot.title = element_text(hjust = 0.5), legend.position = "bottom")
```



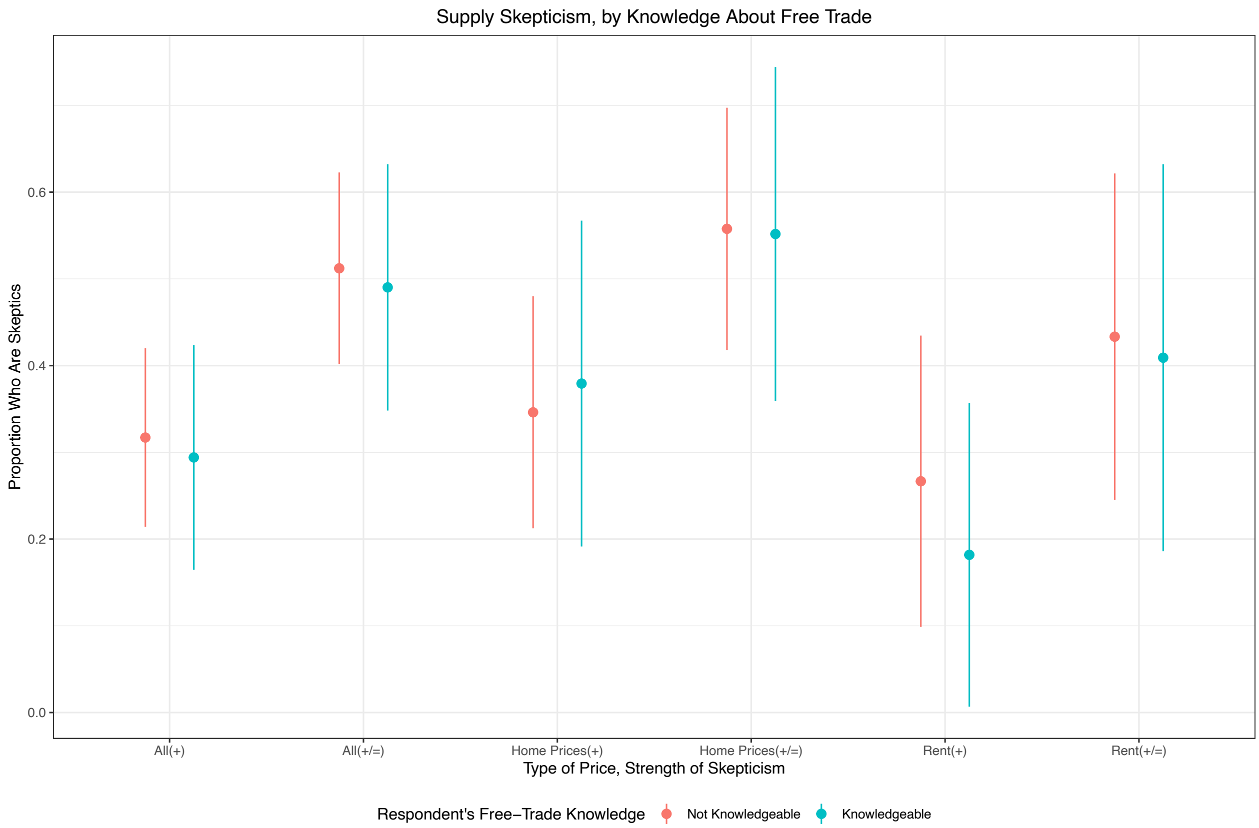

```
# More supply-shock knowledge vs. Less supply-shock knowledge
D_mod %>%
  filter(!is.na(know.ss)) %>%
  pivot_longer(shock.rentskep.str:shock.poolskep.wk,
                         names_to = "DV",
                         values_to = "response") %>%
  nest(data = -c(DV, know.ss)) %>%
  mutate(model = map(data, ~ lm_robust(response ~ 1, data = .)),
         tidied = map(model, tidy)) %>%
  unnest(tidied) %>%
  mutate(xlabel = case_when(
    DV == "shock.rentskep.str" ~ "Rent(+)",
    DV == "shock.rentskep.wk" ~ "Rent(+/=)",
    DV == "shock.hvskep.str" ~ "Home Prices(+)",
    DV == "shock.hvskep.wk" ~ "Home Prices(+/=)",
    DV == "shock.poolskep.str" ~ "All(+)",
    DV == "shock.poolskep.wk" ~ "All(+/=)"
```

```
  )) %>%
  ggplot(aes(x=xlabel, y=estimate, group=know.ss)) +
  geom_pointrange(aes(ymin=conf.low,ymax=conf.high, color=factor(know.ss)),
                  position=position_dodge(width=.5)) +
  ylab("Proportion Who Are Skeptics") +
  xlab("Type of Price, Strength of Skepticism") +
  labs(title = "Supply Skepticism, by Knowledge About Other Shocks") + theme_bw() +
  scale_color_discrete("Respondent's Knowledge of Non-Housing Supply Shocks", labels=c("Not Knowledg
  theme(plot.title = element_text(hjust = 0.5), legend.position = "bottom")
```



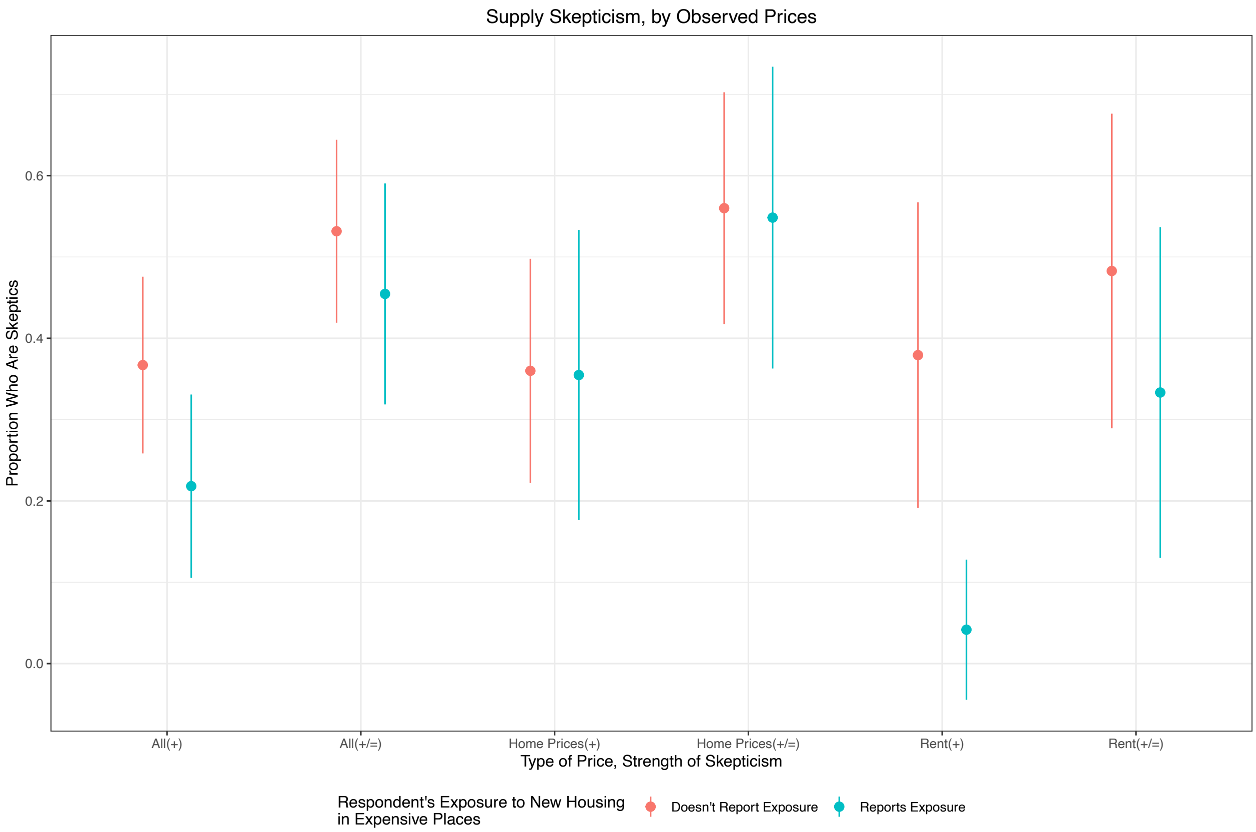

```
# By knowledge about effect of free trade
D_mod %>%
  filter(!is.na(know.trade)) %>%
  pivot_longer(shock.rentskep.str:shock.poolskep.wk,
                      names_to = "DV",
                      values_to = "response") %>%
  nest(data = -c(DV, know.trade)) %>%
  mutate(model = map(data, ~ lm_robust(response ~ 1, data = .)),
         tidied = map(model, tidy)) %>%
  unnest(tidied) %>%
  mutate(xlabel = case_when(
    DV == "shock.rentskep.str" ~ "Rent(+)",
    DV == "shock.rentskep.wk" ~ "Rent(+/=)",
    DV == "shock.hvskep.str" ~ "Home Prices(+)",
    DV == "shock.hvskep.wk" ~ "Home Prices(+/=)",
    DV == "shock.poolskep.str" ~ "All(+)",
    DV == "shock.poolskep.wk" ~ "All(+/=)"
```

```
  )) %>%
  ggplot(aes(x=xlabel, y=estimate, group=know.trade)) +
  geom_pointrange(aes(ymin=conf.low,ymax=conf.high, color=factor(know.trade)),
                  position=position_dodge(width=.5)) +
  ylab("Proportion Who Are Skeptics") +
  xlab("Type of Price, Strength of Skepticism") +
  labs(title = "Supply Skepticism, by Knowledge About Free Trade") + theme_bw() +
  scale_color_discrete("Respondent's Free-Trade Knowledge", labels=c("Not Knowledgeable","Knowledgea
  theme(plot.title = element_text(hjust = 0.5), legend.position = "bottom")
```



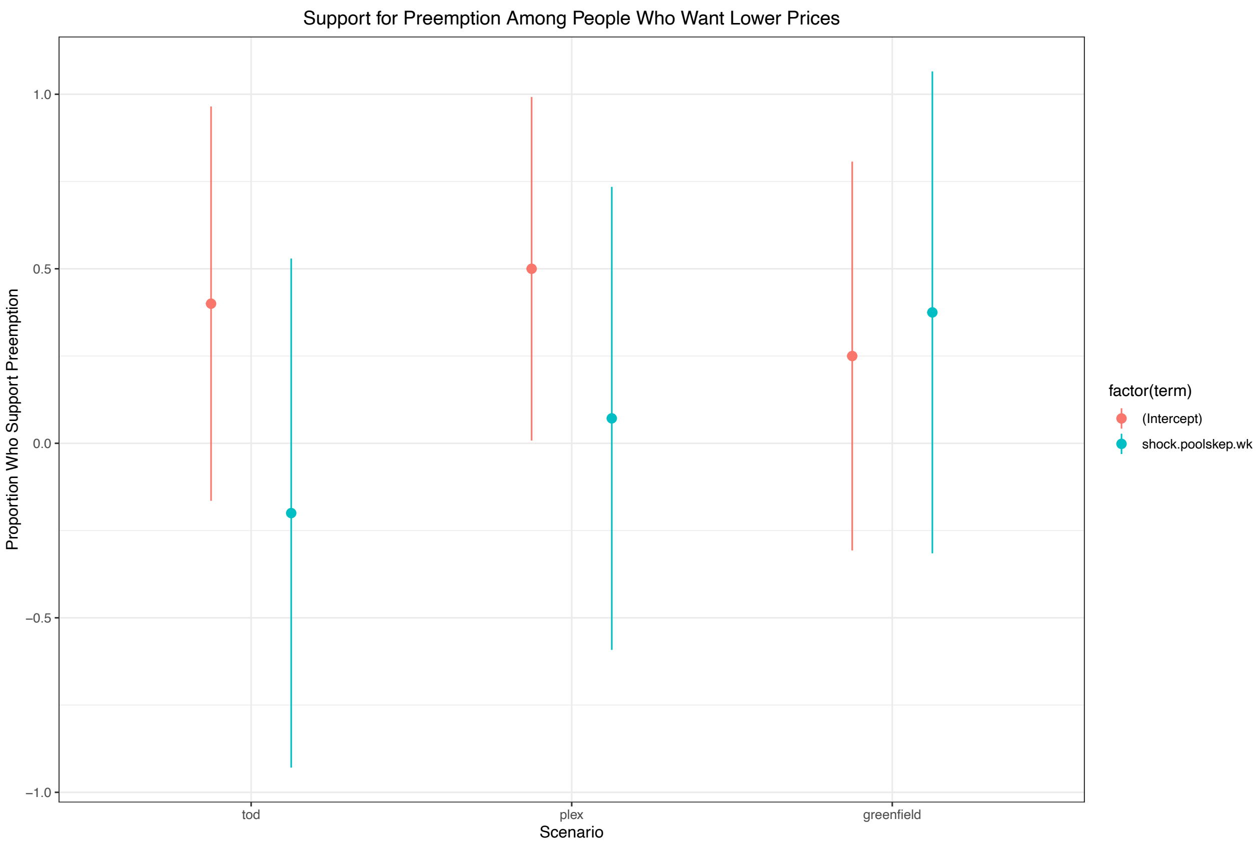

```
# By self-reported exposure to new housing in expensive places
D_mod %>%
  filter(!is.na(lay.empirics)) %>%
  pivot_longer(shock.rentskep.str:shock.poolskep.wk,
                      names_to = "DV",
                      values_to = "response") %>%
  nest(data = -c(DV, lay.empirics)) %>%
  mutate(model = map(data, ~ lm_robust(response ~ 1, data = .)),
         tidied = map(model, tidy)) %>%
  unnest(tidied) %>%
  mutate(xlabel = case_when(
    DV == "shock.rentskep.str" ~ "Rent(+)",
    DV == "shock.rentskep.wk" ~ "Rent(+/=)",
    DV == "shock.hvskep.str" ~ "Home Prices(+)",
    DV == "shock.hvskep.wk" ~ "Home Prices(+/=)",
    DV == "shock.poolskep.str" ~ "All(+)",
    DV == "shock.poolskep.wk" ~ "All(+/=)"
```

```
  )) %>%
  ggplot(aes(x=xlabel, y=estimate, group=lay.empirics)) +
  geom_pointrange(aes(ymin=conf.low,ymax=conf.high, color=factor(lay.empirics)),
                  position=position_dodge(width=.5)) +
  ylab("Proportion Who Are Skeptics") +
  xlab("Type of Price, Strength of Skepticism") +
  labs(title = "Supply Skepticism, by Observed Prices") + theme_bw() +
  scale_color_discrete("Respondent's Exposure to New Housing \nin Expensive Places", labels=c("Doesn
  theme(plot.title = element_text(hjust = 0.5), legend.position = "bottom")
```




```
# Support among those who want lower prices, by prediction. Subset to people who made prediction abo

# This plot is kinda hard to follow. It even took me a second to get it and I'm more familiar with t

D_mod <- D %>% mutate(
  want = fct_collapse(as_factor(want.price), NotLower = c("Higher", "Same"), Lower = "Lower"),
  ownscenario.preempt = case_when(scenario == "tod" ~ hous.TOD.preempt,
                                  scenario == "plex" ~ hous.GD.preempt,
                                  scenario == "greenfield" ~ hous.sprawl.preempt)
)


D_mod %>%
  filter(want == "Lower",
         !is.na(shock.poolskep.wk),
         scenario != "tech"
         ) %>%
```

```
nest(data = -scenario) %>%
mutate(model = map(data, ~ lm_robust(ownscenario.preempt>3 ~ shock.poolskep.wk, data = .)),
       tidied = map(model, tidy)) %>%
unnest(tidied) %>%
ggplot(aes(x=scenario, y=estimate, group=term)) +
scale_x_discrete(limits = c("tod","plex", "greenfield")) +
geom_pointrange(aes(ymin=conf.low,ymax=conf.high, color=factor(term)),
                position=position_dodge(width=.5)) +
ylab("Proportion Who Support Preemption") +
xlab("Scenario") +
labs(title = "Support for Preemption Among People Who Want Lower Prices") +

theme_bw()+
theme(plot.title = element_text(hjust = 0.5))
```



–>

```
#For ZST paper, the key predictor is whether respondent believes the scenario will result in new hou
#NB: if local amenity predictions drive price predictions, then it's pretty obvious why people who w
```

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