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HOW DOES REGIONAL HOUSING MARKET SENTIMENT AFFECT THE FORMATION OF HOUSE PRICE EXPECTATIONS?

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Abstract

This thesis studies how regional housing market sentiment influences households' expectations about future house-price growth. Using monthly behavioural indicators from Zillow to construct a Regional Sentiment Index and matching it to individual expectations from the New York Fed's Survey of Consumer Expectations, the analysis links local market conditions to subjective beliefs across states. A national sentiment measure from Fannie Mae serves as a benchmark. Results show that regional sentiment strongly predicts expected price growth, while national sentiment contributes little. Further analysis reveals marked differences across states: sentiment plays a much stronger role in places with more volatile housing markets, while expectations in more stable states react only modestly.

Keywords: Microeconomics, Behavioural Economics, Household Expectations, Household Sentiment

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1 Introduction

Expectations about future house prices are central to both household decisions and regional housing dynamics. Because housing is the largest asset for most U.S. households, beliefs about future price movements shape choices such as buying, selling, refinancing, and relocating (Case, Shiller, and Thompson 2012). At the market level, shifts in sentiment can amplify cyclical patterns: optimistic expectations tend to strengthen demand and reduce supply, while more pessimistic views can discourage activity and contribute to slowdowns (Burnside, Eichenbaum, and Rebelo 2016). Understanding how these expectations are formed therefore helps explain not only individual behaviour but also broader fluctuations in housing markets.

A growing literature shows that expectations do not arise from fully rational forecasting. Instead, they reflect recent price experiences, personal exposure to local market outcomes, and information circulating within social networks (Kuchler and Zafar 2019; Bailey et al. 2018). These findings suggest that the regional environment in which households are embedded may play an important role in shaping how they interpret current market conditions. This possibility has gained relevance as housing markets across U.S. states have diverged substantially in recent years, with some regions experiencing pronounced volatility and others experiencing relatively stable price developments (FHFA 2025).

The analysis investigates whether regional housing market sentiment helps explain how households form their expectations about future house-price growth. To capture local sentiment, a Regional Sentiment Index is constructed using Zillow housing market indicators. The index is merged with individual-level expectation data from the New York Fed's Survey of Consumer Expectations by assigning each respondent the RSI value of their state and interview month. This produces an individual-level panel in which expectations vary across households while sentiment varies at the state-by-month level. National sentiment, measured through the standardized Home Purchase Sentiment Index, is included to compare the influence of regional conditions with broader narratives about the housing market.

There are three main ways in which this thesis contributes to existing literature. First, it develops a behavioural measure of regional housing market sentiment based on actual market activity, which differs from existing approaches that rely on survey expectations (Bork, Møller, and Pedersen 2020), media tone (Soo 2018), or broader boom-bust indicators (Burnside, Eichenbaum, and Rebelo 2016). Second, it provides direct evidence on how regional and national sentiment are reflected in the house-price expectations reported by individual households, offering insight into the information they seem to rely on. Third, it documents considerable differences across states in how strongly expectations respond to sentiment, pointing out the importance of local housing market histories and information environments.

The empirical findings indicate that regional sentiment is a meaningful determinant of households' house-price expectations. In the specification with state and month fixed effects, a one-unit increase in the RSI is associated with an increase of about 1.3 percentage points in expected house-price growth, a noticeable effect relative to the sample mean of 5%. However, national sentiment contributes little explanatory power once month fixed effects are included, suggesting that households place considerably more weight on conditions in their own regional markets. The analysis also shows significant variations between states in the degree to which expectations react to regional sentiment, signalling that local information environments and long-lasting differences in housing market conditions help determine how sentiment shapes expectations.

This paper is organized as follows. Section 2 reviews related literature on housing markets and expectations, while Section 3 outlines the empirical strategy and describes the methodology and data utilized. Section 4 reports the results, including the baseline estimates, the state-level heterogeneity analysis, and robustness checks, and Section 5 concludes with a summary and implications of the paper.

2 Literature Review

House price expectations play a key role in household decisions such as buying, selling, or financing a home. A broad literature shows that these expectations are shaped by simple heuristics, recent experiences, and the social environment rather than purely rational predictions (Glaeser and Nathanson 2017).

2.1 Formation of House Price Expectations

One of the most notable findings in the literature on house price expectations is that households tend to base their expectations on recent price changes. According to Case and Shiller (1988), homebuyers frequently expect a continuous rise in home values simply because prices have been rising previously. Glaeser and Nathanson (2017) even show how this mechanism is responsible for short-term momentum and long-term mean reversion, both of which are commonly seen in housing markets.

Expectations are also shaped by personal experience. With the help of data from the New York Fed's Survey of Consumer Expectations, Kuchler and Zafar (2019) find that people living in areas with strong recent house price growth report significantly more optimistic national house price expectations. This pattern suggests that households place disproportionate weight on information that is geographically or personally relevant.

A third source of influence is social interactions. Bailey et al. (2018) show that individuals whose Facebook friends experienced strong house price growth become more optimistic about their own local markets, using anonymized data from the social media network. These belief spillovers are particularly present among people who frequently discuss housing with friends and often translate into tangible behaviour, such as a greater willingness to buy a house. The evidence also aligns with Shiller's (2007) idea of seeing housing booms as ”social epidemics of optimism”.

2.2 Measuring Sentiment in Housing Markets

Because expectations are not directly observable, a large literature has relied on different proxies to capture the underlying sentiment in housing markets. An influential approach is to use text-based measures. Soo (2018), for example, constructs sentiment indices from the tone of local newspaper articles and shows that more positive media coverage tends to precede stronger house price growth, even after controlling for fundamentals. These findings suggest that news tone both reflects and shapes the narratives circulating in local markets.

Another approach comes in the form of survey evidence. The Fannie Mae Home Purchase Sentiment Index (HPSI), which summarizes respondents' views on buying and selling conditions as well as their price and mortgage-rate expectations, provides a widely used gauge of national housing sentiment. As documented by Kuchler, Piazzesi, and Stroebel (2022), this type of survey-based measure tracks cyclical shifts in optimism across demographic and geographic groups.

Beyond news tone and survey responses, researchers have also pointed to actual market behaviour as a source of sentiment information (e.g. Burnside, Eichenbaum &

Rebelo 2016). Variables such as bidding intensity, price reductions, or time-on-market patterns can reveal how confident buyers and sellers are at a given point in time. These behavioural indicators offer an alternative way to capture the mood of the market - one that aims to reflect actions rather than stated attitudes.

2.3 Beliefs and Housing Market Behaviour

A key insight from the literature is that expectations do not merely reflect attitudes; they shape concrete economic decisions. Bailey et al. (2019), for instance, show that households with more pessimistic views about future prices tend to choose higher mortgage leverage, reflecting a desire to insure against downside risk. Bottan and Perez-Truglia (2020) provide complementary evidence: when homeowners receive positive information about recent local price growth, they become less inclined to sell, anticipating further appreciation. In a similar vein, Adelino, Schoar, and Severino (2018) find that individuals who perceive housing as a riskier investment are less likely to enter the market at all.

These studies illustrate how variation in expectations translates into meaningful differences in buying, selling, and financing choices. They also highlight the importance of understanding the forces that shape beliefs in the first place: if expectations influence behaviour, then identifying the local environments and informational signals that feed into those beliefs becomes essential. This motivates the empirical strategy of the next section, which examines whether regional sentiment - captured through market behaviour - helps explain differences in households' expectations across U.S. states.

3 Methodology and Data Setup

3.1 Conceptual Framework

Building on the previous section, the analysis assumes that households form expectations based on both economic fundamentals and their local social environment. To measure this dynamic, a Regional Sentiment Index (RSI) was constructed as a behavioural proxy for the prevailing optimism or pessimism within local housing markets. Furthermore, the Fannie Mae Home Purchase Sentiment Index (HPSI) is used to capture overall attitudes towards the housing market on a national level. Six questions in Fannie Mae's National Housing Survey (on topics like buying and selling conditions) are summarized into a single standardized indicator (Fannie Mae 2025). For comparability with the RSI, the HPSI is standardized to have a mean of zero and unit variance before the regression.

Both these indexes are then matched with individual survey responses on house-price expectations from the Survey of Consumer Expectations by the Federal Reserve Bank of New York. The main question is whether households living in more optimistic state-level environments, as measured through observed market behaviour, report higher expected price growth.

3.2 Empirical Specification

The baseline model estimated here is:

$$E_{i,s,t} = \alpha + \beta_1 RSI_{s,t} + \beta_2 HPSI_t + \gamma_s + \delta_t + \varepsilon_{i,s,t}, \tag{1}$$

where

- $E_{i,s,t}$ is the expected 12-month house-price change reported by individual i in state

s at month t,

- $RSI_{s,t}$ is the regional sentiment index,
- $HPSI_t$ is the standardized national Home Purchase sentiment index,
- γ_s and δ_t are state and time fixed effects,
- and $\varepsilon_{i,s,t}$ is an idiosyncratic error term.

The key coefficient of interest, β_1, measures the marginal effect of regional sentiment on subjective price expectations. A positive β_1 implies that individuals in more optimistic regional environments systematically expect higher future price growth, even after controlling for national sentiment and fixed regional characteristics. Since demographic variables are not available in the public SCE microdata used here, the estimation focuses on state and time variation, which is the main source of meaningful identification in this regression.

3.3 Construction of the Regional Sentiment Index

The RSI is constructed using Zillow's monthly metro-level housing indicators from March 2018 to January 2025. As an online housing platform, Zillow provides not only measures of home prices but also other housing-market indicators. Three of these are used as behavioural variables reflecting local market and demand conditions for the index:

1. **Sale-to-List Price Ratio**: A value above one indicates buyers are willing to bid above asking prices, consistent with a positive sentiment; a value below one indicates the opposite.

2. **Share of Listings with Price Cuts**: The more houses are listed with a lower price at the end of each month, the weaker the demand and thus the more negative the sentiment.

3. **Median Days to Pending**: ”Pending” refers to the period after a seller has accepted an offer and the sale is being finalized (Stiver 2025). The longer a house takes to be listed as pending, the more pessimistic the market.

Each indicator is then standardized to a z-score to ensure comparability. As two of the chosen variables are negatively associated with sentiment (price cuts and days to pending), they are multiplied by -1 so that a higher value always indicates a rise in optimism. The RSI for metro m at time t is computed as the unweighted mean of the three variables:

$$RSI_{m,t} = \frac{1}{3} \left[z(\text{Sale/List}) - z(\text{Price Cuts}) - z(\text{Days to Pending}) \right]. \tag{2}$$

3.4 Aggregation to State Level

The public microdata of the New York Fed SCE includes the respondent’s U.S. state of residence. To make the RSI compatible with this structure, the metro-level sentiment values constructed from Zillow data are aggregated to the state level.

For each month t, the state-level RSI is computed as the simple average of all Zillow metros located within that state:

$$RSI_{s,t} = \frac{1}{N_s} \sum_{m \in s} RSI_{m,t}, \tag{3}$$

where N_s is the number of metros contained in state s. This yields a balanced state-by-month panel that matches directly to the survey, with 4,122 observations in total.

It is worth noting that state-level sentiment is still an aggregate measure and likely smooths over meaningful within-state differences, especially in large or diverse states. This means that any significant effect of RSI found in the regressions should be interpreted as a conservative estimate of the influence of local sentiment: if more granular data were available, the true relationship might be even stronger. Overall, however, using states strikes a good balance between granularity and data availability and is well-suited for studying how local sentiment correlates with individual house price expectations.

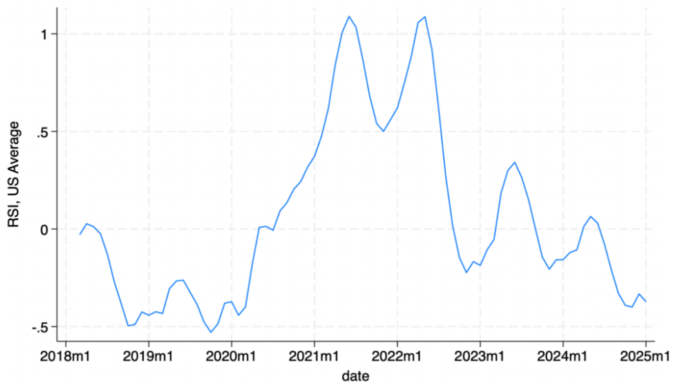

Figure 1: RSI Average, Plotted over Time

The national average of the RSI over the sample period is plotted in Figure 1 to illustrate the behaviour of the constructed index. Values above or below zero should be interpreted in relation to the 2018–2025 average rather than as absolute sentiment levels because the RSI is based on standardized housing market indicators. The series begins at slightly negative levels, rises noticeably starting in 2020, dips and then rises again in 2021, peaks around 2022, and then declines. According to Kuchler, Piazzesi, and Stroebel (2022), these dynamics closely correspond with well-documented developments in the U.S. housing market during the pandemic boom and subsequent slowdown, indicating that the RSI captures significant variation in national housing sentiment.

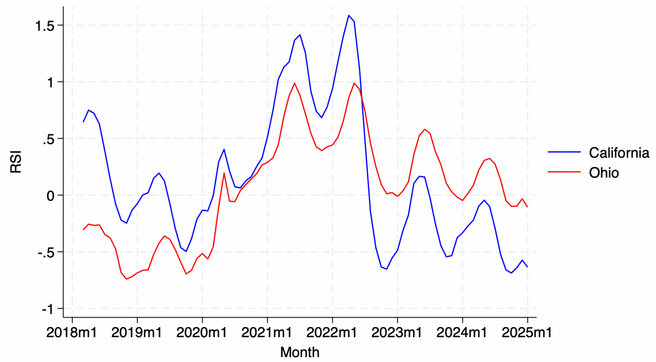

Figure 2: Comparison of the RSI for California & Ohio

Regional sentiment varies greatly among U.S. states, as shown in Figure 2. California exhibits significantly greater sentiment swings, with prominent peaks during the pandemic boom and a sharper decline afterward, in contrast to Ohio, which shows a more muted pattern. Most likely, this reflects California's historically more volatile housing market, where changes in market conditions are amplified by stronger demand cycles and supply constraints (Jackson 2018). In Section 4.3, this heterogeneity will be revisited.

3.5 Merging with Survey and National Data

The final dataset combines three sources of information: the individual responses from the NY Fed Survey of Consumer Expectations (SCE), the state-level RSI constructed from Zillow data, and the standardized HPSI series from Fannie Mae. The SCE data provide the core structure of the panel, since each respondent is observed together with the month of the interview and their U.S. state of residence. These identifiers make it straightforward to attach both local and national sentiment measures to each observation.

The merge proceeds in two steps. First, the state-by-month RSI panel is merged onto the SCE microdata using state and survey month. This assigns the locally relevant sentiment conditions to each respondent in that month. Second, the HPSI series is merged by month only, as national sentiment does not vary across states. After these merges, each individual observation features the respondent's expected 12-month house price change, the corresponding state-level RSI, and the national HPSI for that same month.

Table 1: Overview of the main variables included after merging

Variable	**Description**	**Source**
`exp_price_change`	Expected 12-month house price change (%)	NY Fed SCE
`RSI`	State-level Regional Sentiment Index	Zillow
`HPSI`	Home Purchase Sentiment Index (standardized)	Fannie Mae
`state`	Respondent's state of residence	NY Fed SCE
`date`	Survey month (YYYY-MM)	NY Fed SCE

Overall, the resulting dataset is well suited for analyzing how regional and national sentiment relate to individual house price expectations. While state-level sentiment is coarser than metro-level information, it is the most fitting solution compatible with the publicly available SCE microdata. This makes the merged panel a practical and conceptually coherent foundation for the empirical analysis that follows.

3.6 Estimation and Interpretation

The empirical analysis is based on a panel OLS (ordinary least squares) specification with state and month fixed effects. Standard errors are clustered at the monthly level to allow for shared shocks and survey conditions that may affect all states in a given month. The coefficients on the RSI and HPSI measure how a one-unit increase in regional or national sentiment is associated with changes in expected 12-month house price growth. A positive and statistically significant coefficient on the RSI would indicate that households systematically adjust their expectations in response to changing local housing market sentiment.

State fixed effects control for persistent differences across states, such as long-run market characteristics or structural housing supply conditions. Month fixed effects absorb nationwide shocks and macroeconomic developments. As a result, identification comes from within-state variation over time - specifically, how changes in local sentiment in a given state correspond to changes in the expectations of respondents living in that state.

4 Results

4.1 Key Statistics

The final dataset consists of 4,122 individual-by-month observations from the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE), covering the period from March 2018 to January 2025 across all 50 U.S. states and the District of Columbia.[1] Each observation contains a respondent's expected percentage change in

[1]The SCE microdata is released in cleaned monthly waves; small discrepancies in the number of observations across variables stem from missing responses.

home prices over the next twelve months, the state-level value of the Regional Sentiment Index, and the national Home Purchase Sentiment Index. Since HPSI does not vary across states, meaningful variation in sentiment arises primarily from changes in RSI over time within each state.

Table 2 reports the summary statistics for the main variables. Expected house-price growth varies substantially across respondents, with a mean of 5.01% and a standard deviation of 4.74 percentage points. The distribution ranges from -35% to $+50\%$, consistent with the heterogeneity in subjective house-price beliefs documented in prior work such as Bailey et al. (2019) and Kuchler and Zafar (2019).

The RSI has a mean close to zero by construction (0.066) and a standard deviation of 0.61. The range from -1.67 to 1.98 indicates substantial variation in regional sentiment conditions across states and over time. By construction, the standardized HPSI has a mean of zero and a standard deviation of one, with values ranging from -1.90 to 1.74.

Table 2: Summary Statistics of Main Variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
RSI	4,122	0.066	0.613	–1.672	1.984
HPSI	4,122	0.000	1.000	–1.903	1.736
Expected price change (%)	4,119	5.01	4.74	–35	50

A simple correlation between RSI and expected price change is positive but modest (0.137), suggesting that respondents living in states with stronger local sentiment tend, on average, to report slightly higher expected home-price growth. Appendix Figure A1 provides a binned scatterplot (following Chetty et al. 2019), which visually confirms the positive raw relationship between regional sentiment and mean house-price expectations. This pattern is consistent with the literature discussed in Section 2, where households are shown to place weight on salient local conditions when forming expectations. At the same time, the modest correlation shows the importance of controlling for time-invariant state characteristics and nationwide trends, which will be done in the regression in Section 4.2.

4.2 Results

Table 3: Baseline Regression Results under Alternative Fixed Effects

	(1) No FE	(2) Month FE	(3) State FE	(4) State & Month FE
RSI	1.42***	–0.78*	2.87***	1.30**
	(0.44)	(0.43)	(0.36)	(0.51)
HPSI	0.99***	0 (omitted)	1.16***	0 (omitted)
	(0.24)		(0.23)	
Constant	4.92***	5.06***	4.82***	4.93***
	(0.29)	(0.17)	(0.16)	(0.03)
R-squared	0.06	0.23	0.21	0.32
Fixed effects	None	Month	State	State, Month
Observations	4,119	4,119	4,119	4,119
Clustering	Two-way: state and month			

Notes: Heteroskedasticity-robust standard errors depicted in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3 reports the baseline regression results under different sets of fixed effects. All specifications apply two-way clustering of standard errors by state and month. Column (1) contains the simple pooled regression without fixed effects; column (2) adds month fixed effects; column (3) instead adds state fixed effects; and column (4) includes both state and month fixed effects.

Across all specifications in which it is identified, the coefficient on the RSI is positive and statistically significant, with the exception of column 2, where month fixed effects absorb most of the meaningful variation in sentiment and the remaining cross-state component yields a negative and only weakly significant estimate. In the pooled model without fixed effects (column 1), a one-unit increase in the RSI is associated with a 1.42 percentage point increase in expected home-price growth. When only month fixed effects are included (column 2), the coefficient becomes negative and less significant, as identification then comes from deviations of the RSI across states within a given month. With state fixed effects (column 3), the RSI coefficient rises to 2.87, suggesting that within-state changes in regional sentiment over time are strongly related to shifts in expectations. In the model with both state and month fixed effects (column 4), which controls for all time-invariant state characteristics and common time shocks, the coefficient settles at 1.30 and remains statistically significant at the 5% level. Given mean expected growth of about 5%, the effect is economically meaningful.

The behaviour of the HPSI coefficient across columns illustrates the different roles of national and regional sentiment. In the pooled regression and the model with only state fixed effects (columns 1 and 3), the HPSI coefficient is strong (around 1) and highly significant, implying that a one-standard-deviation increase in national housing sentiment is associated with roughly a one percentage point increase in expected house-price growth. However, once month fixed effects are introduced (columns 2 and 4), HPSI is dropped from the regression because it is perfectly collinear with the month dummies: it varies only over time and is constant across states within each month. This pattern shows that the supposed explanatory power of HPSI in the simpler specifications is largely driven by national time trends, such as the pandemic housing boom and the slowdown afterwards, which month fixed effects fully absorb. Re-estimating the model with HPSI as the sole regressor yields similar results: it appears correlated with expectations only in specifications without month fixed effects and is otherwise absorbed by them (see Appendix Table A1). The RSI, however, displays a robust association with expectations even after these common shocks are taken into account.

The overall explanatory power of the model is modest but reasonable given the well-documented noise in subjective expectation data (see Kuchler, Piazzesi, and Stroebel 2022). When month fixed effects are added, the R-squared increases from 0.06 in the pooled specification without fixed effects to 0.23, and when state fixed effects are added, it increases to 0.21. This implies that a significant part of the variation in expectations is related to both nationwide shocks over time and persistent differences across states. About one-third of the variation in individual expectations can be explained by regional sentiment in combination with state and month fixed effects, as indicated by the full model's R-squared of 0.32. State-specific, time-varying conditions - rather than individual traits or sentiment alone - seem to drive a large share of the belief variation, as shown by the substantial improvement over the pooled regression.

4.3 Heterogeneity within States

A natural follow-up question is whether this relationship is uniform across the United States or whether some states exhibit stronger sensitivity to sentiment than others.

To properly investigate heterogeneity on a state level, a separate regression is estimated for each state s of the form

$$\mathrm{E}_{s,t} = \alpha_s + \beta_s \, RSI_{s,t} + \varepsilon_{s,t}, \tag{4}$$

where β_s captures the sensitivity of households' expectations in state s to changes in regional sentiment. This specification is estimated using the Statsby method in Stata, which runs the regression in Equation (4) separately for each state and stores the estimated coefficients and the number of observations used in each estimation. Unlike the baseline specification, month fixed effects are not included in the state-level regressions, as they would absorb the majority of the within-state time variation and leave little room to identify the sentiment effect. Since estimating the model independently for each state would reduce state fixed effects to a constant - and thus bring no additional identification - they are also excluded. Similarly, the HPSI only varies at the national level and thus does not provide any identifying variation across states, so the coefficient on the index is not of interest in these regressions.

The resulting dataset contains 51 state-specific estimates for β_s, along with each state's sample size. Appendix Table A2 summarizes the distribution of the estimated β_s coefficients. The average effect of regional sentiment across states is 3.16, but there is a strong dispersion: values range from -1.50 to 9.91, and the standard deviation is 1.94. These numbers indicate meaningful variation in how strongly expectations respond to sentiment across different parts of the country.[2]

To visualize the variation geographically, Figure 3 plots each state shaded according

[2] A small number of states have slightly negative coefficients. This can happen in states with limited time variation in the RSI or noisy expectations data, which makes the state-specific regression imprecise. As the corresponding p-values are large as well, these negative coefficients should be interpreted as statistical noise rather than meaningful relationships.

to the magnitude of its estimated β_s coefficient. Darker shades correspond to stronger sensitivity of expectations to the RSI, while lighter shades indicate the opposite.

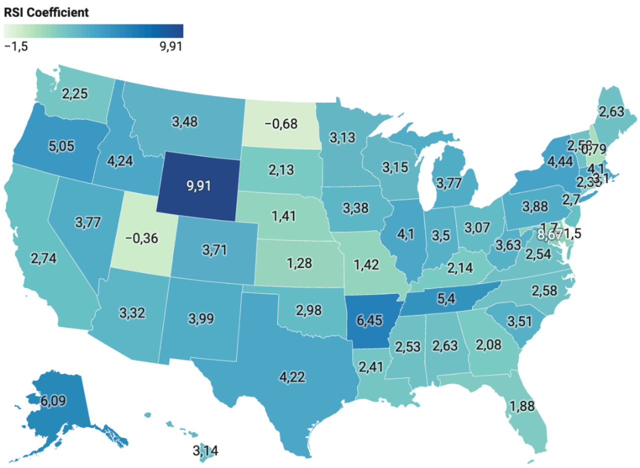

Figure 3: State-Level Sentiment Coefficients

The map reveals some geographical clustering in the strength of the sentiment effect. Especially states in the West and parts of the Northeast tend to show the highest sensitivity, with coefficients well above the national average. By contrast, many Midwestern and Southern states display relatively mild responses, with coefficients between 0 and 2.5. These patterns show that sentiment matters more in some states than in others. A few factors likely contribute to this variation.

First, prior work has shown that house price booms and busts are much more present in coastal, supply-constrained markets, while more elastic inland areas experience smaller price swings and less momentum (Glaeser, Gyourko and Saiz 2008). In these environments, recent price movements are more salient and may serve as a stronger input into belief formation. If households in historically volatile markets are familiar with interpreting local signals as informative about future conditions, they may respond more strongly to changes in sentiment. This mechanism aligns with the relatively high coefficients observed in several Western and Northeastern states.

A second mechanism is experience-based learning. Individuals place disproportionate weight on personally salient past outcomes when forming expectations (Malmendier and Nagel 2011), and it has already been established that local house-price histories strongly shape beliefs (Kuchler and Zafar 2019). States that have experienced substantial appreciation over the past decade, such as Idaho and Wyoming, may therefore have populations that respond more strongly to changes in sentiment. According to the Federal Housing Finance Agency's state-level House Price Index 2025, these states both rank among the ten states with the highest house-price growth since 1991, a pattern that aligns with the elevated coefficients found in the estimation (e.g., 5.05 for Wyoming and 4.24 for Idaho). Oppositely, in more stable markets, like parts of the Midwest, households may view sentiment as less informative, yielding weaker estimated effects.

Finally, social interaction and information environments vary significantly between regions. Soo (2018) reports that local media sentiment predicts local housing market activity, and Bailey et al. (2018) demonstrate how social network experiences impact people's beliefs about housing markets. Therefore, sentiment may spread faster or more forcefully in areas with denser social networks, higher migration inflows, or more active local news environments. States with sizable, information-rich urban centers, like New York (New York City, 5.40) or Massachusetts (Boston, 4.1), show a stronger sensitivity to the RSI, which can be explained by this mechanism.

In sum, these dynamics imply that a mix of information environments, local histories, and market features influence how sentiment affects expectations. Therefore, the heterogeneity seen in the state-level estimates is consistent with trends found in the housing literature and emphasizes that the same sentiment shocks may have different effects depending on where they occur.

4.4 Robustness Checks

To assess the stability of the results, several robustness checks are conducted for both the main specification and the state-level regressions. First, Appendix Table A3 reports the baseline specification for the main regression under alternative clustering choices (state clustering and month clustering). The coefficient on regional sentiment remains stable across these alternatives, confirming that the main finding does not depend on the assumed error structure.

Second, a lagged version of the Regional Sentiment Index is introduced. RSI_{t-1} is used to determine whether sentiment possesses predictive power for expectations and therefore to mitigate concerns about simultaneity. The coefficient remains positive and statistically significant (1.13, $p < 0.001$), and only slightly smaller than in the baseline, indicating that the relationship is not driven by contemporaneous noise and that sentiment is able to maintain its explanatory power.

Finally, the main regression is re-estimated excluding the four largest states in terms of population (California, Texas, Florida, and New York; Tikkanen 2025). These states account for a disproportionate share of SCE respondents and housing market activity, raising the question of whether they overly influence the estimates. The coefficient on the RSI remains practically unchanged (1.29, $p < 0.001$) when these states are omitted, indicating that the baseline result is not driven by a small set of influential states.

Two methods are also used to assess robustness for the state-level regressions. First, the distribution is trimmed to remove outlier states with very high or very low coefficients (states with $\beta > 6$ or $\beta < -0.2$). When these seven observations are eliminated, a distribution of state-specific coefficients with a comparable mean (3.02) and significantly lower variance is obtained, suggesting the results are not driven by outliers.

Lastly, the RSI is standardized within each state before estimation, ensuring that differences in the scale or dispersion of sentiment across states do not generate heterogeneity in the coefficients. After normalization, the distribution of state-level effects remains centered around a similar mean (1.24) and the relative ranking of states is largely preserved. These results suggest that the observed heterogeneity across states comes from meaningful differences in how households incorporate sentiment into their expectations, not from technical features of the RSI.

5 Conclusion

This thesis examined how regional housing market sentiment shapes households' expectations about future house-price growth. Using a constructed Regional Sentiment Index derived from Zillow indicators and individual-level data from the New York Fed's Survey of Consumer Expectations, the analysis linked behavioural signals in local markets to subjective beliefs across U.S. states and compared these effects to those of national sentiment.

The findings show that regional sentiment is a strong predictor of house-price expectations. In the specification with state and month fixed effects, a one-unit increase in the RSI corresponds to roughly 1.3 percentage points higher expected price growth, a meaningful effect relative to the mean expectation of 5%. National sentiment, in comparison, contributes little once month fixed effects are included, implying that households rely more on local conditions than on nationwide narratives.

The analysis also finds cross-state heterogeneity: some states respond strongly to changes in sentiment, while others react only modestly. These differences align with variation in market volatility, local housing histories, and information environments.

Robustness checks confirm that the main results hold when sentiment is lagged, major states are removed, or alternative normalizations are applied.

Taken together, the evidence suggests that households anchor parts of their expectations in local housing market signals. This has implications for research and policy. Models of expectation formation should incorporate geographically disaggregated sentiment, and national-level communication from institutions such as the Federal Reserve, government agencies, or national media may have limited influence when local housing conditions diverge sharply.

Future research could examine more granular variation within states, combine regional sentiment with demographic information, or study how sentiment interacts with credit conditions or migration patterns. It would also be valuable to study whether behavioural sentiment measures improve forecasting accuracy relative to survey-based indicators. Finally, future work could investigate how sentiment-driven expectations translate into actual housing decisions, such as home purchases or refinancing.

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Appendix

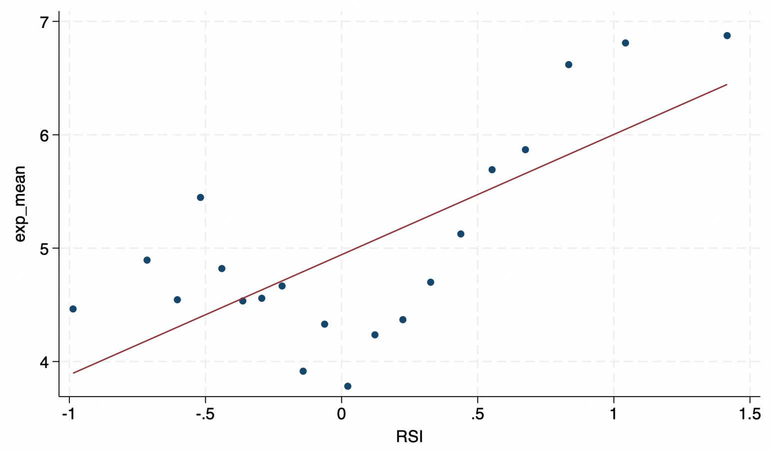

Figure A1: Binned Scatterplot of Averaged Expectation against Sentiment

Table A1: HPSI-Only Regression Results

	(A) No FE	(B) State FE	(C) Month FE
HPSI (standardized)	0.797***	0.762***	0 (omitted)
	(0.262)	(0.260)	
Constant	5.008***	4.931***	4.857***
	(0.216)	(0.139)	(0.173)
Fixed effects	None	State	Month
Observations	4,119	4,119	4,119
Clustering	Two-way: state and month		

Notes: Robust standard errors clustered by state and month in parentheses.

Table A2: Summary of State-Level Coefficients

Statistic	Mean	Std. Dev.	Min	Max
β_s (RSI coefficient)	3.16	1.94	–1.50	9.91
Observations per state	80.76	6.39	57	83

Table A3: Alternative Clustering Regression Results

	Dependent variable: Expected price change (%)	
	(1) FE, cluster(state)	(2) FE, cluster(month)
RSI	1.30165**	1.30165***
	(0.50706)	(0.24427)
HPSI	0.01399	0.01399**
	(0.04639)	(0.00616)
State FE	Yes	Yes
Month FE	Yes	Yes
Observations	4,119	4,119
R-squared	0.3184	0.3184

Notes: Robust standard errors in parentheses. Model (1) uses standard errors clustered at the state level; Model (2) uses standard errors clustered at the month level. * p<0.10, ** p<0.05, *** p<0.01.