State Projections of Remodeling (SPR)

Methodology

May 2026
Eric Lynch, CBE
Economics & Housing Policy
National Association of Home Builders

Introduction

Within the quarterly GDP report, there is a category which measures residential remodeling spending called 'Improvements'. This category is under 'Residential Fixed Investment' and 'Other Structures' (See Publication Category: Underlying Detail → NIPA Tables: Section 5 → Table 5.4.6U. Private Fixed Investment in Structures by Type, Chained dollars). Currently, this category is only aggregated at the national level and does not break out this figure by state.

The NAHB State Projections of Remodeling (SPR) is intended to model estimates addressing the research gap: state shares of remodeling spending on a quarterly basis.

Methodology

Modeling

NAHB created an econometric model using the Fay-Herriot model. The Fay–Herriot model combines noisy direct estimates with auxiliary variables to produce improved small-area estimates. In this application, NAHB constructs proxy-based direct estimates of state-level remodeling activity, which are then refined using the Fay–Herriot framework. The U.S. Census Bureau utilizes a similar model for their Small Area Income and Poverty Estimates (SAIPE) program. Based on this framework and usage by a government statistical agency, NAHB determined that the Fay-Herriot Model is the best approach for estimating state-level remodeling spending with available external data.

Variable Identification

The first step in the data collection process is to identify a variable that serves as a benchmark for our estimations as part of the sampling model. The benchmark can differ in frequency and be incomplete because it is used to anchor the relationship between proxies and remodeling activity, not as a direct quarterly measure. As the NAHB Economics team develops remodeling spending projections by state annually, this was determined to be the "best available" external benchmark.

The next step is to decide on a vector, or set, of the proxy variables that is used to create the estimated values as part of the linking model. These proxy variables create parameter estimates that are used in the sampling model as articulated in the previous paragraph. Five (5) proxy variables are chosen:

1) Durable Goods- Furniture & Furnishings[1]
2) Durable Goods- Household Appliances[2]
3) Home Price Index (HPI)[3]
4) Average number of employees working in the construction of buildings[4]
5) Average weekly wages of employees working in the construction of buildings[5]

The rationale for choosing these proxy variables was for their connection to potential remodeling expenditures. If spending on both furniture & furnishings and household appliances categories increases, this implies more individuals are undertaking some type of remodeling activity. As home prices appreciate, the amount of equity that existing homeowners are able to utilize for remodeling projects increases. If the number of employees within the industry increases, this implies that business conditions for remodeling are strong. If wages for employees within the industry increase, then there is more desire for potential workers to work in the sector due to increased activity.

For the first and second proxy variables, there were additional steps taken to prepare the data for the model. As the furniture & furnishings and household appliances categories within durable goods is only available by state annually, these variables need to be estimated quarterly to function within the model. To make these variables useable we:

1) Obtain the durable goods manufacturing figure by state quarterly from GDP report[6].
2) Obtain the furniture & furnishings and household appliances categories within durable goods by state annually[7].
3) Calculate the percentage of furniture & furnishings and household appliances within durable goods by state from Step #2.
4) Apply state-specific annual shares to the quarterly durable goods manufacturing figure by state quarterly from Step #1.

Thus, we were able to create these two proxy variables from durable goods.

To assess the strength of the relationship, a correlation analysis was performed for each of the five proxy variables on the 'Improvements' category within the GDP Report. The results from the analysis can be seen in Table 1 below. Other than average number of employees, the proxy variables have in general a high correlation with improvement spending.

[1] Gross Domestic Product (GDP); Bureau of Economic Analysis (BEA).
[2] Ibid.
[3] Federal Housing Finance Agency (FHFA)
[4] NAICS Code 236; State and Metro Area Employment, Hours, & Earnings (SAE) from the Bureau of Labor Statistics (BLS)
[5] Ibid.
[6] The specific table utilized is SQGDP9 entitled "*Real GDP by state*".
[7] The specific table utilized is SAPCE3 entitled "*Personal consumption expenditures (PCE) by state by type of product)*".

Table 1: Correlation Analysis of Proxy Variables and Improvement Spending

Proxy Variable	Correlation with Improvement Spending
Durable Goods- Furniture & Furnishings	0.853
Durable Goods- Appliances	0.756
Home Price Index	0.847
Average Number of Employees	0.016
Average Weekly Wages	0.836

While the simple correlation is low, average number of employees is nonetheless included to capture structural labor market capacity, as well as lagged remodeling activity not reflected in these correlations. Therefore, including this measure helps preserve theoretical completeness and improves model stability.

Model Specification

Before running the model, we address the time variation between our benchmark and proxy variables, as the former is annual while the latter is quarterly. The first step uses a standardization process known as z-score[8] globally across all states and time periods to ensure comparability across variables. The aggregation technique used for producing corresponding z-scores for durable goods variables was summation while it was averaging for HPI, employees, and wages.

With z-scores calculated for each of the proxy variables, a composite direct estimate is specified in Equation 1:

$$B_{i,t} = \alpha + Z'_{i,t}\gamma + \varepsilon_{i,t} \quad t \in T_{bench}, \tag{1}$$

where B= benchmark estimate produced annually, Z= matrix of all five proxy variables, γ = weights for each covariate, i=state, and t=year.

Equation 1 is estimated using ordinary least squares (OLS) on annual state-level data, where benchmark values are regressed on standardized proxy variables. A synthetic direct estimate was created using Equation 2 and the sampling variances for composite estimate was created using Equation 3:

$$\tilde{Y}_{i,t} = \hat{\alpha} + Z'_{i,t}\hat{\gamma} \quad \forall i,t \tag{2}$$

$$\hat{V}_{i,t} = \tilde{Z}'_{i,t}Var(\hat{\gamma})\tilde{Z}_{i,t} + \hat{\sigma}^2 \quad \forall i,t, \tag{3}$$

where, $\hat{\sigma}^2$= residual variance from benchmark regression from Equation 1 and $Var(\hat{\gamma})$= covariance matrix of coefficient estimates from Equation 2.

8 https://en.wikipedia.org/wiki/Standard_score

Sampling variances are derived from the residual structure of the benchmark regression, reflecting uncertainty in the proxy-based direct estimates. This approach provides a data-driven approximation in the absence of "true" variances. Once $\tilde{Y}_{i,t}$ and $\hat{V}_{i,t}$ were calculated, we were able to run the Fay-Herriot model. The first step involved running a sampling model as seen in Equation 4:

$$\tilde{Y}_{i,t} = Y_{i,t} + e_{i,t}, \; e_{i,t} \sim N\left(0, \hat{V}_{i,t}\right) \tag{4}$$

The second step was to run the linking model as seen in Equation 5:

$$Y_{i,t} = X'_{i,t}\beta_t + u_{i,t}, \; u_{i,t} \sim N\left(0, \sigma^2_{u,t}\right) \tag{5}$$

When combining Equation 4 and Equation 5, the final model can be seen in Equation 6:

$$\tilde{Y}_{i,t} = X'_{i,t}\beta_t + u_{i,t} + e_{i,t}, \quad i = 1, \ldots, 51 \tag{6}$$

Once Equation 6 has been run, the model then creates an unscaled empirical best linear unbiased predicator (EBLUP) per state and quarter as shown in Equation 7:

$$\hat{Y}^{EBLUP}_{i,t} = X'_{i,t}\hat{\beta}_t + \hat{u}_{i,t} \tag{7}$$

To completely match the 'Improvements' figure from the GDP report, each state's unscaled EBLUPs will need to be summed by quarter (Equation 8) to produce a scaling factor (Equation 9);

$$\hat{Y}^{EBLUP}_{t} = \textstyle\sum_i \hat{Y}^{EBLUP}_{i,t} \tag{8}$$

$$s_t = \frac{Y^{BEA}_t}{\hat{Y}^{EBLUP}_t}, \tag{9}$$

where Y^{BEA}_t = the 'Improvements' figure by quarter from GDP Report.

This scaling step ensures full consistency with the 'Improvements' total figure, meaning that the summation of market shares each quarter will equal 100%. A final state dollar estimate is produced using Equation 10 and converted in a market share percentage in Equation 11:

$$\hat{Y}^{final}_{i,t} = s_t * \hat{Y}^{EBLUP}_{i,t} \tag{10}$$

where $\hat{Y}^{final}_{i,t}$ = quarterly dollar estimates by state.

$$\hat{\pi}_{i,t} = \frac{\hat{Y}_{i,t}^{EBLUP}}{\sum_j \hat{Y}_{j,t}^{EBLUP}}, \tag{11}$$

where $\hat{\pi}_{i,t}$ = quarterly market share by state.

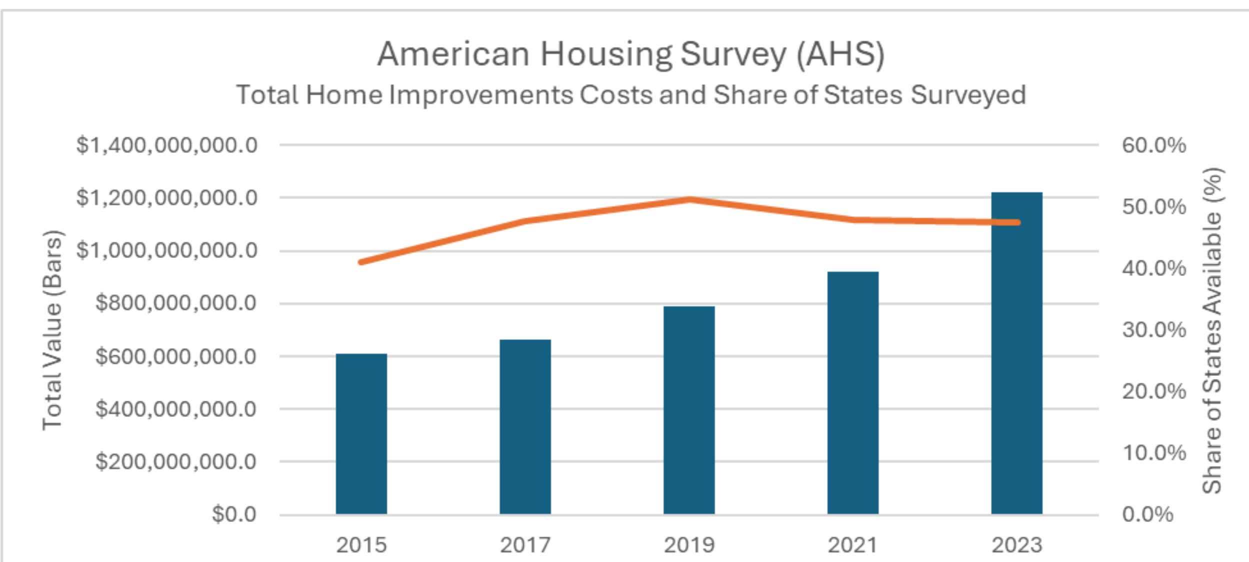
Comparative Testing

American Housing Survey (AHS)

To gauge the model results, we compared the model's results produced from Equation 10 to the data available through the American Housing Survey (AHS). This biennial survey through the U.S. Census Bureau compiles Home Improvement Costs overall along with other housing characteristics. Starting in 2015, AHS broke down this data by certain states, ranging from seven to nine states per year. As a result, AHS is used as a directional validation rather than a definitive benchmark due to limited geographic coverage.

We find the home improvement costs figure for a given state and divided by the overall figure for each AHS year as seen in Chart 1. Based on these calculations, the states surveyed within each AHS year accounted for between 41% and 51% of the overall figure. Viewing the states that are surveyed, they tend to be larger states based on population. For example, California, Florida, New York, Pennsylvania, and Texas are in all five years and, subsequently, are the largest states by population in both the 2020 decennial Census[9] and 2024 annual estimate[10].

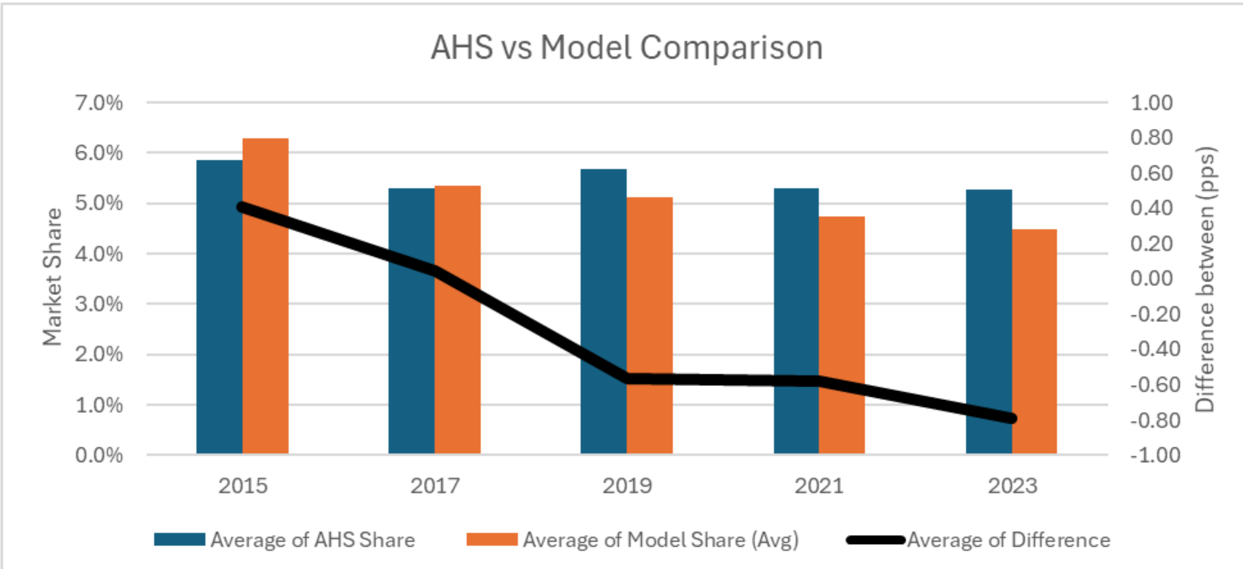
Chart 1: Total Home Improvements Costs and Available Market Share by State



[9] https://www2.census.gov/programs-surveys/decennial/2020/data/apportionment/population-change-data-table.pdf
[10] https://www.census.gov/newsroom/press-releases/2024/population-estimates-international-migration.html

Next, we took the average quarterly share from the model for the same year and state and calculated the difference between the two data sets as seen in Chart 2. Initially, the model was higher than the AHS shares in 2015, with 2017 being close to zero (0.04 pp) but has flipped to lower in the subsequent years.

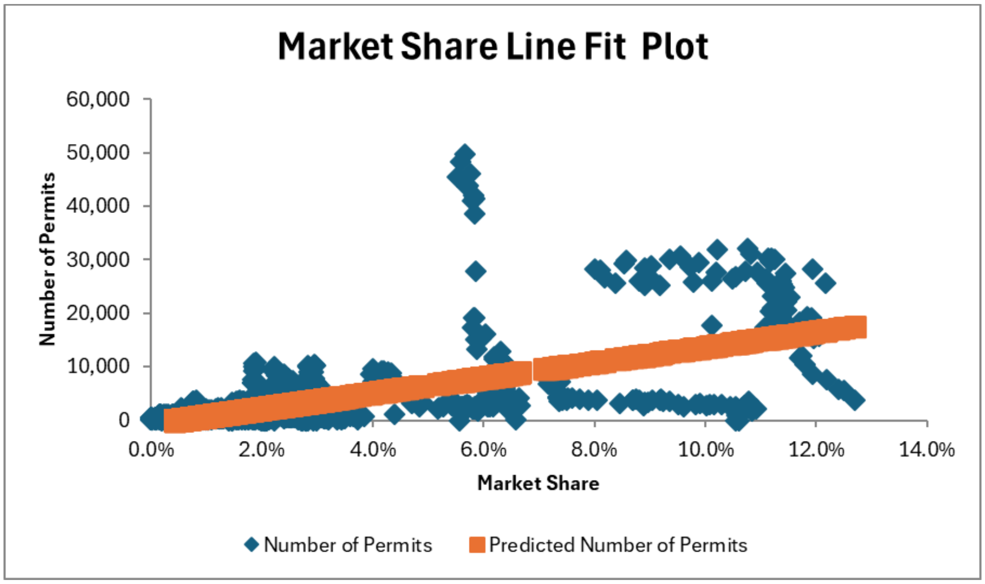
Chart 2: Comparing Model Results with AHS



Construction Monitor

In collaboration with Construction Monitor, NAHB was able to obtain monthly residential remodeling permit data by state. When regressing permit data from Construction Monitor on the market shares produced by the model, this analysis achieved an r-squared value of 0.43. This means that the market share variable can explain around 43% of the variance in the permit data. Given differences in measurement (i.e., permits vs spending), this level of explanatory power suggests meaningful alignment between the model and observed remodeling activity. The regression also produced a high F-value ($F=1929.58$), thus, producing a statistically significant p-value ($\alpha \approx 0$).

Chart 3: Line Fit Plot of Market Share and Number of Permits



A perfect correlation is unlikely, due to the fact that the two data sources do not have data for all states every quarter for the entire time series, especially since AHS is only conducted biennially. This step is meant to serve as a check to see if the model results are measurably different. Based on this analysis, it is reasonable to conclude that the model's results are plausible when comparing these two data sources.

Addressing Challenges

Changing Data Sources for Average Number of Employees and Weekly Wages

When we were performing the data collection process for two of the proxy variables; average number of employees and weekly wages for those working in the construction of buildings, we initially utilized a different data source also produced by the BLS called the Quarterly Census of Employment and Wages (QCEW)[11]. There were two reasons why it was initially chosen:

1) robustness (i.e., covering more than 95 percent of U.S. jobs) and
2) administrative (i.e., non-survey based) since it is compiled from state workforce agencies (SWAs) and the Unemployment Compensation for Federal Employees (UCFE) program for covered federal workers.

However, given the lagged nature of the release schedule for QCEW (i.e., approximately six months after close of quarter), it was determined a different source might need to be chosen even if it is less robust and survey based which is why SAE was a possible alternative. When comparing the model's results along with comparative testing against AHS and Construction Monitor data, there were no significant differences in outcomes between data from QCEW vs SAE. Additionally, when computing a

[11] https://www.bls.gov/cew/

composite score based on several diagnostic factors (e.g., share stability, variance, coefficient stability), the model results using SAE data performed slightly better than results using QCEW data.

Furthermore, SAE was the data source selected for the model.

Zero Lower Bound Application

When we analyzed the results from the market, we noticed that there were multiple instances where the market share for a state is negative. Two states account for 60% of the negative share instances (Wyoming: 42 and South Dakota: 36) and the most states with negative shares within a given quarter is six (Q3 2007 and Q1 2014). However, the total number of instances is relatively small (~3.4% of all instances) and the last quarter with a negative market share value is Q1 2019.

Intuitively, it is not theoretically possible for a state to have a negative share. A lower bound threshold needed to be introduced into the model to eliminate this situation from occurring. The constraint is applied after estimation but before final scaling to ensure valid market shares. Thus, the lowest quarterly market share that can be estimated for a state is 0%.

Conclusion

The NAHB Economics team provides the SPR as a valuable resource to NAHB membership, especially for NAHB Remodelers. Given the current prospects and expected future growth for this sector, it is important that NAHB can provide insights to help the industry better understand the geography of the industry's evolution.

Technical Appendix: SPR

Model

$$\tilde{y}_{it} = X_{it}\beta + u_i + e_{it} \tag{1}$$

$$\hat{\theta}_{it} = \gamma_{it}\tilde{y}_{it} + (1 - \gamma_{it})X_{it}\hat{\beta} \tag{2}$$

$$\gamma_{it} = \frac{\sigma_u^2}{\sigma_u^2 + V_{it}} \tag{3}$$

Scaling

$$s_t = \frac{Y_t}{\sum_i \hat{\theta}_{it}} \tag{4}$$

$$\hat{y}_{it} = s_t\hat{\theta}_{it} \tag{5}$$

Market Share

$$\hat{m}_{it} = \frac{\hat{y}_{it}}{Y_t} \tag{6}$$