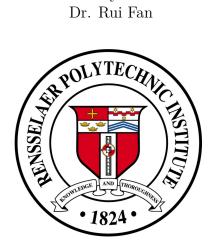
Market factors affecting housing prices

Subtitle

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Realtor Data

To see the effect of various market features on the median listing price of houses, we use Resedential Data from Realtor.com which includes various housing market features listed by county Federal Information Processing Series (FIPS) codes and by date. We extract year from the date field and, for parsimony, deselect all time variables with the exception of year and summarize the dataset by mean over year and fips. This greatly reduces dimensionality and aids computation.

The data set contains 10,176 NA values from 4,761 observations (approximately 16.9% of all observations) which predominantly belong to rural counties where such information is difficult to obtain or is simply unavailable. Consequently, we elide these variables in coming analysis. Even with 16.9% of observations removed, Figure 1 indicates that most of the country is still represented (counties with data are colored red):

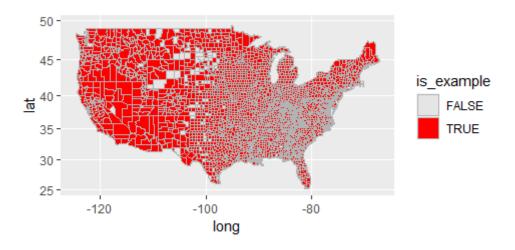


Figure 1: Counties Represented by Realtor with NAs Elided

We further augment the data set by adding annually averaged consumer price index (CPI)

as a measure of inflation. Table 1 visually summarizes the adjusted data set:

$\mid \hspace{0.5cm} \mu \hspace{0.5cm} \mid$	σ	\mathbf{Min}	\mathbf{Max}
30642.6	14957.9	01001	56045
2020.3	2.54931	2016	2024
270042.4	196290.3	35750	4780104.1
337.33	920.55	1	21778.8
71.108	23.526	4	283
154.409	422.650	0	8615.33
11.18	47.42	0	1106.67
97.23	317.94	0	9120
165.70	498.57	0	11212
143.27	99.41	20	1877.11
1874.96	326.90	576	4844.09
377056.26	353401.63	35750	11998834.08
501.50	1361.03	1	30349.33
0.541	0.472	0	5.581
0.031	0.0219	0.012	0.08
	30642.6 2020.3 270042.4 337.33 71.108 154.409 11.18 97.23 165.70 143.27 1874.96 377056.26 501.50 0.541	30642.6 14957.9 2020.3 2.54931 270042.4 196290.3 337.33 920.55 71.108 23.526 154.409 422.650 11.18 47.42 97.23 317.94 165.70 498.57 143.27 99.41 1874.96 326.90 377056.26 353401.63 501.50 1361.03 0.541 0.472	30642.6 14957.9 01001 2020.3 2.54931 2016 270042.4 196290.3 35750 337.33 920.55 1 71.108 23.526 4 154.409 422.650 0 11.18 47.42 0 97.23 317.94 0 165.70 498.57 0 143.27 99.41 20 1874.96 326.90 576 377056.26 353401.63 35750 501.50 1361.03 1 0.541 0.472 0

Table 1: Realtor Data Set Summary

Realtor Data Processing

Before we begin our analysis, we start with an exploratory ordinary least squares (OLS) regression on the dependent variable median_listing_price to identify variables with a variance inflation factor (VIF) greater than 10, and then deselect those variables as well as those that *cheat* by also reflecting pricing information. In so doing, we remove active_listing_count, total_listing_count, pending_listing_count, median_listing_price_per_square_foot, and average_listing_price. We further subset the data to exclude entries for 2024, which is incomplete and does not have an annual average CPI value.

We further observe that a handful of counties are significantly wealthier than others, and consequently have much larger median listing prices. Thus, we programatically remove outliers within the bottom 5% and top 5% of median_listing_price. To account for time effects in the panel data, we encode year as a factor which ensures they enter our regression

as a dummy variable. We then adjust each observation's value of median_listing_price by its respective inflation rate. Finally, we eliminate spatial effects by group demeaning the median_listing_price by FIPS and by introducing state factors which we favor in place of FIPS factors.

Realtor Analysis

We now specify an unrestricted OLS regression with median_listing_price as our dependent variable and employ backward stepwise selection to produce a model with only the most important features.

We arrive at a model of the form

$$medianListingPrice = 44338.1 - 622.5 \cdot medianDaysOnMarket$$
 $-5.1 \cdot newListingCount$
 $-111.9 \cdot priceIncreasedCount$
 $-2.4 \cdot medianSquareFeet$
 $+23065.3 \cdot pendingRatio$
 $+ state\ factors$

With $\bar{R}^2 = 0.2$ and F = 93.1. Figure 2 depicts the relationship between medianListingPrice against year, with data points in blue and our predicted $median\widehat{ListingPrice}$ in red:

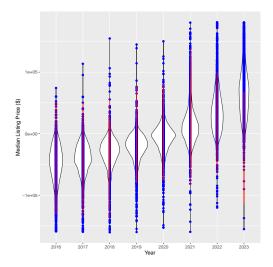


Figure 2: Median Listing Price vs. Year Violin Plot

Despite controlling for inflation, we have a strong time trend. Of interest is the relatively large and highly significant coefficient on pendingRatio: $\hat{\beta} = \$23,065$ with p << 0.05. Figure 3 shows the change in pendingRatio with time:

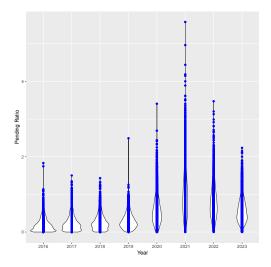


Figure 3: Pending Ratio vs. Year

As the pending ratio of housing is calculated as the share of pending listings over the share of active listings, an increase therefore indicates either a great leap in pending listings, or a major contraction in active listings. Because the bump takes place during the COVID-19 pandemic, it is likely the decrease comes from a precipitous drop in active listings as work

from home became the norm and people were largely locked in place. The Realtor data for active Listing Count supports this, marking a continuous downward trend starting in March 2020 and having a point of inflection in February 2022. These findings are consistent with those of Yörök (2022).