Brayden Bulloch

12/9/2021

Professor Eide

Econ 388

**Data Assignment 3**

*What effect did county-level per-capita Covid-19 mortality rates in 2020 have on housing prices in 2021?*

**FIND MY DATA HERE:**

**https://github.com/bullochb/Econ-388-Data-Assignment-3**

The Covid-19 pandemic has caused numerous changes to our economy. In this analysis, I look at how county-level per capita Covid-19 mortality rates in 2020 have affected housing prices in 2021. This is an interesting question because different people may have different opinions on the topic. One could argue that if people are dying, then this will lead to vacant homes, increasing supply, so possibly decreasing housing prices. Another argument could be that increased mortality rates actually increase housing prices because of the disruption that is caused to that particular county’s economy. For example, in Utah, we have seen housing prices boom upwards, but is this related to Covid deaths at all? Or what other things are affecting these drastic changes in housing prices?

I use four data sources for my analysis:

1) County-level Covid-19 mortality data. Source: NY Times

This data is compiled by the New York Times. It shows daily data on Covid-19 cases and deaths by county.

2) County-level population data. US Census

This data contains population data for each county in the United States. This county population data is used as the base to create per capita mortality rates.

3) ZIP-level housing price data. Source: FHFA

This dataset shows housing price indices over many years. “The FHFA HPI is a broad measure of the movement of single-family house prices. The FHFA HPI is a weighted, repeat-sales index, meaning that it measures average price changes in repeat sales or refinancings on the same properties. This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975.”

4) ZIP-county crosswalk. Source: US Department of Housing and Urban Development. This data is essentially a link table between zip code and county. We have data for, and are interested in, county-level data; however, HPI data is by ZIP. In order to merge with the mortality data, we need to condense the ZIP data into county data.

I compiled all this data together to create a master data file that contains our main variables of interest. Those variables are summarized below:

Graphical user interface, text

Description automatically generated

Using this data. I first run an extremely basic regression to see how mortality rates affect the HPI.

A picture containing graphical user interface

Description automatically generated

This regression shows that the average HPI would be 259.77. With each unit increase in the mortality rate, you could expect to see the HPI drop by 44 units. These results are statistically significant at the 5% level. These results help show that when the mortality rate increases, the home price index decreases. This could support in some ways that assumption that more housing is now available since people are dying. However, there are a lot of problems with this model. There are so many other factors that go into HPI. The trends need to be examined with more controls in place.

Next, I ran another regression, where I included specific states, cases, and population into the model as control variables. An entire output of this can be found at the end of this paper.

The mortality rate coefficient now drops to only -25.88. This is almost a 20 point drop. So, controlling for states, cases, and populations takes some of the economic effect out of the regression results above.

Almost all of these variables are now significant though. Cases and Population don’t have an incredible effect on the changes in HPI (the coefficients are relatively small). Each state has a large impact though. Due to other economic conditions, we see states have major effects on the HPI. For example in Utah and California, the HPI is increasing significantly simply by being associated with this state. Other economic patterns are affecting this. In Arkansas for example, the HPI is decreasing. So, controlling for the states was actually important in showing that each state has a large effect on the housing price index. We can then interpret the coefficient on mortality rate more easily.

In conclusion, from these results we could say that mortality rates do have negative impact on the housing price index. But, there are so many other things that need to be considered. Other control variables such as market factors, economic growth, state inflation, and more need to be considered. I just don’t have the desire to actually go get this data. A ton more variables need to be added to the model to really get an accurate picture. In a couple years’ time, once we are slightly removed from Covid, a diff-in-diff could be run to get a better idea of the shock effect that covid had on the housing market. Mortality rates did affect the HPI, but I wouldn’t bet my life on these results. More analysis needs to be conducted.

|  |  |
| --- | --- |
|  | (1) |
| VARIABLES | HPI |
|  |  |
| mortalityrate | -25.88\*\*\* |
|  | (5.700) |
| 2.statenum | 19.45\*\*\* |
|  | (5.752) |
| 3.statenum | 77.51\*\*\* |
|  | (6.896) |
| 4.statenum | -8.159\*\* |
|  | (4.042) |
| California | 107.2\*\*\* |
|  | (4.440) |
| 6.statenum | 113.0\*\*\* |
|  | (4.208) |
| 7.statenum | -4.705 |
|  | (9.026) |
| 8.statenum | 30.85\*\* |
|  | (14.19) |
| 9.statenum | 292.6\*\*\* |
|  | (24.28) |
| 10.statenum | 87.88\*\*\* |
|  | (4.171) |
| 11.statenum | 16.37\*\*\* |
|  | (3.505) |
| 12.statenum | 36.75\*\*\* |
|  | (11.23) |
| 13.statenum | 120.6\*\*\* |
|  | (4.673) |
| 14.statenum | -26.30\*\*\* |
|  | (3.786) |
| 15.statenum | -0.934 |
|  | (3.861) |
| 16.statenum | 20.39\*\*\* |
|  | (3.807) |
| 17.statenum | 12.92\*\*\* |
|  | (3.759) |
| 18.statenum | 8.258\*\* |
|  | (3.679) |
| 19.statenum | 23.23\*\*\* |
|  | (4.218) |
| 20.statenum | -4.734 |
|  | (6.722) |
| 21.statenum | 22.92\*\*\* |
|  | (5.745) |
| 22.statenum | 19.53\*\*\* |
|  | (7.118) |
| 23.statenum | 11.97\*\*\* |
|  | (3.953) |
| 24.statenum | 54.51\*\*\* |
|  | (3.909) |
| 25.statenum | -2.945 |
|  | (3.983) |
| 26.statenum | 14.27\*\*\* |
|  | (3.699) |
| 27.statenum | 116.1\*\*\* |
|  | (4.354) |
| 28.statenum | 33.78\*\*\* |
|  | (3.855) |
| 29.statenum | 70.35\*\*\* |
|  | (6.536) |
| 30.statenum | 39.17\*\*\* |
|  | (8.173) |
| 31.statenum | 69.25\*\*\* |
|  | (6.067) |
| 32.statenum | 20.51\*\*\* |
|  | (5.112) |
| 33.statenum | 15.85\*\*\* |
|  | (4.355) |
| 34.statenum | 21.56\*\*\* |
|  | (3.806) |
| 35.statenum | 90.28\*\*\* |
|  | (4.451) |
| 36.statenum | -9.944\*\* |
|  | (3.905) |
| 37.statenum | 10.67\*\*\* |
|  | (4.027) |
| 38.statenum | 115.4\*\*\* |
|  | (5.005) |
| 39.statenum | 5.946 |
|  | (4.166) |
| 40.statenum | 27.08\*\*\* |
|  | (4.079) |
| 41.statenum | 57.34\*\*\* |
|  | (11.15) |
| 42.statenum | 29.51\*\*\* |
|  | (4.604) |
| 43.statenum | 77.70\*\*\* |
|  | (4.225) |
| 44.statenum | 43.99\*\*\* |
|  | (3.835) |
| 45.statenum | 67.71\*\*\* |
|  | (3.307) |
| Utah | 104.5\*\*\* |
|  | (5.365) |
| 47.statenum | 48.66\*\*\* |
|  | (7.094) |
| 48.statenum | 30.90\*\*\* |
|  | (3.615) |
| 49.statenum | 94.48\*\*\* |
|  | (4.895) |
| West Virginia | -9.525\*\* |
|  | (4.386) |
| 51.statenum | 29.21\*\*\* |
|  | (4.083) |
| 52.statenum | 75.73\*\*\* |
|  | (5.815) |
| population | 5.90e-05\*\*\* |
|  | (5.50e-06) |
| cases | -0.000607\*\*\* |
|  | (7.90e-05) |
| Constant | 221.0\*\*\* |
|  | (3.023) |
|  |  |
| Observations | 3,208 |
| R-squared | 0.729 |