**US Housing Market During Covid-19: Aggregate and Distributional Evidence, Zhao, Yunhui (2020); IMF Working Paper**

* Argues there are several major factors at play in the Covid-19 pandemic as it relates to housing: First is the negative income shock of lower (or expected) lower employment. Additionally, there may be a negative supply shock caused by sellers being reluctant to sell and a stop in the growth of housing construction [although there may also be a growth in up-sizing – my comment]. Finally, the monetary responses prior to and during the pandemic of very low interest rates will increase the demand as well.
* This paper uses a non-parametric structural break model.
* Data is from zip-code level panel database released in realtor.com database covering the dates from July 2017 through August 2020. Databases used are the realtor.com residential listing database for the median listing price per square foot and the realtor.com market hotness index for housing demand.
* Also included is the Primary Mortgage Market Survey (Freddi Mac), the daily effective Federal funds rate, ACS Zip Code level median income (5-year estimate).
* Methodology includes zip-code level regression clustered at the month level; a structural break method, and the Nadaraya-Watson kernel to estimate distribution effects non-parametrically.
* Results
  + There was a small slowdown in March and April of 2020, but then median housing prices quickly bounced back and exceeded previous growth trends.
  + The decreasing trend in supply increased during Covid.
  + Online views increased greatly after April 2020.

Mostly a descriptive paper with very little econometric analysis and no consideration of spatial concerns.

**Covid-19 Impact on US Housing Markets: Evidence from Spatial Regression Models; Lee, Jim & Yuxia Huang (2002), Spatial Economic Analysis.**

* Covid-19 lead to decrease in home sales due to lock down policies; however, housing market rebounded in May and the trends were divergent between urban and suburban markets. Most of this is based on media accounts with little scientific analysis except for Liu and Su (2020) showing some movement to the suburbs through June of the pandemic.
* Uses both an SAR and GWR model to estimate shifts in migration.
* Expansion of Liu and Su (2020) and Zhoa (2020) [above].
* Uses Zip-Code level data with prices from Zillow and other data from Realtor.com including home views, number of homes sold and median sales price.
* This paper divides the zip code areas into groups based on (1) distance from the CBD and (2) population density. The data is then sorted by the distance or density and then graphs show the average for the top 25%, middle 50%, and bottom 5% of the areas. The trends in the average online views, sales, and median price are basically similar across “groups” with the top 25% measures in distance being higher while the lower 5% in density being the highest. That said, they are likely not significantly different.
* To capture the COVID effect, they use an average number of confirmed cases within that zip code, although this data on Covid is at the county level. Analysis also increases the number of jobs and share of jobs compatible with remote work.
* The spatial weight matrix used is based on contiguity of zip codes. The GWR method simply lets the coefficient vary by location. The model is estimated using the KP 2SLS process.
* Data is a balanced monthly panel from April to December 2020, including individual zip code and time fixed effects and then key variables are interacted with a one-month lag of the COVID variable.
* To determine the impact of their distance and density groupings, they interact with the COVID variable with these variables.
* Argue that results support the Liu and Su (2020) conclusion that there is urban flight that persisted through 2020, however, this depends on geographic location. They tell the story that in the East and West, demand outstripped supply leading to higher values with larger increases in suburban compared to urban (CBD) markets.

**The Impact of the Coronavirus Pandemic on New York City Real Estimation: First Evidence; Cohen, Jeffery, Felix Friedt, & Jackson Lautier (2022), Journal of Regional Science**

* Start discussing the D’Lima (2022) paper and show are in areas with lockdown orders, housing prices fell (elasticity estimate of 0.9).
* Chong and Liu (2020) look at the Chinese market and show that the response of housing prices to an increase in the number of deaths depends on the number of deaths previously so areas with lower death rates reacted less so compared to areas with higher death rates to the same shock.
* This paper focuses on the “big city” of New York and looks at cumulative case numbers rather than shutdown to assess heterogenous effects.
* Argue there are two effects: (1) the contagion effect is related to the coefficient of the case load in the hedonic regression and find that areas with higher outbreaks and more unemployment see decreases in value. They then use a repeat sales methodology and find a similar negative impact. The second effect, or the income effect, shows that a rise in unemployment also reduces the home price.
* They also show that homes valued in the lower part of the distribution saw bigger impacts than higher valued homes and they relate this owner income. This result: however, is only present in the first wave for lower valued homes (the impact is insignificant in the second wave).
* Numerical results do show in graphs that there is an initial negative shock to the housing market in terms of volume at the outset of the pandemic; however, this is not the case for later waves.
* In their empirical model, they attempt to capture the contagion impact using the caseload data and the income impact using the unemployment rate in the standard hedonic model. They then use a repeat sales model to try to avoid selection bias in the data such as the case of all wealthy individuals moving which would put upward bias on the coefficients of interest.
* Data is from NYC government (PLUTO database maintained by Planning department with property characteristics, and sales data from the NYC Department of Finance). They clean the data by removing all “zero” observations and sale prices below $10K. They then limit the data to owners without “investor sounding” attributes such as LLC, CO, or INC [this is according to Cohen and Harding (2020)]. Final data has 306K observations between 2003 and July 2020 with 9947 curing covid. Unemployment data data is from DEEP-MAPS project and the BLS. Covid data is from the NYC Dept. of Health.
* The unit of analysis is at the MODZCTA (Modified Zip Code Tabulation Area) level, of which there are 176 throughout the five boroughs. The MODZCTA are based on ACS areas to easily use ACS data. The authors have their own model to connect the boroughs and the MODZCTA.
* Initial findings show that the severity of the outbreak differs by borough, the number of sales is negatively correlated with the number of cases, and the year-over-year change in sale price is rather volatile of the area.
* The Results:
  + The hedonic model shows negative impacts on price from the number of cases and the effect is larger in the second wave.
  + Additionally, the hedonic model shows negative impacts on price from higher unemployment numbers.
  + The repeat sales approach shows similar findings with a significant impact in the second wave, but a much smaller one in the first wave. On average, 1000 cases per 100K within a MODZCTA leads to a $70K drop in price. In this model, the unemployment effects are no longer statistically significant. In the second wave, however, the unemployment effects are much more pronounced with a 10% increase in unemployment leading to a $60,000 drop in price.
  + To control price effects across income groups, they interact the variables with ACS based measure such as density, median income, share of rentals, and share of population using public transit. In areas with high density and high public transit use, the negative contagion impact vanishes; however, the income effect intensifies. In higher income areas, the contagion effect is more pronounced while the income effects are less present.
  + For Robustness they no longer limit their sample to the times around the start of the two waves and the estimates remain consistent. They also control for outliers (major increases or decreases in prices for repeat sales)
* Overall results indicate the Covid outbreak lowered values by between 0.8 and 50% depending on the severity of the outbreak and about 14% on average. They show that is equivalent to a loss of about three to four years’ worth of “typical” appreciation in value lost in a span of 5-months.
* Furthermore, they find these results vary by the income of the neighborhood in which the home is located and the state of the local employment market.

**The impact of COVID-19 on home value in major Texas cities. Bhat, Mira B., Junfeng Jiao, & Amin Azimian, International Journal of Housing Markets and Analysis, 16(3), 20203, 616-627.**

* Key covid papers cites are Zhou (20), Yoruk (20) and Wang (21).
* The paper includes interest rate measures and a business cycle index (BCI) measure.
* The study area is for major metro areas in Texas: Austin, Dallas, Houston, and San Antonio at the zip code level.
* Data includes the use of cases, foot traffic and unemployment claims aggregated to the zip code level while other data including median housing price, percentage of single-family homes, mortgage rates, and BCI are at the city level.
* Mortgage rates are from FRED at the national level, argued that this is a macro-indicator. The BCI data is from the Fed in Dallas. Foot traffic is from Google mobility reports.
* Model is a simple OLS model with random effects for city-level unobserved factors.
* Results indicate a positive relationship between covid cases and median home price and argue this is a demand side push as supply was curtailed.
* Foot traffic shows a negative relationship with housing.
* Overall, not a very rigorous or insightful paper.

**Analyzing housing market dynamic and residential location choice concurrent with light-rail transit investment in Kitchener-Waterloo, Canada. Huang, Yu (2020). University of Waterloo, Dissertation for Ph.D. in Planning.**

This paper does a good summary of the Pace, et. al. model and shows some resources on the next iteration. The problem is that interpreting the ST and TS coefficients are difficult which is what led to the creation of the W matrix with the Hadamard Product [Dube, et. al. 2013] which combines the S and T matrix into a unique W and turning the rho estimate into a spatial temporal. Specifically

The Dube, et. al. (2018) paper uses various cutoffs for the S and T and show that STAR model with this unique W outperforms the standard SAR model and the dominance of the “unidirectional spatio-temporal connection in price determination and thus confirming the influence of the ‘comparable sales approach’”. This was further expanded by Thanos, et. al (2016) who broke down the W into the “comparable sales” effect (current period sales), the “contemporaneous spatial peer” effect (sales with a month), and the “seller’s expectations” effect (sales from the future period of about a quarter). Other papers highlighted are Habib and Knockelman (08), Osland, et. al. (16), and Zolnik (19). Unfortunately, this paper does not pre-multiply the set of X variables with the spatial matrix making it a true STAR model rather than a Spatio-temporal Durbin.

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Dube, Jean and Diego Legros. (2014) Spatial econometrics and the hedonic pricing model: what about the temporal dimension? *Journal of Property Research*, 31(4):333-359

Jean Dube, Diego Legros, and Sotirios Thanos. (2018) Past price `memory' in the housing market: testing the performance of different spatio-temporal specifications. *Spatial Economic Analysis*, 13(1):118-138

Fuss, Roland and Jan A. Koller.(2016) The role of spatial and temporal structure for residential rent predictions. *International Journal of Forecasting*, 32(4):1352-1368

Thanos, Sotirios, Jean Dube, and Diego Legros.(2016) Putting Time into Space: The Temporal Coherence of Spatial Applications in the Housing Market. *Regional Science and Urban Economics*, 58:78-88

Hyun, Dongwoo and Stanimira Milcheva. (2018) Spatial dependence in apartment transaction prices during boom and bust. *Regional Science and Urban Economics*, 68:36-45.

Osland, Liv, Ingrid Sandvig Thorsen, and Inge Thorsen.(2016) Accounting for Local Spatial Heterogeneities in Housing Market Studies. Journal of Regional Science, 56(5):895-920.

Thanos, Sotirios, Jean Dube, and Diego Legros.(2016) Putting Time into Space: The Temporal Coherence of Spatial Applications in the Housing Market. *Regional Science and Urban Economics*, 58:78-88

The goal of this paper is to set up a Hedonic Price model to account for three key factors of housing prices: (1) the Comparable Sales Effect, (2) the Seller Expectation Effect, and (3) the Contemporaneous Spatial Peers Effect.

Define the following prices:

The HP model is then:

In this specification, is the comparable sales effect, is the sellers expectation effect, and is the contemporaneous peer effect. The key contribution of the paper is the creation of the terms.

To create the weights, one first orders the data by sales date and then assumes that time is discrete (in this paper they assume there are time periods so that the number of sales in each is likely not equal. The author then decides on a distance cutoff () which they set at the average distance between all neighbors, and then creates the spatial matrix as:

The larger spatial matrix is then set as an matrix:

This is the same matrix that is typically used in spatial models (W). The authors then show that this can also be expressed as a matrix of matrices where each sub-matrix is a matrix containing all the sales within the distance cutoff and within a given time frame.

For example, the matrix indicates the spatial connection among transactions occurring in the first period (t=1). The sub-matrix would indicate the spatial connection between all the observations in the second period with sales in the previous period. Finally, is the spatial connection between sales today () and next period (in the future).

For the temporal matrix, the authors define the temporal weight for any two observations as:

Like the spatial matrix, we can create a matrix of matrices such that:

This matrix can also be split into the lower-triangle, diagonal, and upper-triangular matrix. Further note the upper-triangular measures are pre-multiplied with a negative given the fact that these are future sales. Given this notation, then is composed of a lower-triangular matrix (), a diagonal matrix (), and an upper-triangular matrix ().

Given these two sets of matrices, we can then crate three key weight matrices:

which is the comparable past sale

which is the contemporaneous peer

which is the seller expectation matrix

With these definitions, the HP equation then becomes:

The problem with this is that because of the structure of the weight matrix, the is not full rank so the inverse cannot be taken. Furthermore, also contains a block of zero. The author overcomes this using a set of “false zeros” in the data [Dube, et. al. (2014)].

The authors use a semi-log functional form and ML estimation (after using the false zeros). They argue that the coefficient is the dynamic effect of a shock in prices at a given time, propagating into the next period and thus, a “long-run” effect can be calculated by multiplying a specific by . Likewise, given the estimate of , the total effect of a change in some variable can be calculated by multiplying the corresponding by .

Using data from Aberdeen Scotland, they estimate three versions of the model: (1) a standard spatial-temporal model using only past prices, (2) the model shown above, and (3) a standard SAR model using the typical multi-directional W matrix. The results show that the two STAR models have similar estimates for the parameter measure the impact of past sales, but that the spatial coefficient () found in the standard SAR model is much smaller than the modified STAR model. Furthermore, they can find a statistically significant impact from future sales () on the current sale price through the seller expectations indicating an importance of including seller’s expectations about the future.