Manufactured Homes and Spatial Contagion Effects in Los Angeles County

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Abstract:

Manufactured homes (MHs) have received considerable support from governments within the United States and nonprofit organizations to aid in housing affordability. However, some residents are concerned MHs can be of substandard quality or access to resources, which can also negatively affect the sale prices of adjacent properties. The net effects of MHs – both direct and indirect – are the questions we examine in this paper. Using a spatial Durbin model, we examine the impact that sales of MHs in several cities in Los Angeles County have on adjacent lots, and we find differential impacts depending on MHs density within each city and year of sale. There are positive indirect effects that are also stronger where MHs are more dispersed, which we attribute to differences in average assessed values in these more scattered MHs cities. There are negative indirect effects in cities where MHs are more clustered. We also find MHs sell for more than other homes in cities where MHs are comparatively more dispersed.

1. Introduction

The housing affordability crisis in many major metropolitan areas in the US has led to the need for exploration of and reliance upon alternatives that could offer greater homeownership opportunities for residents. Among the alternatives that have grown in popularity are manufactured housing. Manufactured housing is relatively inexpensive to build, and in turn, is associated with lower construction cost savings that can be passed along to potential homebuyers in the form of lower housing prices. Lower housing sales prices also may be associated with lower property taxes. When the living area of manufactured housing is small relative to other types of housing, there may also be lower maintenance cost for the homeowners.

The popularity of manufactured housing in the US has led to increased attention and interest in this issue by both academic researchers as well as statistical agencies. For instance, the Federal Housing Finance Administration (FHFA) recently released a new nationwide home price index for manufactured housing, which is an innovative dataset that could lead to greater research in this area. While this data set focuses on national level data, there's also a need to study the issue of manufactured housing at a more disaggregate or micro level.

Therefore, in this paper, we explore how the price of manufactured housing may be different from the price of other housing in cities in one of the largest counties in the United States, which is Los Angeles county. Los Angeles county is a fertile ground for studying these issues since it is so large, it therefore has a larger number of transactions of manufactured homes than many other parts of the United States. At the same time, the findings for Los Angeles could carry over to other geographic locations, including rural, urban and/or suburban areas. Our findings include that we observe primarily negative direct effects: classification as an MH has a negative impact on one's own sale price, after controlling for other characteristics of the homes and the locations of the homes within Los Angeles county. Also, we find some evidence that manufactured homes have a positive effect on neighborhood home prices in areas with a lower density of manufactured housing. These findings are limited in scope in terms of geographic areas within Los Angeles County, as there is evidence in some neighborhoods of such effects but not in others. On the other hand, we also find some evidence of negative effects of manufactured homes on neighborhood home sale prices, and this can be because perhaps some residents view manufactured homes nearby as being less aesthetically attractive than more traditional types of houses. These spillover effects again are generally isolated to areas with a higher degree of clustering of MHs and are not universally present throughout the entire geographic region nor through the time period we focus on, which is 2017 to 2021.

The remainder of this paper proceeds as follows. First, we summarize the growing literature of manufactured housing by describing studies that have been undertaken by others. We also describe some of the basic background underlying the terminology of manufactured housing. We next describe the data that we have used in our analysis, followed by a methodological section that outlines the econometric techniques we rely upon in order to understand the contagion and spillover effects of manufactured housing. We describe our empirical results for the sample of Los Angeles county manufactured housing that we consider in the following section. Finally, the conclusion section discusses potential for future work as well as summary of the main findings of this particular paper.

2. Background and Literature Review

According to the Lincoln Institute of Land Policy[1], MHs are homes that "are built in the controlled environment of a factory and are transported in one or more sections on a permanent chassis." They are meant for primarily lower income households: according to a 2014 report

[1] See *https://www.lincolninst.edu/centers-initiatives/innovations-manufactured-homes-network*

from the Consumer Financial Protection Bureau, the median income of MH households is half of that of conventional households[2].

Prior work examining MHs approaches them from a policy perspective. Apgar et al. (2002) advocate for consumer education, financing processes, rigorous installation standards, and improvements to existing mobile homes. Boehm and Schlottmann (2008) look at American Housing Survey data between 1993 and 2001 and find that manufactured owned housing are of higher quality on average than rented housing and that measures of quality are similar between manufactured owned housing and conventional owned housing.

Regarding the impact that MHs have on neighborhood property values, Wubneh and Shen (2004) examine property appreciation rates and property values in Buncombe, Wake, and Pitt Counties in North Carolina. They find that further distance from MHs increases property values, but the influence of MHs as a factor is minimal compared to other hedonic variables such as square footage and year built.

Aman and Yarnal (2010) examine potential challenges associated with mobile homes in rural Pennsylvania. They use surveys to find that residents of MHs have problems with land tenure, financing, and social stigma. Though mobile homes are largely in rural areas, factors such as social stigma can negatively affect home sale prices of other properties in the neighborhood.

Another work that examines MHs in Los Angeles County is Pierce, Gabbe, and Gonzalez (2018). They find that mobile home parks contain 75% of all mobile homes in the county. Furthermore, they find that MHPs are located in lower density neighborhoods and that many MHPS are located in areas zoned for commercial or industrial purposes, as well as areas with more negative environmental externalities. Lastly, they find that MHPs' access to public services are lacking compared to other neighborhoods.

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[2] See *https://files.consumerfinance.gov/f/201409_cfpb_report_manufactured-housing.pdf*

One recent work that explores in depth the differences between conventional homes and MHs is Durst and Sullivan (2019). Using data from the 2013 American Housing Survey, they find that owning the land the MH is on as well as the structure itself is the most affordable housing option among MHs. They also note that roughly 4% of conventional housing is located within a block of an MH.

Brooks and Mueller (2019) examine the county-level factors that determine the prevalence of MHs in the US in 2015. Using a spatial lag model, they find that poverty level, labor force participation rate, and population employed in natural resource occupations were the primary determining factors for MH prevalence.

3. Data

We obtained data on the most recent sale of all single-family homes, going back to the 1960s through 2021, for Los Angeles County from the Los Angeles County Assessor's Office. In order to limit the impact of outliers, we exclude sales of under $50,000 and over $10,000,000, as well as sales with a lot size of less than 1,500 square feet and over 500,000 square feet. To ensure an adequate number of sales of manufactured homes in a reasonably short time frame, we examine sales from 2017 to 2021.

We identify manufactured homes (MHs) and manufactured home parks (MHPs) using the design codes specified in our sample. Manufactured homes and manufactured home parks are identified as those with “07” and “09” respectively in the first and second places in the four-digit design code field.

We obtain the parcels shapefiles data from Los Angeles County's planning department. With this shapefile, we determine the contiguous neighbors to each lot.

We present summary statistics for our sample in Table 1, which includes all single-family home sales from 2017 to 2021 in the cities of Acton, Lancaster, Littlerock, and Long Beach.

These 4 cities have approximately 15,000 sales overall, and they have the highest number of identified MH sales among all cities in Los Angeles County during our sample period. Therefore, we focus our attention on these 4 cities. Among all sales in this time period, approximately 1.54% are classified as MHs. In other words, we identify 234 MH sales in these four cities from 2017 to 2021. Of these, 83 were in Acton, 63 were in Lancaster, 24 were in Littlerock, and 64 were in Long Beach. Percentage wise, Acton has the highest percentage of its house sales that are MH sales, with almost 15% of the total property sales in our sample period. Lancaster and Long Beach have the lowest share of their sales being MH, at approximately 0.85% and 0.93%, and Littlerock has 7.45% of its property sales classified as MHs.

We present the transactions in our sample by year and city in Table 2. Acton and Littlerock have far fewer transactions compared to Lancaster and Long Beach, but all cities have a high density of MHs compared to other cities in Los Angeles County. For all cities except Littlerock, the greatest number of transactions occur in 2020.

Lastly, we present the location density of MHs in each of the four cities in Figure 1. Acton, Littlerock, and Long Beach exhibit some clustering of MH sales. In fact, Long Beach – which has the second highest number of MH sales among the 4 cities – appears to have virtually all of its MH sales clustered in a very small geographic area in the west of the city. On the other hand, Lancaster exhibits higher dispersion of MH sales throughout the city.

4. Methods

To evaluate the impact of MHs on contiguous property sales, we conduct spatial analyses using the spatial Durbin model, following the approach of Feng, Yasar, and Cohen (2023). To limit the impact of temporal causality, we conduct separate regression analyses for each year, from 2017 to 2021. We present our findings for four cities in Los Angeles County with high numbers of MH sales in these years: Acton, Lancaster, Littlerock, and Long Beach. These cities have the highest number of identified MH sales out of all cities in our sample. We are interested in estimating a spatial hedonic model, where the dependent variable is the (log of) sale price, and the explanatory variables are the house characteristics, an indicator for whether the sale is of a MH, and a spatial lag of the dependent variable and spatial lags of the explanatory variables. This spatial Durbin model is discussed in more detail below.

Spatial Durbin Model

Spatial models enable the researchers to divide the impact of each covariate's parameter estimates into "direct", "indirect", and "total" effects. Each of these 3 effects is defined for each independent covariate in the model.

A direct effect evaluates the change affecting the subject location. For our models, whether a property is classified as an MH, in addition to other hedonic variables, affects its sale price. On the other hand, the spatial indirect effects measure the impact of contiguous locations on the subject location. In other words, we use spatial indirect effects to examine how classification as an MH, as well as variation in other hedonic variables, affect the neighboring property sale prices. Finally, the total effects combine the direct and indirect effects, which is defined for each variable individually.

We specify the spatial Durbin model (SDM) in Model (1):

$$y = \alpha l_n + \rho W y + X\beta + WX\delta + \varepsilon \tag{1}$$

$$y = (I_n - \rho W)^{-1}(\alpha l_n + X\beta + WX\delta) + (I_n - \rho W)^{-1}\varepsilon$$

$$\varepsilon \sim (0, \sigma^2 I_n)$$

where I_n is an n by n identity matrix and l_n is an n by 1 column of 1s, **W** is the contiguity weighting matrix, and **W**y is a spatial lag term. The SDM enables a rich set of interactions between y, X, and disturbances ε. We estimate equation (1) separately for each city in each year. The variable y in (1) is the natural log of house sale price, and X represents the house characteristics (including house age, lot size, living area, number of bedrooms, number of bathrooms, and an indicator variable for MH).

For the *k*th independent variable – in this case, the indicator for MH – the direct and indirect effects are defined as follows (Elhorst 2014):

$$\left[\frac{\partial E(y)}{\partial X_{1k}} \cdots \frac{\partial E(y)}{\partial X_{nk}}\right] = \begin{bmatrix} \frac{\partial E(y_1)}{\partial x_{1k}} \cdots & \frac{\partial E(y_1)}{\partial x_{nk}} \\ \vdots \quad \ddots & \vdots \\ \frac{\partial E(y_n)}{\partial x_{1k}} \cdots & \frac{\partial E(y_n)}{\partial x_{nk}} \end{bmatrix} = (I_n - \rho W)^{-1} \begin{bmatrix} \beta_k & w_{12}\delta_k & \cdots & w_{1n}\delta_k \\ w_{21}\delta_k & \beta_k & \cdots & w_{2n}\delta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}\delta_k & w_{n2}\delta_k & \cdots & \beta_k \end{bmatrix} \tag{4}$$

The indirect effects are specified by the diagonal elements, while the spillover effects are specified by the off-diagonal elements. Elhorst (2014) notes that the direct and indirect effects could differ due to the endogenous interaction effects in **W***y*, the neighbors' house prices, which can result in feedback effects. Furthermore, Elhorst (2010b) notes that the interpretation of the direct and indirect effects depend on the structure of **W**, as well as the number of observations.

Like Feng, Yasar, and Cohen (2023), our SDM specification combines a spatial autoregressive model (SAR) and a spatial error model (SEM). The SAR uses the dependent variable with a spatial lag (in this case, the sale price of adjacent properties), and the SEM uses a spatial autoregressive term in the regression error term. Using shapefiles for the county of Los Angeles together with a routine in Stata ®, we construct spatial weight matrices **W** outlining which properties are directly adjacent to each other in Los Angeles County and normalize the nonzero elements such that each row adds to 1.

Spatial models have the distinct advantage of accounting for not only the impact of sale price changes in one location on contiguous locations (the indirect effect), but also the impact on its own price (the direct effect), including feedback effects. For example, if Property A is classified as an MH, it could influence the sale price of adjacent property B (which may be a MH or a non-MH), which in turn affects the sale price of property A through property B's impact on its own contiguous properties, etc.

5. Empirical Findings

We first present our findings for the direct effects, or the impact that being classified as an MH has on the sale price of the property, in Table 2. The impact of MH classification is largely negative, with the most dramatic in Long Beach for all years. For Long Beach, the heightened negative direct effect could be a result of negative stigmas associated with manufactured housing. Any possible negative stigma associated with MH could be weaker in other cities, which are not as densely populated. In terms of magnitude, the strongest negative direct effects indicate as much as an 65% decrease in price for Long Beach. However, these price changes are compounded as a result of feedback effects from adjacent sales, which could explain the high magnitudes. Negative direct effects are also primarily restricted to earlier years for the cities of Lancaster and Littlerock, while they are more present in 2020 and 2021 for Acton. These temporally isolated direct effects are likely a result of heightened sales of MHs for these years.

We next present the indirect effects associated with MHs in Table 3. The indirect effects associated with MH sales, or the impact that the sale of an adjacent MH has on one’s own property sale price, is positive and significant for Long Beach in 2021 and Lancaster in 2018 and 2020. In other words, MH sales increase adjacent property sale prices in these time periods and locations. In terms of magnitudes, the indirect effect of an adjacent MH increases the sale price by a factor of as much as 15%. We attribute the positive contagion effects associated with MHs for the city of Lancaster to the lower degree of MH clustering. In other words, with fewer houses nearby in a city such as Lancaster, the negative aesthetics associated with contagion effects of MH are felt by fewer neighboring houses because there are not as many neighbors. Also, perhaps the non-MH in Lancaster are of poorer quality than the MH stock in that city, and therefore having MH nearby enhances the house prices in the entire neighborhood. For Long Beach, the magnitude of the positive contagion effect is empirically weaker, amounting to approximately 0.3%. On the other hand, the impact of adjacent MH sales is negative in 2019 for

Littlerock. Littlerock exhibits a higher density with respect to the locations of MHs within the city, so disutility from nearby MHs could compound greatly compared to Lancaster. For 2019, the negative impact of adjacent MHs amounts to a reduction in sale price of almost 9%.

Figure 1 displays the locations of identified MHs in each of the four noted cities. The MHs in Long Beach are concentrated in the western part of the city. In contrast, Lancaster has MHs spread out across the city. Acton and Littlerock exhibit similar concentration of MHs to Long Beach, but they have far fewer residential real estate transactions. The relative lack of transactions in Acton and Littlerock may explain the relatively weak effect that MHs have in these cities. We conclude that the positive impact MHs have on adjacent property sales is due to differences in average assessed values for these MH cluster areas.

6. Conclusion

Manufactured housing has become increasingly popular in the United States in recent years. While some attention has focused on attempting to understand issues related to manufactured housing, further attention to this issue is warranted. In this paper, we study manufactured housing in Los Angeles County, California during the period of 2017 to 2021. Our findings are innovative because of our focus on house-level data that enable us to understand how house prices for manufactured homes are positive and significant, but not significantly different from other homes in the nearby neighborhoods, after controlling for other determinants of house prices.

Also, an innovation of our research is our focus on potential contagion and feedback effects of manufactured housing. We find that there is a significantly positive spillover effect from manufactured housing because of the fact that in some instances manufactured housing is not associated with lower subject property sale prices, which impacts nearby house prices through neighborhood effects, and in turn, these effects spill over or feed back again to other houses in the neighborhood. These indirect effects are important to understand because focusing only on one particular home's price does not give a complete picture of the dynamics in the neighborhood that could arise due to the presence of manufactured housing. On the other hand, we also find some evidence that the aesthetic drawbacks of some manufactured homes could lead to a situation where nearby house prices actually decline because of the presence of manufactured homes. Whether or not we find one or the other of these two effects, the positive indirect effects or the negative indirect effects, depends on the location within Los Angeles County of the manufactured homes. The outcomes also depend on the time frame considered. In other words, in some years we see some evidence of the indirect effects in one direction, while in other years we see the opposite direction, and importantly, in some instances, we see that there are no significant effects of manufactured housing in either direction.

Future work in this area could consider a nationwide analysis, or at least an analysis across additional regions of the United States, in order to understand how manufacturing housing impacts on general house price trends are different based on location within the country. In other words, in rural areas where housing may be more spread out in some situations, we might expect there to be less of a contagion effect due to the sparsely populated nature of those neighborhoods. In urban areas where all types of housing are more closely situated, the contagion and feedback effects may be expected to be somewhat more significant, because of the more densely populated terrain. These are the results that are uncovered to some extent in our work for Los Angeles county.

Another potential area of interest regarding manufactured housing could be development of an MSA level analysis that relies on FHFA price indices. In other words, if/when FHFA develops an MSA level price index for manufactured housing, one might examine the question of whether or not there is competition among MSAs for manufactured homes, or whether or not some MSA are attempting to drive out or keep out manufactured homes from their region and push them into other regions.

Finally, an understanding of the relationships between vacancies in single-family homes and manufactured housing could be of interest. For instance, do we see more manufactured homes popping up in areas where there are much lower vacancy rates, and single-family homes overall? If so, manufactured housing may be a potential approach to alleviating the ongoing housing affordability and supply crises.

7. **References**

Aman, Destiny D., and Brent Yarnal. "Home sweet mobile home? Benefits and challenges of mobile home ownership in rural Pennsylvania." *Applied Geography* 30, no. 1 (2010): 84-95.

Apgar, William C. *An examination of manufactured housing as a community-and asset-building strategy: report to the Ford Foundation*. Joint Center for Housing Studies, Graduate School of Design [and] John F. Kennedy School of Government, Harvard University, 2002.

Boehm, Thomas P., and Alan Schlottmann. "Is manufactured owned housing a good alternative for low-income households? Evidence from the American housing survey." *Cityscape* (2008): 159-224.

Brooks, Matthew, and Tom Mueller. "Factors affecting mobile home prevalence in the United States: Poverty, amenities, and natural resource employment." (2019).

Durst, Noah J., and Esther Sullivan. "The contribution of manufactured housing to affordable housing in the United States: Assessing variation among manufactured housing tenures and community types." *Housing Policy Debate* 29, no. 6 (2019): 880-898.

Elhorst, J. Paul. "Applied spatial econometrics: raising the bar." *Spatial economic analysis* 5, no. 1 (2010): 9-28.

Elhorst, J. Paul. *Spatial econometrics: from cross-sectional data to spatial panels*. Vol. 479. Heidelberg: Springer, 2014.

Feng, Ping, Mahmut Yasar, and Jeffrey P. Cohen. "Do higher house prices crowd-out or crowd-in manufacturing? A spatial econometrics approach." *The Journal of Real Estate Finance and Economics* (2023): 1-26.

Pierce, Gregory, C. J. Gabbe, and Silvia R. Gonzalez. "Improperly-zoned, spatially-marginalized, and poorly-served? An analysis of mobile home parks in Los Angeles County." *Land Use Policy* 76 (2018): 178-185.

Wubneh, Mulatu, and Guoqiang Shen. "The impact of manufactured housing on adjacent residential property values: A GIS approach based on three North Carolina counties." *Review of Urban & Regional Development Studies* 16, no. 1 (2004): 56-73.

8. Figures and Tables

Figure 1: Concentration of Manufactured Homes

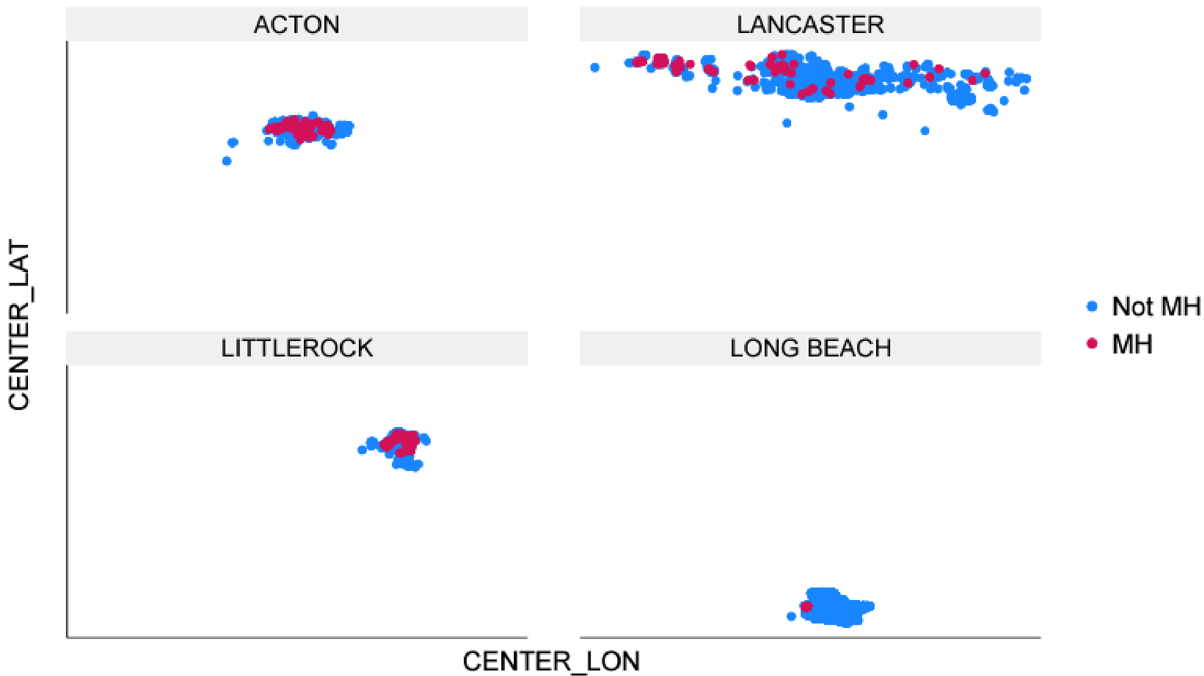

Table 1: Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
SaleAmount	15,210	816,817	961,583	10,330	10,000,000
MH Indicator	15,210	0	0	0	1
Age	15,148	43	28	0	136
Lot Size (sqft)	15,157	38,317	325,490	950	7,029,770
Interior (sqft)	15,210	2,736	3,786	1,500	290,000
Bedrooms	15,210	4	3	0	99
Bathrooms	15,210	3	3	0	99

This table shows summary statistics for the sale amount and key covariates for all sales in the sample from 2017 to 2021. *MH Indicator* is an indicator variable equal to 1 if the property is classified as a manufactured home or manufactured home park at time of sale. *Age* is the difference between the sale year and the year built. *Lot size* and *Interior* are given in square feet.

Table 2: Sample by Year and City

	Acton	Lancaster	Littlerock	Long Beach
2017	90	2,157	134	3,273
2018	94	2,236	155	3,343
2019	122	2,560	149	3,430
2020	171	2,650	138	3,712
2021	117	2,256	125	3,543

This table shows the sample breakdown by year and city for 2017 to 2021 and the four cities in our spatial regression analyses. Acton and Littlerock have comparatively fewer real estate transactions compared to Lancaster and Long Beach.

Table 3: Manufactured Home Direct Effects

Acton	dy/dx	marg. eff.	std. err.	z	p-val	95% CI LB	95% CI UB
2017	-0.038	-3.73%	0.078	-0.48	0.629	-0.19	0.115
2018	-0.117	-11.04%	0.08	-1.46	0.143	-0.274	0.04
2019	0.028	2.84%	0.198	0.14	0.889	-0.361	0.416
2020	-0.151	-14.02%	0.06	-2.5	0.012	-0.269	-0.033
2021	-0.097	-9.24%	0.049	-1.99	0.047	-0.193	-0.001
Lancaster	**dy/dx**	**marg. eff.**	**std. err.**	**z**	**p-val**	**95% CI LB**	**95% CI UB**
2017	-0.274	-23.97%	0.118	-2.33	0.02	-0.505	-0.043
2018	-0.457	-36.68%	0.163	-2.8	0.005	-0.777	-0.137
2019	-0.193	-17.55%	0.136	-1.42	0.155	-0.46	0.073
2020	0.08	8.33%	0.153	0.52	0.601	-0.22	0.38
2021	-0.149	-13.84%	0.078	-1.9	0.057	-0.303	0.005
Littlerock	**dy/dx**	**marg. eff.**	**std. err.**	**z**	**p-val**	**95% CI LB**	**95% CI UB**
2017	-0.226	-20.23%	0.072	-3.12	0.002	-0.367	-0.084
2018	-0.228	-20.39%	0.077	-2.96	0.003	-0.379	-0.077
2019	-0.342	-28.97%	0.078	-4.36	0	-0.496	-0.188
2020	-0.12	-11.31%	0.103	-1.17	0.243	-0.322	0.082
2021	-0.275	-24.04%	0.17	-1.61	0.106	-0.608	0.059
L. Beach	**dy/dx**	**marg. eff.**	**std. err.**	**z**	**p-val**	**95% CI LB**	**95% CI UB**
2017	-1.118	-67.31%	0.079	-14.2	0	-1.273	-0.964
2018	-0.885	-58.73%	0.089	-9.97	0	-1.059	-0.711
2019	-0.805	-55.29%	0.129	-6.23	0	-1.059	-0.552
2020	-0.421	-34.36%	0.039	-10.75	0	-0.497	-0.344
2021	-0.461	-36.93%	0.041	-11.21	0	-0.542	-0.381

This table shows the direct effects of MHs on sale prices in the spatial Durbin model by city and year. The dependent variable is the property's log sale price. The coefficients listed are for the variable of whether the property is classified as an MH. One spatial regression is done per city and year. The regressions use a generalized two-stage least squares estimator and include heteroskedastic standard errors. Classification as an MH has a mostly negative effect on sale price, with a statistically stronger effect in Long Beach.

Table 4: Manufactured Home Indirect Effects

Acton	dy/dx	marg. eff.	std. err.	z	p-val	95% CI LB	95% CI UB
2017	0.004	0.40%	0.009	0.42	0.676	-0.014	0.022
2018	0	0.00%	0	0.92	0.357	0	0.001
2019	0	0.00%	0.001	-0.13	0.895	-0.002	0.002
2020	0	0.00%	0	-0.26	0.796	-0.001	0.001
2021	0.022	2.22%	0.018	1.28	0.202	-0.012	0.057
Lancaster	**dy/dx**	**marg. eff.**	**std. err.**	**z**	**p-val**	**95% CI LB**	**95% CI UB**
2017	0.036	3.67%	0.042	0.84	0.402	-0.048	0.119
2018	0.075	7.79%	0.036	2.1	0.036	0.005	0.145
2019	0.001	0.10%	0.001	1.03	0.302	-0.001	0.002
2020	0.143	15.37%	0.055	2.58	0.01	0.034	0.251
2021	0.048	4.92%	0.04	1.2	0.23	-0.03	0.125
Littlerock	**dy/dx**	**marg. eff.**	**std. err.**	**z**	**p-val**	**95% CI LB**	**95% CI UB**
2017	0.001	0.10%	0.001	1.46	0.145	0	0.003
2018	0	0.00%	0.001	-0.46	0.644	-0.003	0.002
2019	-0.088	-8.42%	0.039	-2.25	0.025	-0.165	-0.011
2020	0.001	0.10%	0.001	1.03	0.301	-0.001	0.002
2021	-0.001	-0.10%	0.001	-1.32	0.186	-0.002	0
L. Beach	**dy/dx**	**marg. eff.**	**std. err.**	**z**	**p-val**	**95% CI LB**	**95% CI UB**
2017	0.148	15.95%	0.162	0.91	0.361	-0.169	0.464
2018	-0.004	-0.40%	0.173	-0.02	0.98	-0.344	0.335
2019	0.066	6.82%	0.116	0.57	0.57	-0.162	0.293
2020	0.026	2.63%	0.077	0.33	0.739	-0.125	0.177
2021	0.003	0.30%	0.001	3.39	0.001	0.001	0.005

This table shows the indirect effects of MHs on sale prices in the spatial Durbin model by city and year. The dependent variable is the property's log sale price. The coefficients listed are for the variable of whether the adjacent properties are classified as an MH, scaled by the number of adjacent properties. One spatial regression is done per city and year. The regressions use a generalized two-stage least squares estimator and include heteroskedastic standard errors. Adjacency to an MH has a positive effect on sale price in some years in Lancaster and Long Beach, and a negative effect in Littlerock.

Table 5: Manufactured Home Total Effects

Acton	dy/dx	marg. eff.	std. err.	z	p-val	95% CI LB	95% CI UB
2017	-0.034	-3.34%	0.069	-0.49	0.625	-0.169	0.101
2018	-0.117	-11.04%	0.08	-1.46	0.143	-0.274	0.04
2019	0.028	2.84%	0.197	0.14	0.889	-0.359	0.414
2020	-0.151	-14.02%	0.06	-2.5	0.012	-0.269	-0.033
2021	-0.075	-7.23%	0.057	-1.32	0.185	-0.186	0.036
Lancaster	**dy/dx**	**marg. eff.**	**std. err.**	**z**	**p-val**	**95% CI LB**	**95% CI UB**
2017	-0.239	-21.26%	0.137	-1.74	0.082	-0.508	0.03
2018	-0.382	-31.75%	0.146	-2.62	0.009	-0.669	-0.096
2019	-0.192	-17.47%	0.135	-1.42	0.155	-0.458	0.073
2020	0.223	24.98%	0.185	1.2	0.229	-0.14	0.586
2021	-0.101	-9.61%	0.098	-1.03	0.301	-0.294	0.091
Littlerock	**dy/dx**	**marg. eff.**	**std. err.**	**z**	**p-val**	**95% CI LB**	**95% CI UB**
2017	-0.224	-20.07%	0.072	-3.12	0.002	-0.365	-0.084
2018	-0.228	-20.39%	0.077	-2.95	0.003	-0.38	-0.077
2019	-0.43	-34.95%	0.092	-4.69	0	-0.61	-0.25
2020	-0.119	-11.22%	0.102	-1.17	0.243	-0.32	0.081
2021	-0.275	-24.04%	0.171	-1.61	0.106	-0.61	0.059
L. Beach	**dy/dx**	**marg. eff.**	**std. err.**	**z**	**p-val**	**95% CI LB**	**95% CI UB**
2017	-0.971	-62.13%	0.166	-5.84	0	-1.296	-0.645
2018	-0.889	-58.89%	0.18	-4.94	0	-1.242	-0.537
2019	-0.74	-52.29%	0.141	-5.25	0	-1.016	-0.463
2020	-0.395	-32.63%	0.083	-4.76	0	-0.558	-0.232
2021	-0.458	-36.75%	0.041	-11.3	0	-0.538	-0.379

This table shows the total effects of MHs on sale prices in the spatial Durbin model by city and year. The dependent variable is the property's log sale price. The coefficients listed are for the combined variable of whether the property and its neighbors are classified as an MH. One spatial regression is done per city and year. The regressions use a generalized two-stage least squares estimator and include heteroskedastic standard errors.