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Wireless Towers and Home Values: An Alternative Valuation Approach Using a Spatial Econometric Analysis

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Abstract This is the first study to use an hedonic spatial autoregressive model to assess the impact of wireless communication towers on the value of residential properties. Using quantile analyses based on minimum distances between sold properties and visible and non-visible towers, we examine the relationship between property values and wireless tower proximity and visibility within various specified radii for homes sold after tower construction. For properties located within 0.72 kilometers of the closest tower, results reveal significant social welfare costs with values declining 2.46% on average, and up to 9.78% for homes within tower visibility range compared to homes outside tower visibility range; in aggregate, properties within the 0.72-kilometer band lose over $24 million dollars.

JEL Classifications C5 · K32 · Q51 · R21 · R32 · R38 · R58

Keywords Hedonic analysis · Housing value · Land planning · Public planning · Spatial econometrics · Urban externalities · Wireless tower impacts

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In less than 20 years, the number of wireless devices in use[1] in the United States increased 1045%, growing from 340,213 in 1985 to over 355 million in 2014 (CTIA 2015). A growing number of Americans now rely solely on their wireless phones for communication. As of the end of 2014, the Centers for Disease Control and Prevention's National Center for Health Statistics reports that 44% of American households no longer subscribe to landline telephone service; they predict that by the end of 2015, a majority will have severed the cord (Centers for Disease Control and Prevention 2015). U.S. wireless device numbers are truly staggering: 2014 usage comprised 2.45 trillion voice minutes, 4.06 trillion megabytes of data, 1.92 trillion text messages, and 151.99 billion multimedia messages (CTIA 2015). Incredibly, even on the heels of a doubling of wireless data usage from 2012 to 2013, analysts expect data use to surge, growing by more than 650% by 2018 (Cisco 2013). In 2012, wireless industry employment topped 3.8 million people—2.6% of the U.S. workforce (Entner 2012). Analysts predict the industry will create 1.2 million new jobs by 2017 (Pearce et al. 2013). U.S. wireless carriers' capital investment exceeded $33 billion in 2013—a record annual high—and wireless industry experts project an additional $260 billion in new capital investment over the next 10 years (CTIA 2015), adding $2.6 trillion to U.S. gross domestic product (Summers 2010). Perhaps the most surprising, yet at the same time most impressive statistic is that by comparison, the total value of the U.S. wireless industry—currently $196 billion in 2012—exceeds that of agriculture, hotels and lodging, and air transportation (Entner 2012).

Without question, there are many societal benefits offered by the last two decades' myriad advances in wireless technologies. Ease of use and convenience, lower equipment pricing, increasingly competitive rate plans, surges in wireless industry employment, considerable economic multiplier effects from large-scale wireless industry capital investment, and significant realized and projected annual contributions to GDP all work to make the U.S. wireless industry an ever-increasing, important part of our daily lives and our national economy. Yet to date, a largely overlooked societal cost is the potential negative impact on residential property values caused by the exponential proliferation of the number of cell sites[2] necessary to support the wireless industry's rapid growth. In 1985, there were only 900 cell sites in the U.S., but by the end of 2014, the number had increased by 22,778% (CTIA 2015). Of the more than 298,000 cell sites in the U.S., nearly 70% are located on tower structures (Airwave Management, LLC 2013). Amidst intense competition to meet seemingly unceasing demand, providers work continually to improve their wireless service coverage. As they do so, it is logical to expect construction of an increasing number of new wireless towers, located closer and closer together in many urban and suburban areas. As this happens, it is also logical to expect an increasing number of homeowners to question if, and to what extent proximity to a wireless tower affects home values. Those concerned with such questions might also hope that public policy makers will begin asking the same questions, and more importantly, consider the ramifications of the answers as they manage the increasing pressures placed on wireless tower regulatory planning and approval processes.

[1] Wireless devices include special feature phones, smartphones, and tablets.

[2] CTIA defines a cell site as the location of wireless antenna and network communications equipment necessary to provide wireless service in a geographic area (CTIA 2015).

Considering the expected future increases in wireless device users and the cell sites supporting them, this is a critically important question for our time. However, only a few researchers have examined this issue, all yielding somewhat mixed results. In all, the extant literature includes six relevant studies. The first is perceptions-based, offering residents' opinions of how tower proximity influences property values (Bond and Beamish 2005). The second combines a similar perceptions-based component with an hedonic model to estimate sales price impacts (Bond and Wang 2005). The remaining four studies take a strictly empirical approach using hedonic modeling estimations and different types of spatial analysis techniques (Bond 2007a, b; Filippova and Rehm 2011; Locke and Blomquist 2016). Unfortunately, each study suffers from flaws of one sort or another—time invariant issues, inaccurate spatial modeling techniques, or other troublesome variable misspecifications. In essence, the results of these studies are either inconclusive or show only minimal negative price effects due to wireless tower proximity.

In our study though, we use a robust approach for gauging home values relative to tower proximity. Similar to others, our study includes hedonic modeling to capture distinctive property characteristics, yet it is distinctly different from others in two important respects. By performing the analysis within varying radii bands based on quartiles of the distance from the closest wireless tower, we are able to detect potential marginal price gradients of each property across the banded space. More importantly, by conducting a series of robust spatial econometric tests, we are able to identify and use the most unbiased, efficient spatial model that is best suited for the inferential analysis of our research question. The results underscore our concerns that previous studies may potentially suffer from bias due to their failures to address spatial correlation issues typical in hedonic model studies. Two significant reasons contribute to our apprehensions. The first is that Ordinary Least Squares (OLS) estimations are biased and inefficient in the presence of spatial correlations of dependent variables and residuals. The second is that by not accounting for spatial autocorrelation, it is unlikely any hedonic model can correctly disentangle either direct and/or indirect effects of (dis)amenities on housing prices. Research shows the latter is particularly useful when assessing the impact of corrective policy solutions subsequent to market failures (LeSage and Pace 2009). This is important because our research poses potentially significant policy implications, all of which we believe will most likely, yet for substantially different reasons, be of keen interest to governmental and planning officials, wireless tower operators and service providers, neighborhood activist groups, and private property rights' advocates.

In the second section of our paper, we discuss the relevant literature. In the third section, we delineate our data and define our variables. In the fourth section, we develop our hypotheses and methodology. In the fifth section, we present our empirical results, and the final section concludes.

Literature Review

McDonough (2003) states "…proximity to a wireless tower needs to be considered as a negative amenity that may reduce property valuation" (McDonough 2003, p. 29).

Despite this recognition and the ongoing rapid expansion of the wireless industry, research examining the relationship between wireless tower proximity and home values remains quite limited. Two early studies commissioned by a major wireless service provider look at potential health and visual impacts that wireless towers[3] may have on property values. Bond and Beamish (2005) report that although the studies' results remain secretive, their private review of the results confirms no statistically significant relationships exist. They note, however, that because the studies involve limited sales data, and the underwriter is also a service provider, the question of biased results is potentially concerning.

Some researchers tackle the question using perceptual studies. Bond and Beamish (2005) survey residents in ten Christchurch, New Zealand suburbs—half being study areas (residents living within 300 m of a tower) and half being a control group (residents living more than 1 km from a tower). The authors aim to gauge residents' perceptions about whether and to what extent wireless tower proximity influences property values. Not surprisingly, those living far from a tower express less concern than those living close to one. Distance from a tower largely drove respondents' answers, but in sum, the authors find expectations of more than a 20% price reduction for properties within close tower proximity.

Bond and Wang (2005) combine a perceptual study with an empirical investigation. The perceptual component outcomes are quite similar to those of Bond and Beamish (2005). Their survey's respondents believe that proximity to a wireless tower causes property values to decrease from 10% to more than 20%. The empirical portion of their study includes approximately 4000 home sales spanning from 1986 to 2002 in four different suburbs. The authors' hedonic model includes a dummy variable that captures whether sales occur before or after tower construction. A potential shortcoming of this study could be the authors' choice to measure distances from cell towers not to individual homes, but rather, to a particular street within the study area. Their hedonic models do not account for potential spatial dependence of price and error structure. Their estimations produce mixed results, with negative price effects in two suburbs, a positive price effect in a third, and no significance in the fourth.

Bond (2007a) offers a methodological improvement by calculating exact distances between towers and included properties. Using a dummy variable to capture if a sale occurs before or after tower construction, the author also accounts for sales price time-effects by deflating sales prices to the consumer price index, and includes a time of sale variable in the estimations. Using four of the same suburbs from the earlier work of Bond and Wang (2005), the results show sales price reductions of approximately 15% after tower construction, diminishing as distance from a tower increases. Past 300 m, the negative price effect is negligible. Unfortunately, the results lack consistency, producing a positive price effect in one of the four neighborhoods. This may suggest a possible model misspecification error, or the effect of some other unobservable externality.

Bond (2007b) conducts a similar study using Orange County, Florida wireless tower and sales transaction data. Empirical results indicate a tower's presence yields a statistically significant and negative impact on price. Even so, the author notes the negative price effects are of little consequence.

[3] In their paper, the authors refer to wireless towers as cellular phone base stations.

Filippova and Rehm (2011) investigate tower proximity impacts on property values using property sales data from Auckland, New Zealand. Their final geocoded dataset includes approximately 56,000 sales observations dating from 2005 to 2007, and 521 tower locations. Highly critical of earlier studies' methodologies, the authors emphasize they took care to "ensure that integration dates of nearest cell towers did not occur after the date of sale" (Filippova and Rehm 2011, p. 250). To account for negative impacts that non-residential areas might have on residential area property values (for example, see Bowes and Ihlanfeldt 2001; Grass 1992; Nelson and McCleskey 1990; Mahan et al. 2000), the authors divide their sample into two parts. The first group includes only the 49 towers within residential areas, and all properties within a 500-m radius of existing towers. They also include a dummy variable for tower type, which they describe as lamppost, single monopole, or armed monopole (one with a triangular structure at the top). Generally, their residential area estimations produce no statistical significance. Not surprising, given the extremely close proximity to a tower, the lone exception is for houses located within 100 m of an armed monopole, which suffer a 10.7% price reduction. Estimations for the second group, which includes all towers in the entire study area, yield results similar to those in the first group. As such, the authors conclude that with the exception of a small number of armed monopole towers, wireless tower proximity does not negatively affect sales price.

More recently, Locke and Blomquist (2016) explore the question at hand. They use housing sales (including repeat sales) from 2000 to 2012 occurring in Louisville and Elizabethtown, Kentucky, geocoding each sold property to the street address listed in the sales data. They develop a number of tower location-specific characteristics such as census tract, and distances to major roads, railroads, and military bases. The authors state that, "Holding all else constant, the owner of a communication antenna will attempt to locate the antenna in an area that minimizes the antenna owner's cost" (Locke and Blomquist 2016, p. 134). At first glance, this statement seems obvious, if for no other reason than it makes good business sense. Further thought, however, draws question to the authors' additional statement that, "It appears that communication antennas are in fact located in areas where properties are less valuable" (Locke and Blomquist 2016, p. 134). One might infer from this that carriers strive mainly to construct towers in low-value areas simply to save money. Yet because intuition suggests carriers increase earnings by increasing subscribers, locating towers only in low-valued areas, and hence, providing service coverage only to presumably low-income people does not make good business sense. It seems, therefore, that the authors miss the other side of the coin, which is, in fact, not all towers appear in areas where properties are less valuable, but rather, owners will also construct towers in areas where properties are more valuable in order to fill holes in their service coverage. Indeed, tower location may be a source of endogeneity. However, income, population density, and other unobserved neighborhood characteristics could be instrumental for both homeowners' property and wireless carriers' tower location choices.

Inclusion of spatial considerations in addition to hedonic characteristics in their modeling is a good choice, as it adds robustness to their results. However, as with previous studies, across all model estimations, the authors do not account for potential spatial correlation of price and error structure, finding only slight degrees of price reductions due to tower proximity, again, diminishing with distance.

Data

To investigate if and to what extent wireless tower proximity impacts home values we combine two datasets. The first includes 23,309 residential property sales occurring in Mobile County, Alabama between 1999 and 2015.[4] We deflate housing prices to a base year of 2014 using the U.S. Bureau of Labor Statistics' Housing Consumer Price Index. The second includes 149 wireless towers located in Mobile County, Alabama.[5] In addition to certain property characteristics, we also include key census tract-level demographic data.[6]

Following Locke and Blomquist (2016), we conduct a visibility analysis of the wireless towers located in the study area. We do so using Viewshed[7] and a 30-m resolution digital elevation map of Mobile County, Alabama.[8] Following Paterson and Boyle (2002), we calculate the visibility for a 360° circle and 1-km radius, including the aboveground tower height, and assume that the average height of an observer's eyes is 1.75 m above the ground at each property's location. Figure 1, Panel A illustrates the spatial distribution of towers, and Fig. 1, Panel B illustrates the Mobile County, Alabama property locations.

At a larger scale, Fig. 2 shows the visibility of towers and properties located in the most urbanized portion of the Mobile County, Alabama.[9] Fig. 2 helps to clarify graphically the idea of the indirect effect of a wireless tower. For example, although some properties lie immediately outside of the border of the visibility range (indicated in the red area), they are contiguous to properties that lie within the border of the visibility range. If there are spatial correlations between property values and tower locations, then we argue that a tower affects both the value of the property location from which the tower is visible, and indirectly, the values of neighboring properties from which the tower is not visible. Additionally, towers that are farther away, but that are still visible from a property, may potentially influence a property's value through a sort of spillover effect carried over across neighboring properties within the tower visibility space.

We compute the minimum distance from each housing unit to the closest wireless tower using the Haversine distance formula, which takes into account the curvature of the Earth. We calculate the distance of housing unit i to the closest wireless tower j as:

[4] Sold properties data draw from the Gulf Coast Multiple Listing Service, Inc., a wholly owned subsidiary of the Mobile Area Association of Realtors, Inc.

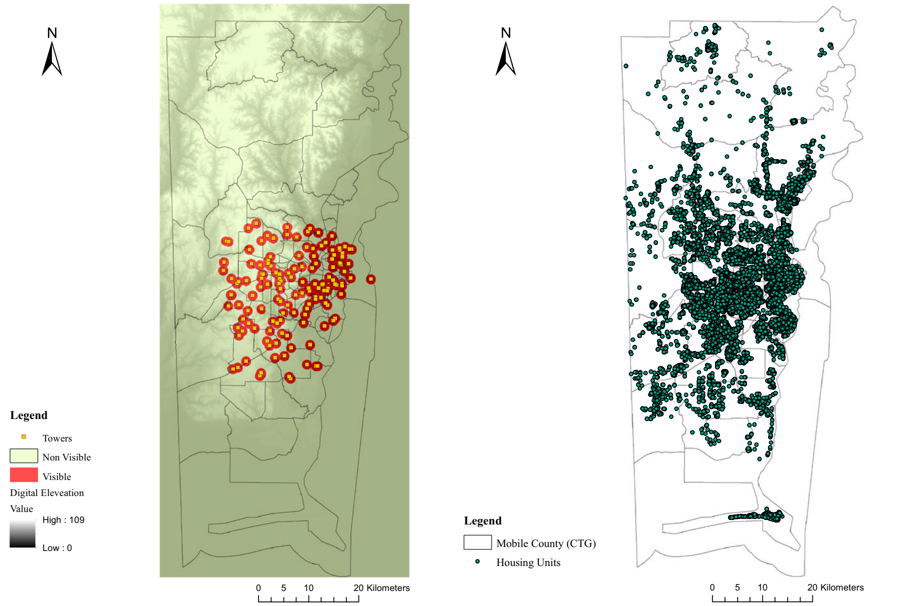
[5] These data draw from the U.S. Federal Communication Commission's Antenna Structure Registration database, available at http://wireless.fcc.gov/antenna/index.htm?job=home.

[6] These data draw from the U.S. Census Bureau, available at http://www.census.gov.

[7] The Viewshed tool is available as part ESRI ArcGIS® software package.

[8] Digital elevation maps draw from publicly available information hosted by the Geospatial Data Gateway of the U.S. Department of Agriculture's Natural Resources Conservation Service.

[9] An anonymous referee observed that every property within a 1 km radius of a tower is also within the towers' viewshed. We believe that this unusual result is consistent with the average height of a wireless tower in our dataset of approximately 60 m, and, more importantly, with the fact that our property sales data draw from a fairly flat coastal geographical area (i.e., the average housing elevation of our sample ≈ 11 m above sea level).



(a) Spatial Distribution of Tower (b) Spatial distribution of properties.

Fig. 1 Visibility Analysis: smaller scale

$$d_{ij} = min\left\{2r\ arcsin\left[\left(haversine\left(\varphi_j - \varphi_i\right) + cos(\varphi_i)cos\left(\varphi_j\right)haversine\left(\lambda_j - \lambda_i\right)\right)^{0.5}\right]\right\} \quad (1)$$

where r is equal to the Earth's radius of 6371 km, φ and λ are latitudes and longitudes of property and wireless tower locations expressed in radians. The average minimum distance of a property to a tower is 2.98 km, and we expect a negligible price impact for properties located farther away from a tower than this average. To investigate further the impact of towers on those dwellings that are closer, we conduct a sensitivity analysis using four subsamples based on quartiles of the minimum distance to the closest tower. The first, second, third, and fourth subsamples include houses within radii bands of between 0 to 0.72 km, 0.72 km to 1.13 km, 1.13 km to 1.88 km, and 1.88 km to 41 km of the closest tower, respectively. Table 1 lists and defines all of the variables we use in our analysis and summarizes the statistics for the whole sample of 23,309 properties. Table 2 presents the descriptive statistics of the variables across all four subsamples.

Methodology

Consistent with the literature, we use an hedonic model to investigate the relationship between property value and wireless tower proximity. Rosen (1974) was the first

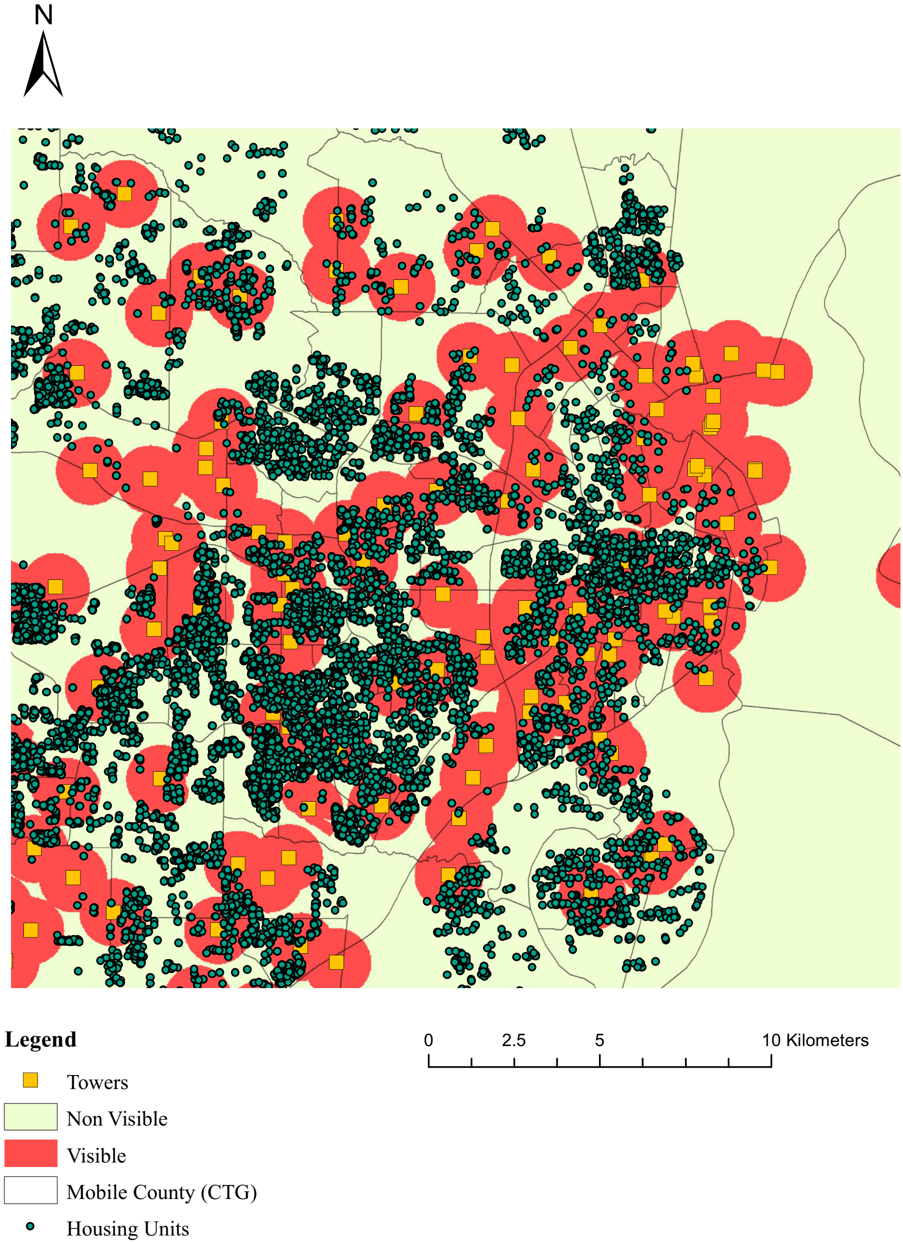


Fig. 2 Visibility Analysis: larger scale

researcher to derive a relationship between the price of a good and its characteristics. His work is widely used in real estate and urban economics research as an indirect method of revealing preferences used to analyze environmental externalities. As such, we assume that the property price is a function of the intrinsic characteristics of the property, neighborhood qualities, demographic characteristics, distance to wireless towers, and a spatial process (essentially, the spatial relationship between objects).

Table 1 Summary Statistics

Variable	Definition	Full Sample	
		Mean	SD
Price	inflation adjusted property sales price	167,592.3	124,777.1
Distance	distance between the property and the tower	2.980	5.453
D*	1 if property sale occurs after tower construction	16,393	69.742
V*	1 if the tower is visible	9448	74.956
h_tower	height of the tower	59.148	21.050
Age	age of property in years	23.566	19.389
Bedrooms	number of bedrooms in a property	3.285	.675
Bathrooms	total number of bathrooms in a property	2.135	.671
Onestory*	1 if number of stories is 1	1860	41.371
Twostories*	1 if number of stories is 2	2275	45.310
Car shelter*	1 if a property has a car shelter	15,023	73.078
Fireplace*	1 if a property has a fireplace	15,080	72.965
Fence*	1 if exterior has a fence	9375	74.862
Deck*	1 if exterior has a deck	5377	64.317
Pool*	1 if exterior has a pool	189	13.692
Brick*	1 if construction is primarily brick	16,500	69.426
Rural*	1 if population is less than 2500 per census tract	2644	48.416
distCBD	distance to downtown Mobile in kilometers	17.957	8.695
Towers	number of wireless towers per census tract	4.305	5.709
Income	median income per census tract	66,768.36	20,299.91
Black	African-American population per census tract expressed in units	1070.72	812.315
Unemployment	unemployment rate per census tract expressed in percentage points	9.207	5.417
N	number of observations	23,309	

The table above presents the summary statistics for the variables included in the entire dataset; year and zip code dummies are not shown;

*binary variables (assumed to follow the binomial distribution): means and standard deviations for these variables are computed for the binomial distribution

Hence, the econometric model used to examine the potential external impact of a wireless tower on property price takes the following form:

$$\begin{gathered}\ln(Price)_i = \beta_0 + \beta_1\ln(Distance_i) + \beta_2 D + \beta_3 D\cdot\ln(Distance_i) + \beta_4 V + \beta_5 V\cdot\ln(Distance_i) + \\ \beta_6 h\_tower_i + \beta_7 V\cdot h\_tower_i + \beta_8 Age_i + \beta_9 Bedrooms_i + \beta_{10}(Bedrooms_i)^2 + \\ \beta_{11} Bathrooms_i + \beta_{12} Onestory_i + \beta_{13} Twostories_i + \beta_{14} Carshelter_i + \beta_{15} Fireplace_i + \\ \beta_{16} Fence_i + \beta_{17} Deck_i + \beta_{18} Pool_i + \beta_{19} Brick_i + \beta_{20} Rural_i + \beta_{21}\mathrm{distCBD}_i + \beta_{22}\mathrm{T}owers_i + \\ \beta_{23}\ln(Income_i) + \beta_{24}\ln(Black_i) + \beta_{25} Unemployment_i + \textstyle\sum_{t=2008}^{2013}\tau_t Year_{ti} + \\ \textstyle\sum_{j=1}^{31}\delta_j Zipcode_{ji} + \varepsilon_i\end{gathered} \tag{2}$$

where ln(*Price*) is the natural log of the property sales price; ln(*Distance*) is the natural log of the distance between a property and a wireless tower measured in

Table 2 Summary Statistics for Variables in Each of the Four Subsamples

	Sample 1[a] (0.00–0.72Km)		Sample 2[b] (0.72Km – 1.13Km)		Sample 3[c] (1.13Km – 1.88Km)		Sample 4[d] (1.88Km – 41Km)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Price	163,008.8	107,361.6	170,634.6	133,366.5	170,212.1	136,985.5	166,518.6	119,035.9
Distance	0.497	0.156	0.920	0.116	1.425	0.202	9.080	8.295
D*	4087	34.942	4256	33.874	4246	33.942	3804	36.341
V*	5759	8.257	3667	36.869	22	4.682	0	0
h_tower	53.920	20.199	53.436	19.845	56.434	19.090	72.803	18.778
Age	26.148	21.949	25.455	20.128	23.876	18.816	18.784	15.158
Bedrooms	3.269	0.629	3.322	0.634	3.312	0.735	3.238	0.695
Bathrooms	2.113	0.667	2.156	0.710	2.167	0.700	2.104	0.598
Onestory*	459	20.563	499	21.360	528	21.912	374	18.708
Twostories*	573	22.730	615	23.454	642	23.901	445	20.274
Car shelter*	3832	36.227	3858	36.106	3695	36.769	3638	36.968
Fireplace*	3806	36.338	4028	35.265	3910	35.866	3336	37.764
Fence*	2521	37.822	2576	37.910	2380	37.522	1898	35.774
Deck*	1222	31.077	1404	32.645	1369	32.363	1382	32.469
Pool*	51	7.110	44	6.608	47	6.828	47	6.828
Brick*	3856	36.121	4142	34.608	4179	34.379	4323	33.404
Rural*	787	26.091	601	23.217	460	20.584	796	26.216
distCBD	14.625	5.891	15.037	5.601	16.037	5.524	26.131	10.758
Towers	5.523	5.743	5.152	6.474	4.671	6.242	1.875	2.881
Income	68,790.18	23,488.16	69,418.33	22,687.17	67,058.06	20,669.78	61,806.5	10,912.01
Black	1214.973	910.131	1139.579	801.164	1217.888	835.001	710.429	543.371
Unemployment	9.408	6.073	8.900	5.640	8.827	5.130	9.692	4.678
N	5828		5827		5827		5827	

The table above presents the summary statistics for the variables within each of the four subsamples included in the analysis;

*binary variables (assumed to follow the binomial distribution): means and standard deviations for these variables are computed for the binomial distribution

[a] *Sample 1* is a subsample of properties selected within the first quartile of the minimum distance to the closest wireless tower (radius ≤ 0.72Km);

[b] *Sample 2* is a subsample of properties within the second quartile of the minimum distance to the closest wireless tower (0.72Km ≤ *distance* ≤ 1.13Km);

[c] *Sample 3* is a subsample of properties within the third quartile of the minimum distance to the closest wireless tower (1.13Km ≤ *distance* ≤ 1.88Km);

[d] *Sample 4* is a subsample of properties within the fourth quartile of the minimum distance to the closest wireless tower (1.88Km ≤ *distance* ≤ 41Km)

kilometers; *D* is a dummy variable that takes the value of one if the property was purchased after tower construction, and zero otherwise; *V* is a dummy variable that takes the value of one if the closest tower is visible from the property, and zero otherwise; *h_tower* is a continuous variable that measures the height of the closest tower above the ground in meters; *Age* is the age of a property in years; *Bedrooms* is the total number of bedrooms in a property; *Bathrooms* is the total number of bathrooms and/or half-bathrooms in a property; *Onestory* and *Twostories* are binary variables equal to one if the property has one story or two stories above the ground level, respectively; *Carshelter, Fireplace, Fence, Deck, Pool* and *Brick* are dummy variables that take the value of one if a property has a car shelter, a fireplace, a fence around the house, a deck, a pool and/or the exterior construction is made of bricks respectively, and zero otherwise; *Rural* is a binary variable proxy for less dense populated areas that takes value one if the number of inhabitants per census tract is less than 2500, and zero otherwise; *dist*CBD is a continuous variable that measures the distance of each property from the Central Business District of Mobile, Alabama, the largest city in the study area; *Towers* is the number of wireless towers per census tract; ln*(Income)* is the natural log of the median income per census tract; ln*(Black)* is the natural log of the African-American population expressed in units per census tract; and, *Unemployment* is the unemployment rate per census tract expressed in percentage points. As in Jensen et al. (2014), we add the interaction between distance to (dis)amenities and tower visibility (*V*), which we label ln*(Distance)*·*V*. We use *Year*, property sale year dummy variables, to control for the impact of the subprime mortgage crisis. Finally, following Caudill et al. (2014), we include *Zipcode*, a set of dummy variables that attempt to capture additional unobserved neighborhood heterogeneities at a higher resolution than the census tract. Since we are interested in examining the price sensitivity of buyers of homes closest to a wireless tower, we follow Locke and Blomquist (2016) in stating the dependent variable being in logarithmic form. However, we also use the Akaike Information Criterion (AIC) to test several functional forms for hedonic price equations by varying the specification of the variables in the right-hand side of Eq. (2). We do so because by selecting the functional form having the lowest AIC value, we are able to produce a theoretical specification with the least possible information loss.

We calculate the average impact of a wireless tower on housing price by subtracting expected housing values before tower construction from expected housing values after tower construction, using the equation taking the following form:

$$\mathbb{E}\left[e^{Ln\left(\widehat{\text{price}}\right)}|D=1\right]-\mathbb{E}\left[e^{Ln\left(\widehat{\text{price}}\right)}|D=0\right]. \tag{3}$$

We also calculate the total social welfare impact as:

$$\Delta W=\sum_{i=1}^{N}\left[\left(e^{Ln\left(\widehat{\text{price}}\right)_i}|D_i=1\right)-\left(e^{Ln\left(\widehat{\text{price}}\right)_i}|D_i=0\right)\right]. \tag{4}$$

In addition, to examine the spatial price sensitivity of home buyers—the price elasticity of tower proximity—we partially differentiate Eq. (2) with respect to ln*(Distance*), using the equation taking the following form:

$$\frac{\partial ln(Price)}{\partial ln(Distance)}=[\beta_1+\beta_3 D+\beta_5 V]\%. \tag{5}$$

We evaluate Eq. (5) as $D = 0$ and $V = 0$ (β_1) for sales occurring before tower construction, and $D = 1$ and $V = 1$ $(\beta_1 + \beta_3 + \beta_5)$ for sales occurring after the visible tower construction. We additionally include $D = 1$ and $V = 0$ $(\beta_1 + \beta_3)$, which accommodates comparison of price sensitivity of buyers of properties from which the closest tower is not visible.

In certain hedonic studies, it is appropriate to perform statistical tests for spatial correlation. This is a consequence of Tobler's first law of geography, which premises the interrelationship of all things, but that closer things are more related than distant things (Tobler 1970). We use spatial correlation tests to account for spatial processes in the dependent variable and estimation residuals. In matrix notation, such a model reads as:

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + (\mathbf{I}-\lambda\mathbf{W})^{-1}\mathbf{u} \tag{6}$$

where $\mathbf{y}$ is a n × 1 vector of property prices (previously defined); ρ is a scalar coefficient of spatial correlation; $\mathbf{W}$ is an n x n row, standardized spatial contiguity matrix based on the three closest neighbors as outlined by Caudill et al. (2014); $\mathbf{X}$ is an n × 63 (number of parameters of Eq. 1 including intercept) data matrix with first column vector $\mathbf{1_n}$; $\boldsymbol{\beta}$ is a 63 × 1 vector of parameters; $\mathbf{I}$ is an n x n identity matrix, λ is a scalar coefficient of residuals spatial correlation; and, $\mathbf{u}$ is an n × 1 vector of Gaussian innovations.

We estimate the spatial model by maximizing the log-likelihood function (MLL) with respect to the model's parameters, coefficients of spatial correlation (ρ and λ), and residual standard errors (σ) using the equation taking the following form:

$$\begin{aligned} LL(\boldsymbol{\beta}, \rho, \lambda, \sigma|\mathbf{y}) &= -0.5\ n \ln(\pi) - 0.5\ n \ln\left(\sigma^2\right) \\ &\quad + (\ln|\mathbf{I}-\lambda\mathbf{W}| + \ln|\mathbf{I}-\rho\mathbf{W}|) - \left[0.5\left(\sigma^{-2}\right)(\mathbf{u}')(\mathbf{u})\right] \end{aligned} \tag{7}$$

where n is the sample size, $\mathbf{u} = (\mathbf{I} - \lambda\mathbf{W})^{-1}(\mathbf{I} - \rho\mathbf{W})\mathbf{y} - (\mathbf{I} - \lambda\mathbf{W})^{-1}\mathbf{X}\boldsymbol{\beta}$; and, $\ln|\mathbf{I} - \lambda\mathbf{W}|$ and $\ln|\mathbf{I} - \rho\mathbf{W}|$ are the terms of the log-Jacobian transformation of $\mathbf{u}$ into $\mathbf{y}$. Assuming the same geographic processes for the dependent variable and residuals (same $\mathbf{W}$), the large sample Moran's I test for spatial correlation of the residuals is:

$$Z_I = [I-E(I)]/Var(I)^{0.5} \sim N(0, 1) \tag{8}$$

where I is calculated from the residuals of Eq. (2) as $\boldsymbol{\varepsilon}'\mathbf{W}\boldsymbol{\varepsilon}/\ \boldsymbol{\varepsilon}'\boldsymbol{\varepsilon}$. Since this test is asymptotically normal, if $Z_I > 1.96$, with 95% confidence, we reject the null hypothesis that there is no spatial autocorrelation of the residuals.

The econometric models presented in Eqs. (6) and (7) are generic representations of a spatial model which includes both a spatial autoregressive model—model with dependent variable spatially autocorrelated: $\lambda = 0$, and a spatial error model—model with residuals spatially autocorrelated: $\rho = 0$. Following Anselin (1988), in practice, we select only one of the two models. Following the suggestion of Anselin et al. (1996), we use Robust Lagrangian Multiplier (RLM) tests (H_0: no spatial autocorrelation) of the residuals, using equations taking the following forms:

$$\mathrm{RLM}_\rho = \left[\boldsymbol{\varepsilon}'\mathbf{W}\mathbf{y}/\sigma^2 - \boldsymbol{\varepsilon}'\mathbf{W}\boldsymbol{\varepsilon}/\sigma^2\right]^2 / \left\{\sigma^2\left[(\mathbf{W}\mathbf{X}\boldsymbol{\beta})'\mathbf{M}(\mathbf{W}\mathbf{X}\boldsymbol{\beta}) + n\sigma^2\right] - n\right\} \tag{9}$$

$$\mathrm{RLM}_{\lambda} = \left[\boldsymbol{\varepsilon}'\mathbf{W}\boldsymbol{\varepsilon}/\sigma^2 - n\left(\sigma^2\left[(\mathbf{WX\beta})'\mathbf{M}(\mathbf{WX\beta}) + n\sigma^2\right]\right)^{-1}\boldsymbol{\varepsilon}'\mathbf{Wy}/\sigma^2\right]^2 \Big/ n\left[1 - n\left(\sigma^2\left[(\mathbf{WX\beta})'\mathbf{M}(\mathbf{WX\beta}) + n\sigma^2\right]\right)\right]^{-1} \tag{10}$$

Both Eqs. (9) and (10) follow the χ^2 distribution with one degree of freedom and include $\mathbf{M = I\text{-}X(X'X)^{-1}X}$ as an idempotent projection matrix. Following Florax and De Graaff (2004), we select the model with the largest RLM statistics.

Results and Discussion

In this study, we conduct a pseudo-quantile analysis based on quartiles of the distance of each property from the closest tower. We refer to it as a pseudo-quantile analysis because we force the estimation of the conditional mean of the response variable on different values of the distance to the closest tower by subsampling the full data set for the four quartiles of this variable. The idea is to test our research hypothesis for properties located within different distance gradients from wireless towers. We do so by creating four spatial contiguity matrices (one for each sample). In Table 3, we report the results of both the Moran's I and RLM tests for spatial correlation across all four samples.

Table 3 Tests for Spatial Correlation

Statistic	Sample 1[a] (0.00–0.72Km) Value	Sample 2[b] (0.72Km – 1.13Km) Value	Sample 3[c] (1.13Km – 1.88Km) Value	Sample 4[d] (1.88Km – 41Km) Value
Moran's I	0.22	0.21	0.20	0.18
Z_I	26.43***	24.81***	24.52***	21.53***
	(0.00)	(0.00)	(0.00)	(0.00)
RLM_{ρ}	436.83***	438.42***	490.10***	365.60***
	(0.00)	(0.00)	(0.00)	(0.00)
RLM_{λ}	0.041	0.24	0.31	0.49
	(0.84)	(0.62)	(0.58)	(0.48)

The table above presents the results of spatial correlation tests for all three samples;

H_0 No Spatial Autocorrelation, Z_I follows the standard normal distribution, RLM_{ρ} *and* RLM_{λ} follow the χ^2 distribution with one degree of freedom

Confidence intervals presented as ***99%; *p*-values in parentheses;

[a] *Sample 1* is a subsample of properties selected within the first quartile of the minimum distance to the closest wireless tower (radius ≤ 0.72Km);

[b] *Sample 2* is a subsample of properties within the second quartile of the minimum distance to the closest wireless tower (0.72Km ≤ *distance* ≤ 1.13Km);

[c] *Sample 3* is a subsample of properties within the third quartile of the minimum distance to the closest wireless tower (1.13Km ≤ *distance* ≤ 1.88Km);

[d] *Sample 4* is a subsample of properties within the fourth quartile of the minimum distance to the closest wireless tower (1.88Km ≤ *distance* ≤ 41Km)

Based on the Moran's I test results, with 99% confidence for each sample, we reject the null hypothesis that there is no spatial correlation of the residuals. Based on the results of the RLM test for dependent variable spatial correlation, we reject the null hypothesis of no spatial correlation for each subsample with 99% confidence. In contrast, based on the results of the RLM test for residual spatial correlation, we fail to reject the null hypothesis of no spatial correlation across all subsamples. Consequently, the spatial autoregressive model is the most appropriate econometric tool to conduct our analysis (Florax and De Graaff 2004). In Tables 4 and 5, we report the results of our analysis, comparing the OLS estimates (Table 4) of Eq. (2) to the MLL estimates (Table 5) of Eq. (6) with λ restricted to zero as a natural consequence of the Moran's I and RLM diagnostic tests discussed above.

Although biased, OLS estimates have good explanatory power across all four samples (the coefficient of determination ranges from 60% to 72%). However, comparison of the lower values of the AIC of the spatial autoregressive models to the corresponding OLS models confirms the hypothesis that the spatial autoregressive models represent the reality with minimum information loss. Therefore, this additional information supports our contention that the spatial autoregressive model is the most appropriate framework for statistical inference in our study.

In general, the spatial autoregressive model estimates have good statistical power and the expected coefficient signs across the four subsamples. Curiously, though, we find that the prices of properties purchased in 2009 after the U.S. financial crisis (compared to the baseline year 2007) are not statistically significant within 1.88 km from the closest tower (across the first three quartiles of the distance to the closest wireless tower). On the other hand, although the coefficients for dwelling age, unemployment rate, and the percentage increase in the African American population per census tract are all statistically significant, none seems to be economically significant in Mobile County. As expected, the numbers of bedrooms and bathrooms, as well as income are important predictors of property value in terms of economic magnitude. However, as in Locke and Blomquist (2016), it appears that the impact of these variables is relative to property location with respect to the towers. For example, an average household would be willing to pay between 7% to 8.5%[10] more than the average price of a property for an additional bedroom across the four samples while the household's willingness to pay for an additional bathroom ranges between 21% to 27% more than the average across the four subsamples. Moreover, commensurate with a 10% increase in median income per census tract, the property price increases range from between 18% to 21% for those properties located beyond 1.88 km from the closest tower (across Samples 2–4). However, it seems that the price of properties located within 0.72 km from the closest tower (Sample 1) is only negligibly sensitive to median income changes.

Turning our analysis to the impact of the wireless tower on the value of residential properties, our first assessment of the spatial autoregressive model estimate of D for the properties located within 0.72 km from the closest tower (Sample 1) shows a statistically

[10] There is a quadratic relationship between the logarithm of the property price and the number of bedrooms. We evaluate the semi-elasticities at the mean values of the number of bedrooms as reported in Table 2.

Table 4 Ordinary Least Squares

	Sample 1[a] (0.00–0.72Km)	Sample 2[b] (0.72Km – 1.13Km)	Sample 3[c] (1.13Km – 1.88Km)	Sample 4[d] (1.88Km – 41Km)
Constant	9.872*** (16.26)	6.362*** (12.2)	6.009*** (15.53)	6.311*** (11.59)
Age	-0.004*** (−12.86)	-0.006*** (−16.64)	-0.007*** (−18.07)	-0.008*** (−21.77)
Bedrooms	0.365*** (7.14)	0.417*** (9.76)	0.074*** (6.15)	0.115*** (9.07)
Bedrooms^2	-0.043*** (−5.75)	-0.041*** (−6.99)	-0.002*** (−4.03)	-0.003*** (−5.87)
Bathrooms	0.329*** (31.83)	0.277*** (30.66)	0.373*** (37.72)	0.278*** (26.44)
Onestory (0/1)	0.031* (1.65)	0.06*** (3.34)	0.069*** (3.89)	0.17*** (8.14)
Twostories (0/1)	0.058*** (3.28)	0.112*** (6.49)	0.092*** (5.4)	0.191*** (9.50)
Car shelter (0/1)	0.179*** (17.32)	0.187*** (17.77)	0.189*** (18.89)	0.239*** (23.03)
Fireplace (0/1)	0.203*** (17.87)	0.184*** (15.52)	0.158*** (13.74)	0.179*** (17.01)
Fence (0/1)	0.067*** (6.33)	0.019* (1.73)	0.024*** (2.26)	0.036*** (3.23)
Deck (0/1)	0.092*** (7.03)	0.065*** (5.02)	0.075*** (5.96)	0.093*** (7.15)
Pool (0/1)	0.067 (1.36)	-0.004 (−0.08)	-0.026 (−0.51)	0.118** (2.20)
Brick (0/1)	0.118*** (10.6)	0.098*** (8.48)	0.125*** (11.1)	0.096*** (7.56)
Rural (0/1)	-0.065*** (−3.07)	-0.119*** (−4.93)	-0.066** (−2.25)	0.216888 (5.35)
ln(distCBD)	-0.287*** (−10.06)	-0.103*** (−3.44)	-0.163*** (−4.67)	-0.075 (−1.33)
Towers	0.003*** (2.74)	0.003*** (3.63)	0.001 (0.49)	-0.002 (−0.75)
ln(Income)	0.155*** (5.58)	0.379*** (14.38)	0.478*** (16.27)	0.388*** (8.001)
ln(Black)	-0.066*** (−6.66)	-0.091*** (−9.41)	-0.065*** (−6.64)	-0.023** (−2.38)
Unemployment	-0.011*** (−7.44)	-0.004*** (−2.68)	0.009*** (5.27)	0.003*** (1.91)
Year 2008	0.075*** (3.95)	0.129*** (6.84)	0.111*** (5.8)	0.100*** (5.26)
Year 2009	0.009 (0.45)	0.011 (0.54)	0.036 (1.69)	0.019 (0.9)
Year 2010	-0.116*** (−5.02)	-0.087*** (−3.57)	-0.118*** (−5.29)	-0.062*** (−3.02)
Year 2011	-0.288*** (−12.54)	-0.297*** (−13.56)	-0.235*** (−10.48)	-0.185*** (−8.4)
Year 2012	-0.346*** (−15.52)	-0.304*** (−13.11)	-0.26*** (−11.13)	-0.21*** (−9.73)
Year 2013	-0.321*** (−14.58)	-0.331*** (−14.89)	-0.307*** (−13.93)	-0.249*** (−11.76)
ln(Distance)	-1.257*** (−2.95)	0.343 (1.41)	0.055 (0.49)	0.107*** (3.67)
D	-0.191*** (−4.82)	-0.011 (−0.1)	0.005 (0.05)	0.044 (1.200)
ln(Distance)·D	0.51*** (5.41)	0.048 (0.28)	0.009 (0.07)	-0.031* (−1.72)
V	-0.234 (−0.67)	0.123 (0.74)	-4.314 (−0.54)	NA[e]
ln(Distance)·V	0.829** (1.97)	-0.241 (−0.99)	5.59 (0.6)	NA[e]
H_tower	0.007 (1.43)	0.001 (0.62)	0.001 (1.62)	0.001*** (3.06)
H_tower·V	-0.006 (−1.14)	0.001** (2.37)	-0.006 (−0.75)	NA[e]
Adj. R^2	0.715	0.722	0.714	0.605

Table 4 (continued)

	Sample 1[a] (0.00–0.72Km)	Sample 2[b] (0.72Km – 1.13Km)	Sample 3[c] (1.13Km – 1.88Km)	Sample 4[d] (1.88Km – 41Km)
AIC	4257	4308	4157	4685
Deg. of Freedom	5773	5774	5774	5773
Sample Size	5828	5827	5827	5827

The table above presents results of the Ordinary Least Square estimates

Zipcode parameter estimates are not reported to save space (available upon request). Ten, twelve, twelve and eight *Zipcode* dummy variables were dropped from the analysis of *Samples 1, 2, 3* and *4,* respectively, because there were not properties within these zipcode areas

Confidence intervals presented as ***99%, **95%, and *90%; t-values in parentheses;

[a] *Sample 1* is a subsample of properties selected within the first quartile of the minimum distance to the closest wireless tower (radius ≤ 0.72Km);

[b] *Sample 2* is a subsample of properties within the second quartile of the minimum distance to the closest wireless tower (0.72Km ≤ *distance* ≤ 1.13Km);

[c] *Sample 3* is a subsample of properties within the third quartile of the minimum distance to the closest wireless tower (1.13Km ≤ *distance* ≤ 1.88Km);

[d] *Sample 4* is a subsample of properties within the fourth quartile of the minimum distance to the closest wireless tower (1.88Km ≤ *distance* ≤ 41Km);

[e] Visibility variable was dropped from the analysis because there were not visible towers in Sample 4

significant, negative correlation between property price and sales occurring after tower construction. The same estimate is statistically equally to zero for those properties located within 0.72 and 1.88 km from the closest tower (Samples 2 and 3). For properties that are far from the visibility range of a tower (Sample 4 includes properties located beyond 1.88 km), the correlation between property price and tower becomes positive and statistically different from zero. *V*, the visibility of the tower, is not statistically significant across the four samples. However, $\ln(Distance)\cdot V$ is statistically significant at the 5% alpha level for properties that are located within 0.72 km from the closest tower (Sample 1). For these properties, we perform a log-likelihood ratio test for the joint significance of *V*, $\ln(Distance)\cdot V$ and $h\_tower\cdot V$, following the χ^2 distribution with three degrees of freedom equal to the number of restrictions (three estimates simultaneously equal to zero). We reject the null hypothesis that these three estimates are jointly equal to zero (*p*-value =0.071, 90% confidence). Hence, we must include these parameters to model the relationship between housing price and tower proximity for those properties that are closer to the wireless tower (Sample 1). However, the opposite is true for properties located beyond 0.72 km as we fail to reject the null hypothesis when applying the same test to these properties. In addition, the number of wireless towers per census tract (*Towers*) and tower height (*h_tower*) have no significant impact on housing price across the four samples (statistically and economically).

To assess the average social welfare impact of wireless tower proximity on residential property values, we estimate the predicted housing value from sales occurring before and after tower construction using Eq. (3). In Table 6, we report the predicted

Table 5 Spatial Autoregressive Models

	Sample 1[a] (0.03Km – 0.72Km)	Sample 2[b] (0.72Km – 1.13Km)	Sample 3[c] (1.13Km – 1.88Km)	Sample 4[d] (1.88Km – 41Km)
Constant	6.404*** (11.417)	4.315*** (8.984)	4.109*** (11.697)	5.304*** (10.467)
Age	-0.004*** (−11.15)	-0.005*** (−14.236)	-0.005*** (−14.209)	-0.007*** (−19.002)
Bedrooms	0.358 *** (7.728)	0.353*** (9.063)	0.068*** (6.221)	0.104*** (8.902)
Bedrooms^2	-0.044 *** (−6.522)	-0.036*** (−6.755)	-0.002*** (−4.066)	-0.003*** (−5.887)
Bathrooms	0.256*** (26.873)	0.216*** (25.703)	0.279*** (29.698)	0.241*** (24.491)
Onestory (0/1)	0.019 (1.111)	0.039** (2.38)	0.042*** (2.591)	0.133*** (6.847)
Twostories (0/1)	0.043*** (2.673)	0.077*** (4.884)	0.063*** (4.125)	0.155*** (8.296)
Car shelter (0/1)	0.129*** (13.573)	0.136*** (14.052)	0.142*** (15.426)	0.191*** (19.629)
Fireplace (0/1)	0.142*** (13.643)	0.134*** (12.346)	0.117*** (11.156)	0.152*** (15.428)
Fence (0/1)	0.067*** (6.958)	0.026*** (2.621)	0.04*** (4.164)	0.048*** (4.579)
Deck (0/1)	0.08*** (6.74)	0.059*** (5.035)	0.081*** (7.096)	0.084*** (6.965)
Pool (0/1)	0.04 (0.898)	0.039 (0.807)	0.003 (0.071)	0.089** (1.786)
Brick (0/1)	0.078*** (7.743)	0.076*** (7.249)	0.101*** (9.888)	0.085*** (7.262)
Rural (0/1)	-0.015 (−0.791)	-0.064*** (−2.908)	-0.042 (−1.598)	0.153*** (4.063)
ln(distCBD)	-0.218*** (−8.416)	-0.089*** (−3.274)	-0.108*** (−3.421)	-0.084 (−1.612)
Towers	0.002*** (2.666)	0.002** (2.157)	0.001 (0.313)	-0.001 (−0.583)
ln(Income)	0.09*** (3.557)	0.207*** (8.428)	0.274*** (10.083)	0.179*** (3.908)
ln(Black)	-0.04*** (−4.359)	-0.059*** (−6.655)	-0.041*** (−4.66)	-0.02** (−2.165)
Unemployment	-0.007*** (−5.249)	-0.003** (−2.204)	0.006*** (3.715)	0.001 (0.779)
Year 2008	0.078*** (4.552)	0.128*** (7.504)	0.114*** (6.589)	0.108*** (6.124)
Year 2009	0.015 (0.843)	0.007 (0.374)	0.031 (1.615)	0.024** (1.209)
Year 2010	-0.117*** (−5.581)	-0.095*** (−4.276)	-0.12*** (−5.934)	-0.071*** (−3.714)
Year 2011	-0.300*** (−14.474)	-0.304*** (−15.253)	-0.236*** (−11.639)	-0.189*** (−9.255)
Year 2012	-0.340*** (−16.871)	-0.306*** (−14.514)	-0.296*** (−13.986)	-0.228*** (−11.364)
Year 2013	-0.328*** (−16.461)	-0.331*** (−16.388)	-0.322*** (−16.132)	-0.257*** (−13.074)
ln(Distance)	-1.167*** (−3.025)	0.274 (1.232)	0.059 (0.593)	0.09*** (3.318)
D	-0.12*** (−3.35)	-0.007 (−0.066)	0.003 (0.031)	0.06* (1.773)
ln(Distance)·D	0.332*** (3.886)	0.043 (0.27)	0.007 (0.062)	-0.039** (−2.298)
V	-0.453 (−1.432)	0.118 (0.782)	-2.747 (−0.377)	NA[e]
ln(Distance)·V	0.872** (2.291)	-0.193 (−0.869)	3.533 (0.421)	NA[e]
H_tower	0.001 (0.151)	0.001 (0.436)	0.001 (1.414)	0.001* (1.934)
H_tower·V	0.001 (0.02)	0.001 (1.394)	-0.003 (−0.451)	NA[e]
ρ	0.362*** (31.59)	0.349*** (30.53)	0.352*** (32.61)	0.310*** (26.89)

Table 5 (continued)

	Sample 1[a] (0.03Km – 0.72Km)	Sample 2[b] (0.72Km – 1.13Km)	Sample 3[c] (1.13Km – 1.88Km)	Sample 4[d] (1.88Km – 41Km)
σ	0.314*** (33.137)	0.317*** (32.781)	0.311*** (33.286)	0.334*** (31.215)
AIC	3347	3457	3243	4022
Deg. of Freedom	5571	5572	5572	5571
Sample Size	5828	5827	5827	5827

The table above presents results of the maximum log-likelihood estimations of the spatial autoregressive models

Zipcode parameter estimates are not reported to save space (available upon request). Ten, twelve, twelve and eight *Zipcode* dummy variables were dropped from the analysis of *Samples 1, 2, 3* and *4,* respectively, because there were not properties within these zipcode areas

Confidence intervals presented as ***99%, **95%, and *90%; z-values in parentheses;

[a] *Sample 1* is a subsample of properties selected within the first quartile of the minimum distance to the closest wireless tower (radius ≤ 0.72Km);

[b] *Sample 2* is a subsample of properties within the second quartile of the minimum distance to the closest wireless tower (0.72Km ≤ *distance* ≤ 1.13Km);

[c] *Sample 3* is a subsample of properties within the third quartile of the minimum distance to the closest wireless tower (1.13Km ≤ *distance* ≤ 1.88Km);

[d] *Sample 4* is a subsample of properties within the fourth quartile of the minimum distance to the closest wireless tower (1.88Km ≤ *distance* ≤ 41Km);

[e] Visibility variable was dropped from the analysis because there were not visible towers in Sample 4

sales value and t-test results of the sale price means for home sales occurring before and after tower construction.

For properties located within a 0.72-km radius of a wireless tower that are sold after tower construction (Sample 1), it appears there is indeed a tower-related negative price effect. We estimate the social cost tower impact as approximately \$4132 (p-value =0.014), which corresponds to a *2.65% decrease* in property value. As expected, tower impacts are negligible for the stratum of housing units located beyond 0.72 km. Along the same line, we compute the impact of tower visibility for properties sold after tower construction as $E(exp(\mathbf{X\beta}|\mathbf{D} = 1;\mathbf{V} = 1)) - E(exp(\mathbf{X\beta}|\mathbf{D} = 1;\mathbf{V} = 0))$. Our calculations, summarized in Table 7, indicate a tower visible to properties within 0.72 km would effectively depreciate property values an average of 9.78%, equating to an average monetary loss of \$17,037 (p-value =0.00). The impact of tower visibility would be statistically equal to zero for those properties beyond the 0.72 km band. In addition, we use Eq. (4) to gauge the overall social welfare resulting from wireless towers. Computing the sum of the difference between the predicted housing price before and after tower construction across the sample, we find a staggering aggregate value loss of \$24.08[11] million dollars.

[11] This figure was calculated using equation (4). Let $\widehat{\boldsymbol{y}}_1$ be a column vector (5828 × 1) of predicted housing prices obtained by evaluating exp($\mathbf{X\beta}$) at the average values of all of the price predictors with D = 1 (sold after tower construction) and $\widehat{\boldsymbol{y}}_0$ the predicted housing prices counterpart with D = 0 (sold before tower construction). We define the change in welfare of each household i within Sample 1, as the element-by-element subtraction $\Delta W_i = \widehat{y}_{1i} - \widehat{y}_{0i}$. Finally, the aggregate welfare impact was obtained by taking the sum of the elements of the column vector $\Delta \boldsymbol{W}$, i.e., $\sum_{i=1}^{5,828} \Delta W_i = -24,081,385$.

Table 6 Social Welfare Analysis of Wireless Tower Impact on Home Values

	Expected Value		
	Before Tower	After Tower	Impact[a]
Sample 1[b]	155,911	151,779	-4132**
	(91,553)	(89,964)	(1681)
Sample 2[c]	161,865	164,068	2204
	(131,195)	(133,607)	(2453)
Sample 3[d]	162,249	163,485	1236
	(113,627)	(114,428)	(2113)
Sample 4[e]	159,752	161,770	2107
	(101,244)	(103,532)	(1897)

The table above presents the social welfare analysis of wireless tower impacts on home values

After tower = $exp.(X\beta)|D = 1$, *Before tower* = $exp.(X\beta)|D = 0$, *Impact* = $exp.(X\beta|D = 1) - exp.(X\beta|D = 0)$

**95% confidence interval; standard deviation in parentheses;

[a] standard error t-test in parentheses; t-test H_0: $E[exp(X\beta|D = 1)] = E[exp(X\beta|D = 0)]$;

[b] *Sample 1* is a subsample of properties selected within the first quartile of the minimum distance to the closest wireless tower (radius ≤ 0.72Km – sample size =5828);

[c] *Sample 2* is a subsample of properties within the second quartile of the minimum distance to the closest wireless tower (0.72Km ≤ *distance* ≤ 1.13Km – sample size =5827);

[d] *Sample 3* is a subsample of properties within the third quartile of the minimum distance to the closest wireless tower (1.13Km ≤ *distance* ≤ 1.88Km – sample size =5827);

[e] *Sample 4* is a subsample of properties within the fourth quartile of the minimum distance to the closest wireless tower (1.88Km ≤ *distance* ≤ 41Km – sample size =5827)

Because we find no evidence that towers impact prices of properties located beyond 0.72 km of a tower, we focus our analysis on the price sensitivity of homebuyers of properties located within 0.72 km of a tower. Earlier, we mention one of the main strengths of a spatial econometric analysis is it enables disentanglement of the direct and indirect effects of tower proximity on property values. This is because of a spatially correlated dependent variable—that the change in price of house i with respect to the distance to the closest tower of the neighbor's house j within the same sample is not zero (i.e. $\partial \ln(Price)_i / \partial \ln(Distance)_j \neq 0$ with $i \neq j$).

LeSage and Pace (2009) derive:

$$\left\{ \begin{array}{lcl} Average\ \ Direct\ \ Impact & = & n^{-1}\ tr\left[(\boldsymbol{I}-\rho\mathbf{W})^{-1}\boldsymbol{I}\beta_{\mathrm{k}}\right] \\ Average\ Indirect\ Impact & = & n^{-1}\left\{1_n'\left[(\boldsymbol{I}-\rho\mathbf{W})^{-1}\boldsymbol{I}\beta_{\mathrm{k}}\right]1_{\mathrm{n}}-tr\left[(\boldsymbol{I}-\rho\mathbf{W})^{-1}\boldsymbol{I}\beta_{\mathrm{k}}\right]\right\} \\ Average\ \ Total\ \ Impact & = & n^{-1}\ 1_n'\ \left[(\boldsymbol{I}-\rho\mathbf{W})^{-1}\boldsymbol{I}\beta_{\mathrm{k}}\right]\ 1_{\mathrm{n}} \end{array} \right\} \tag{11}$$

for each predictor β_k with k = 1,2,..K. Therefore, we use Eq. (11) to decompose and calculate the average total impact of the wireless tower on property values within Sample 1 as reported in Table 8.

Table 7 Social Welfare Analysis of Wireless Tower Visibility on Home Values

	Expected Value		
	Non-visible Tower	Visible Tower	Impact[a]
Sample 1[b]	174,194	157,157	-17,037***
	(104,007)	(92,447)	(1823)
Sample 2[c]	161,120	164,370	3251
	(132,276)	(133,740)	(2464)
Sample 3[d]	163,113	163,335	222
	(114,055)	(114,297)	(2115)
Sample 4[e]	157,454	NA[f]	NA[f]
	(99,875)	(NA)[f]	(NA)[f]

The table above presents the social welfare analysis of the visibility impact of wireless tower on home values (after tower construction — $D = 1$)

Visible tower = $exp.(X\beta|D = 1;V = 1)$, *Non-visible tower* = $exp.(X\beta|D = 1;V = 0)$, *Impact* = $exp.(X\beta|D = 1;V = 1) - exp.(X\beta|D = 1;V = 0)$;

Confidence intervals presented as ***99%; standard deviation in parentheses;

[a] standard error t-test in parentheses; t-test H_0: $E[exp(X\beta|D = 1;V = 1)] = E[exp(X\beta|D = 1;V = 0)]$;

[b] *Sample 1* is a subsample of properties selected within the first quartile of the minimum distance to the closest wireless tower (radius ≤ 0.72Km – sample size =5828);

[c] *Sample 2* is a subsample of properties within the second quartile of the minimum distance to the closest wireless tower (0.72Km ≤ *distance* ≤ 1.13Km – sample size =5827);

[d] *Sample 3* is a subsample of properties within the third quartile of the minimum distance to the closest wireless tower (1.13Km ≤ *distance* ≤ 1.88Km – sample size =5827);

[e] *Sample 4* is a subsample of properties within the fourth quartile of the minimum distance to the closest wireless tower (1.88Km ≤ *distance* ≤ 41Km – sample size =5827);

[f] Visibility variable was dropped from the analysis because there were not visible towers in *Sample 4*

We then use Eq. (5) to assess the price sensitivity of buyers with respect to the distance to the closest visible and non-visible towers after their construction. It appears that if the tower is not visible, the property price decreases 8.7% for every 10% increase in distance to the closest tower. The spillover effect on property price due to the depreciation of the neighbor's property—the average indirect effect—is 4.41% of price decrease for every 10% increase in the distance to the closest tower. The total

Table 8 Decomposition of the Price Sensitivity of Home Buyers to Tower Proximity

	Average Direct Impact	Average Indirect Impact	Average Total Impact
ln(*Distance*)	-1.213	-0.616	-1.828
ln(*Distance*)·*D*	0.345	0.175	0.520
ln(*Distance*)·*V*	0.906	0.460	1.367

The table above presents the results of the sensitivity analysis designed to compare the price sensitivity of buyers of properties from which the closest tower is not visible

Average Direct Impact = $\partial \ln(\text{Price})_i / \partial \ln(\text{Distance})_i$, *Average Indirect Impact* = $\partial \ln(\text{Price})_i / \partial \ln(\text{Distance})_j$ with $i \neq j$, *Average Total Impact* = Average Direct Impact + Average Indirect Impact depreciation is 13% for 10% increase in the distance. Therefore, it may well be that non-visible towers are a potential external benefit for properties located within 0.72 km of a tower. Although we cannot affirmatively explain this finding, our sense is it may be due to enhanced wireless coverage resulting in a stronger wireless signal.

It is noteworthy that only 69 of 5828 properties within 0.72 km of the closest tower are outside of the visibility range of a tower. In contrast, however, the 5759 homebuyers purchasing properties within 0.72 km of the closest tower that are within visible range of a tower are not particularly sensitive, on average, to the distance to the visible tower, despite their perceptions of a visible tower as a negative externality. In fact, housing prices appreciate approximately 0.4% for each 10% increase in the distance to the closest visible tower. The average indirect impact of towers on those buyers (price spillover due to neighbor's price movement) is approximately 0.2%. This is to say that buyers of properties located an average of 0.497 km (average minimum distance in Sample 1) to the closest tower are willing to pay a premium of approximately 0.6% of the average housing price for every 10% increase in the average distance from a tower (average total impact). Monetarily, this translates into a value of approximately $962 per 50 linear meters[12] of increase in distance from the closest tower.

One limitation of our study is that we cannot control for potential endogeneity associated with the sale date dummy variable (*D*). Even though homeowners could choose to buy or not to buy a property after tower construction, we have no information as to their motivations for buying. Ideally, a difference-in-differences study restricted to repeat sales of the same property occurring pre- and post-tower construction could potentially mitigate this source of bias. Unfortunately, within the entire sample of 23,309 housing sales there are only 42 repeat sales. A difference-in-differences approach based on a sample of 42 observations would clearly suffer from a micronumerosity problem with negative degrees of freedom (the number of parameters would exceed the sample size), and would, therefore, lack empirical viability.

Notwithstanding the slight potential for bias, our results are clear: consumers perceive visible wireless towers as economic externalities. Aggregate social costs are highly significant relative to those properties within a 0.72 Km radius of a tower. Additionally, we must also point out that our study does not assess intangible social benefits of wireless towers, such as high-speed internet access, emergency communications, and digital forensics enabling national security related wireless communication monitoring, all of which provide invaluable services to consumers, businesses, and institutions.

Conclusion

Truly, we currently live in the Age of Information. According to the International Communication Union of the United Nations, the number of wireless phone subscriptions totaled over 7 billion worldwide in 2015, with wireless coverage extending to 95% of the world's population (United Nations, International Communication Union 2015). U.S. wireless usage is no less astounding, as evidenced by the 1045% increase in

[12] We calculate a 10% increase in the average minimum distance for houses in *Sample 1* as 0.49 km · 0.1 ≈ 50 m. A 0.59% increase in the average housing price of *Sample 1* is $163,008.8 · 0.0059 ≈ $ 961.80.

wireless devise demand over the last 20 years (CTIA 2015). The future looks promising as well, with expectations that U.S. wireless industry employment will increase more than 31% from 2012 to 2017 (Pearce et al. 2013). Yet, even with the wireless industry poised for continued growth, it is unlikely it will be without consequences. Certainly, there are private benefits associated with the use of wireless service, yet there are costs as well. In this study, we examine one such cost: the impact of wireless towers on home values.

Although previous researchers have examined this issue, our study differs in two aspects. First, we address the econometric problem of spatial dependence that typically flaws hedonic price estimation analysis. We contend our empirical analyses are more efficient than those used in other studies, and as result, our results reveal greater consistency and reliability. Second, rather than rely solely on neighborhood-based property sales data, we test our hypothesis using recent property sales and current wireless tower locational data for an entire metropolitan statistical area,[13] which also happens to be one of the busiest port cities in the United States.[14]

The results of a series of spatial statistical tests developed by Anselin et al. (1996) suggest that a spatial autoregressive model is the most appropriate econometric approach to test our research hypothesis. We conduct a marginal sensitivity analysis for homes within different radii of distances to the closest visible and non-visible wireless towers, basing the distance bands on quartiles of the distance to the wireless tower. Our results reveal wireless tower capitalization only in the value of those properties that are within approximately 0.72 km of a tower. On average, the potential external cost of a wireless tower is approximately \$4132 per residential property, which corresponds to a negative price effect of 2.65%. The negative price impact of 9.78% is much more severe for properties within visible range of a tower compared to those not within visible range of a tower. This negative impact vanishes as radii distances exceed 0.72 km. In aggregate, the social welfare cost for the properties in our sample located within 0.72 km amounts to an approximate loss of \$24.08 million dollars of value.

U.S. federal law prohibits wireless siting denial if no alternative site is available (FCC 1996; Martin 1997). However, given the apparent social costs associated with negative price effects, local zoning and regulatory authorities should consider granting approvals that include impact-minimizing conditions. For example, wireless tower construction approvals could require development and maintenance of visual or vegetative buffer screening. Concurrently or alternatively, approvals could mandate camouflaging towers to look like trees or flagpoles. Other types of approval conditions could dictate attachment of communication antennae systems to existing structures such as buildings, street light poles, electric utility poles, water towers, billboards, or even sports stadium super-structures. Clearly, society is dependent on wireless communication, and obfuscating efforts to expand or improve coverage makes little sense. Arguably, however, authorities overseeing the process have definitive obligations, perhaps even fiduciary ones, to safeguard the interests and well-being of those whom they serve.

[13] The U.S. Census Bureau list of metropolitan statistical areas ranks Mobile County, Alabama at number 127. Data available at http://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk.

[14] The Port of Mobile is home to the twelfth busiest port in the U.S., and ninth busiest port along the Gulf Coast, ranked by cargo tonnage handled as reported by the U.S. Department of Transportation, available at http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/national_transportation_statistics/html/table_01_57.html.

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