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April 18, 2022

Kentucky Public Service Commission
Executive Director
211 Sower Boulevard, P.O. Box 615
Frankfort, Kentucky 40602
Re: Docket #2021-00398

To Whom It May Concern,

We, the Nicolais, continue to appreciate the consideration of the Kentucky Public Service Commission in all matters regarding Docket #2021-00398.

This case has been, and will continue to be, solely a matter of property value. We will lose property value if the proposed communications compound is erected.

We did not, and do not, assert this fact. Our knowledge is built on peer-reviewed studies from scholars within the Western Kentucky University, the University of South Alabama, and the University of Kentucky. All studies we have submitted prove an expectation of loss, in our property value, is justified.

These studies included sample sizes that were orders of magnitude larger than the real estate study that Pike Legal has introduced. One of the studies we referenced even evaluated properties from the same metropolitan statistical area as the evidence provided by Pike Legal/Glen D. Katz; Louisville. Our referenced studies, unlike the one provided by Mr. Katz, acknowledge rural localities as a uniquely weighted variable when considering impacts on value. Mr. Katz and, by extension, Pike legal seem to think that you can force the round peg of Louisville suburbia into the square hole of rural Kentucky. Further, the authors of the studies we presented considered a swath of interconnected variables other than, solely, raw real estate appreciation.

We find it alarming that anyone, as evidenced in the submitted real estate report from Pike Legal, would dismiss an impact on property value by citing general appreciation. These are two distinct phenomena capable of occurring at the same time. Indeed, the more our property appreciates the more this communications facility will cost us in *actual dollars*. Market appreciation does not disprove or deny any depreciation caused by specific factors. It is disingenuous to argue otherwise.

We have yet to hear anyone dismiss the studies we have cited by arguing contrary results. The evidence we have presented has been clear, forthright, and substantial. Our property value will decrease. We have proven this; in no way has it been disproven. We will be the exclusive recipients of the negative effects of this facility.

Pike Legal has argued against the use of these studies on the basis of submission technicalities. We cited particular studies and provided their publicly available locations. We have provided the PSC with any particular opinions from the study authors in their full context.

To the best of our knowledge, no case where intervention was granted, on the basis of property value, has submitted the substantial forms of evidence that we have provided. It is, therefore, unreasonable for Pike Legal to argue that Equal Protection is violated in any way should this CPCN application be denied.

We recognize the purview of the PSC, and its consideration of property value, as stated in KRS 278.650. It is because of the proven expectation of loss that we continue to ask the PSC to deny this CPCN.

Roger & Janelle Nicolai

Please review the documents included in the email containing this letter:

1. *Wireless Towers and Home Values: An Alternative Valuation Approach Using a Spatial Econometric Analysis* (Study #1)

2. *The Cost of Convenience: Estimating the Impact of Communication Antennas on Residential Property Values* (Study #2)

3. Emails from **Reid Cummings** & **Ermanno Affuso**. Authors of Study #1.

J. Reid Cummings, D.B.A.

Interim Assistant Dean for Financial Affairs

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4. Email **Stephen L. Locke**. Author of Study #2.

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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.

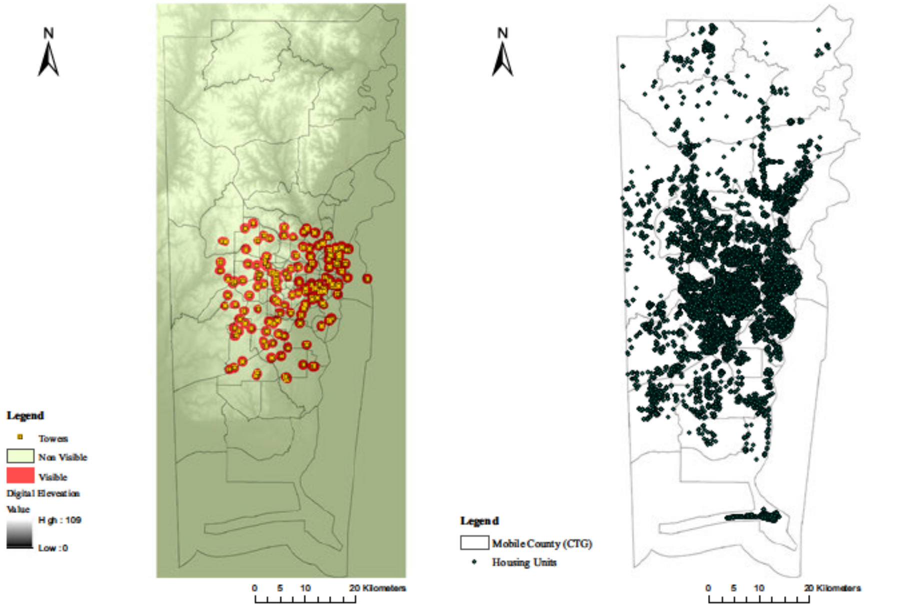
[5] These data draw from the U.S. Federal Communication Commission's Antenna Structure Registration database, available at http://wireless.fcc.gov/antenna/index.htm?job home.

[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

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

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

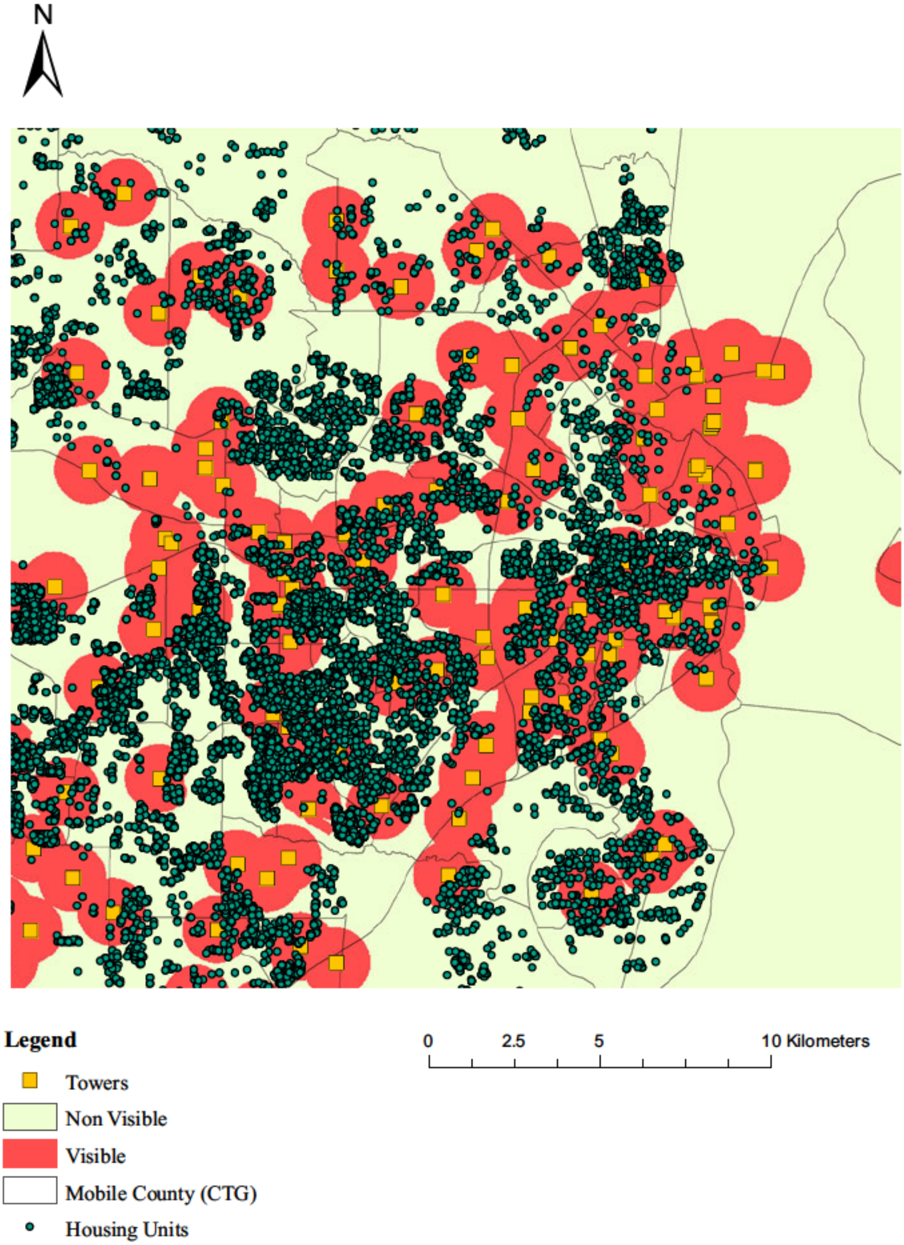


Fig. 2 Visibility Analysis: larger scale

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:

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

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:

$$\frac{\partial ln(Price)}{\partial ln(Distance)}=[\beta_1+\beta_3D+\beta_5V]\%. \tag{5}$$

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 $n \times 1$ 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 $n \times 63$ (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 $n \times 1$ 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:

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

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

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*)·*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*)·*V* and *h tower*·*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 construc tion). We define the change in welfare of each household i within Sample 1, as the element by element subtraction $\Delta W_i \quad \widehat{y}_{1i} \quad \widehat{y}_{0i}$. Finally, the aggregate welfare impact was obtained by taking the sum of the elements of the column vector $\Delta \boldsymbol{W}$, i.e., $\sum_{i\ \ 1}^{5,828} \Delta W_i \quad -24,081,385$.

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

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

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

[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:

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

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 $\leq$ 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 $\leq$ *distance* $\leq$ 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 $\leq$ *distance* $\leq$ 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 $\leq$ *distance* $\leq$ 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 $\cdot$ 0.1 $\approx$ 50 m. A 0.59% increase in the average housing price of *Sample 1* is \$163,008.8 $\cdot$ 0.0059 $\approx$ \$ 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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The Cost of Convenience: Estimating the Impact of Communication Antennas on Residential Property Values

Stephen L. Locke and Glenn C. Blomquist

ABSTRACT. *This paper applies hedonic and quasi-experimental methods to measure the disamenity value of communication antennas. We take advantage of a rich dataset of residential housing sales from central Kentucky that contains an extensive set of structural housing characteristics and precise location information. This allows us to overcome endogeneity issues caused by unobservable characteristics correlated with antenna location. The best estimate of the impact is that a property with a visible antenna located 1,000 feet away sells for 1.82% ($3,342) less than a similar property located 4,500 feet away. The aggregate impact is $10.0 million for properties located within 1,000 feet.* (JEL Q51, R21)

I. INTRODUCTION

Accompanying the desirable growth of cell phone and wireless Internet usage has been the not-so-desirable appearance of communication antennas. Cell phone usage worldwide, and especially in the United States, has grown fast. According to the Cellular Telephone Industries Association, in December of 1998 there were 69.2 million wireless subscribers. Fifteen years later, in December 2013, that number was 335.7 million.[1] To put this in perspective, the U.S. Census Bureau estimated the population to be 270.2 million in 1998 and 316.5 million in 2013. The United States has gone from 25.6% of the population having a wireless subscription in 1998 to more than one subscription per person in 2013. With the advances in mobile technology it is possible to do nearly every task that was once only possible on a desktop computer on a mobile device that fits in the palm of a hand. Like any other good or service, the added convenience of mobile technology has costs.

Economists have long been interested in estimating impacts of disamenities in urban areas. For examples see Mieszkowski and Saper (1978) on airport noise, Kohlhase (1991) on toxic waste sites, and Kiel and Williams (2007) on Superfund sites. An area that has received little attention is the disamenity associated with cell phone towers and communication antennas. As the demand for cell phones and mobile technology increases, it is followed by an increase in demand for reliable coverage, which in turn leads to an increase in the number of antennas. In the mid-1990s there was a sharp increase in the number of antenna structures to accompany the mobile phone technology that was becoming more prevalent. Choosing the location for an antenna involves conflicting incentives for residents. Land owners may want to have an antenna located on their property because it provides an additional source of income and better cell phone reception for residents in its vicinity.[2] However, these structures are visually unpleasant. Residents tend to object to having them located nearby because of the visual disamenity they create or because of adverse health effects they may associate with

[1] Visit http://www.ctia.org/ for more information about the growth of cellular subscriptions in the United States.

[2] Airwave Management, LLC, provides some insight into the amount of income these cell phone towers can generate for a land owner. According to their website, payments can reach as high as $60,000 per year (www.cell-tower-leases.com/Cell-Tower-Lease-Rates.html).

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the antennas.[3] Towers are often highly visible, and potential siting can induce objections from residents in the receiving neighborhood. Municipalities have used delays in the approval process in an attempt to appease protestors and possibly prevent siting.[4] Unlike some disamenities such as airport noise, information about the visual disamenity is available.[5]

Figure 1 illustrates when an externality is likely to exist, and the situation when a nearby antenna could provide a net benefit to nearby residents. In the upper photo, an antenna is located on a property adjacent to a residential subdivision. Regardless of any compensation, the antenna structure is likely to be considered a disamenity by nearby residents.[6] The lower photo shows an antenna that could provide a net benefit to nearby residents. The structure located at point A is hidden behind a thicket of trees and far enough away from the nearest neighbor (point C) so as not to impose any cost. If the owner of the property at point B owns the land where the antenna is located, the owner is receiving payments from the antenna's owner, while nearby residents receive the benefit of improved coverage. In this situation the potential disamenity is mitigated by trees. Having an antenna located nearby should not decrease property values; it probably increases property values where the antennas are located.

The purpose of this paper is to apply hedonic and quasi-experimental methods to measure any disamenity caused by communication antennas, controlling for endogenous antenna location and changes in unobserved housing and neighborhood characteristics. Spatial fixed effects are used to control for any time-invariant unobservables correlated with proximity to an antenna. The repeat sales method and quasi-experimental techniques are used to address time-invariant and time-varying unobserved characteristics that could affect the equilibrium hedonic price function. Quasi-experimental techniques are becoming increasingly common in the environmental economics literature and are used instead of instrumental variables when there is not random assignment into treatment and control groups (Greenstone and Gayer 2009).

II. RECENT WORK ON VALUING AMENITIES/DISAMENITIES

Omitted variables are a concern when estimating hedonic price functions. Following Rosen (1974), the hedonic price function of property i can be represented by $P_i = P(S_i, N_i, Q_i)$, where P_i is the price of property i. S_i, N_i, and Q_i are the structural, neighborhood, and environmental characteristics, respectively. Consumers have utility $U = U(X, S_i, N_i, Q_i)$, which is maximized subject to the budget constraint $P_i + X = M$, where X is a Hicksian composite commodity with price equal to \$1, and M is income. This gives the following first-order condition:

$$\left(\frac{\partial U}{\partial Q_i}\right) \Big/ \left(\frac{\partial U}{\partial X}\right) = \frac{\partial P_i}{\partial Q}. \qquad [1]$$

The marginal rate of substitution between the environmental characteristic and the composite good X is equal to the slope of the hedonic price function (market clearing locus) in the environmental characteristic Q_i. Once the hedonic price function P_i has been estimated,

[3] Despite concerns about negative health effects from the radio waves emitted from mobile devices, a comprehensive study of the health effects related to cell phone and cell phone antennas by Röösli et al. (2010) finds that there is no conclusive evidence that using cell phones or living near cell phone towers harms human health. Nevertheless, the perception of such risks may be sufficient to alter behavior.

[4] See City of Arlington, Texas *v.* Federal Communications Commission, 133 S. Ct. 1863.

[5] A recent article by Alcantara (2012), with AOL Real Estate, highlights the concerns residents have about having a communication antenna located near their property. As reported, a group of residents in Mesa, Arizona, is protesting the siting of a cell phone tower in the group's neighborhood. One resident is quoted as saying, "Apart from the tower being so tall, we all feel that property values will go down if they build it so close. Most people I know wouldn't want to buy a house near a cell phone tower."

[6] If the structure was constructed *before* the residents moved in or built a house in this subdivision, no uncompensated externality exists. They have preferences such that the structure does not affect them, or they were compensated for the visual aspect of the structure though a lower purchase price. However, if the structure was constructed *after* the residents moved in or built in this subdivision, they are affected by the sight of the structure and a lower sales price if they do decide to sell the property. The land owner where the structure is located is receiving payments from the antenna's owner, while all affected nearby residents are not being compensated.

FIGURE 1

Houses Likely Affected *(upper photo)* and Houses Likely Not Affected *(lower photo)* by Nearby Antenna

Source: Google Earth 2014, 2015.

the partial derivative of P_i with respect to the environmental characteristic Q_i is equal to the implicit price of the environmental characteristic. However, when there are characteristics unavoidably omitted from P_i that are correlated with Q_i, the estimate of willingness to pay for Q_i will be biased. Endogeneity in the location of the antenna structures is the greatest concern in estimation. Holding all else constant, owners of the antenna structures are going to locate them in areas where it costs the least. If not taken into account, this incentive will lead to an overestimate of the negative impact these structures have on property values. Other issues that have to be addressed in estimation concern buyers' sorting (Cameron and McConnaha 2006; Bayer, Keohane, and Timmins 2009; Bieri, Kuminoff, and Pope 2012; Kuminoff, Smith, and Timmins 2013) and the stability of the hedonic price function (Kuminoff and Pope 2014; Haninger, Ma, and Timmins 2014). To address the sorting concern, spatial fixed effects are included to control for unobservables that may influence both buyers' location choices and the location of communication antennas. The most recent panel data techniques that address both time-invariant and time-varying unobservables are used to account for the possibility of a changing hedonic price function after the construction of a nearby antenna.

While Rosen (1974) shows that the partial derivative of P_i with respect to Q_i provides an estimate of the willingness to pay for a small change in the environmental good Q_i, the appropriate functional form for the hedonic price function is uncertain. Cropper, Deck, and McConnell (1988) use simulations to determine how different functional forms perform when there are omitted variables in the hedonic price regression. They find that flexible functional forms perform well when all of the attributes are included, but recommend using a more parsimonious functional form when there are omitted variables. Since Cropper, Deck, and McConnell's (1988) work, sample sizes have increased dramatically, advances in geographical information systems allow researchers to control for previously unobserved spatial characteristics, unobserved structural housing characteristics are much less of a concern, and quasi-experimental techniques have become more prevalent. Kuminoff, Parmeter, and Pope (2010) find that Cropper, Deck, and McConnell's (1988) recommendations should be reconsidered. When using cross-section data, Kuminoff, Parmeter, and Pope (2010) find that the quadratic Box-Cox functional form with spatial fixed effects performs best. However, for practical purposes, including spatial fixed effects significantly reduces bias regardless of the functional form used.[7]

Kuminoff, Parmeter, and Pope (2010) also show that exploiting variation in an environmental amenity for properties that sell multiple times can reduce bias in willingness-to-pay estimates compared to pooled ordinary least squares with fixed effects. If the spatially correlated unobservables are time invariant, their effect will be purged from the model when first differences are taken. However, if the unobservables are not time invariant, the estimates from a repeat sales model will be biased. Repeat sales models have recently been used to estimate the impact of changing cancer risks (Gayer, Hamilton, and Viscusi 2002), the siting of wind farms (Heintzelman and Tuttle 2012), Superfund site remediation (Mastromonaco 2014), and reductions in three of the U.S. Environmental Protection Agency's criteria air pollutants (Bajari et al. 2012).

While there are advantages of using the repeat sales method and quasi-experimental techniques to eliminate the bias caused by time-invariant unobservables, these methods estimate a capitalization rate that is not necessarily equal to the marginal willingness to pay. It is possible that the presence of, or change in, an environmental (dis)amenity can cause the hedonic price function to change over time. Kuminoff and Pope (2014) and Haninger, Ma, and Timmins (2014) show that as long as the hedonic price function is constant over time, there should be no difference between the capitalization rate and the marginal willingness to pay. Given that the communication antennas are expected to have relatively small impacts on property values, it is unlikely that the construction of a new antenna structure will lead to a change in the hedonic price function. But, this issue will be addressed.

Kuminoff, Parmeter, and Pope (2010) find that a generalized difference-in-differences estimator with interactions between the time-dummy variables and housing characteristics to allow the shape of the price function to change over time performs best when panel data are available. Linden and Rockoff (2008) provide a technique for defining treatment and control groups so that difference-in-differences can be used to estimate the impact of environmental (dis)amenities when treatment and control groups are not clearly defined. Their technique has recently been used to estimate the impact of brownfield remediation (Haninger, Ma, and Timmins 2014) and shale gas developments (Muehlenbachs, Spiller,

[7] Since the quadratic Box-Cox is still computationally intensive and the coefficients are difficult to interpret, semilog and linear Box-Cox models are commonly used.

and Timmins 2014).[8] Parmeter and Pope (2013) provide a thorough overview of the difference-in-differences method and other quasi-experimental techniques. By differencing over time, the difference-in-differences method controls for time-invariant unobservables, just like the fixed effects and repeat sales methods, but also overcomes problems with time-varying unobservables with the "common trends" assumption.[9]

Mastromonaco (2014) and Bajari et al. (2012) both propose methods for reducing bias caused by time-varying spatially correlated unobservables. Mastromonaco (2014) includes census tract–year fixed effects that allow the effect of unobservables at the neighborhood level to vary over time in a repeat sales model. Bajari et al. (2012) also use a repeat sales model but exploit information contained in the residual from the first sale to learn about the characteristics of the house that the researcher cannot observe directly. In contrast, the data used in this study have house characteristics at the time of each sale and allow for control of time-varying housing characteristics that are typically unobservable. In this study the results below show that the unobservables at the neighborhood level that are correlated with proximity to a communication antenna are time invariant and are adequately controlled for using spatial fixed effects.

III. DATA ON HOUSING AND ANTENNAS

Housing data covering a period of 12 years from 2000 to 2011 were extracted from two multiple listing services that serve the Louisville and Elizabethtown areas in central Kentucky.[10] The housing data contain an extensive set of structural housing characteristics, closing date, and sales price for every property sold. All property addresses were geocoded, and a standardized address and latitude and longitude were assigned to each property.[11] This standardized address is used to identify houses that are sold multiple times.

These data are much richer than data extracted from a local property valuation administrator or data from DataQuick that are commonly used. While data from each of those sources identify properties that are sold more than once, the structural housing characteristics are recorded only for the most recent transaction. The data used here identify properties that are sold more than once during the sample period and record the structural housing characteristics each time the property is sold. This detail allows for a check of the assumption that structural housing characteristics are constant over time, an assumption that is often made when using the repeat sales method.

Data for the communication antennas come from the Federal Communication Commission's (FCC) Antenna Structure Registration database.[12] This database includes all communication antennas in the United States that are registered with the FCC. All antennas that may interfere with air traffic must be registered with the FCC to make sure the lighting and painting requirements are met. These data contain antenna characteristics such as dates of construction and demolition, latitude and longitude, antenna height, and antenna type. It is possible there are antennas located in the study area that are not registered, but this is

[8] Muehlenbachs, Spiller, and Timmins (2014) use a difference-in-difference-in-differences model. They use the Linden and Rockoff (2008) technique to find the distance at which shale gas developments do not impact property values, but also use the local public water service area to define a second treatment group. Similar to owners of land where shale gas wells are drilled, owners of land where communication antennas are located receive payments from the antenna's owner.

[9] In this study, a majority of communication antennas were built several years before the property was sold, making a visual check of the "common trends" assumption difficult.

[10] Please contact the author regarding any questions about the multiple listing service data.

[11] One issue with geocoding addresses is that the coordinates will correspond to the location on the street where the property is located and not the exact coordinates of the actual house; Filippova and Rehm (2011) were able to overcome this using the coordinates where the home was located within the plot. In the current study, properties that were not assigned a standardized address and a unique latitude and longitude were excluded from the final sample. Properties with less than 500 square feet or more than 10,000 square feet, or zero bedrooms or zero full baths were also dropped.

[12] Antenna Structure Registration database available at http://wireless.fcc.gov/antenna/index.htm?job = uls_transaction&page = weekly.

rare. Since the construction date of each antenna needs to be known to ensure the antennas located near houses were standing when the properties sold, antennas that did not include a construction date were dropped.[13] Google Earth[14] was used to verify whether not an antenna was standing when the property sold if there was a dismantled date recorded. Since the images include the date the image was captured, it was possible to identify whether the antenna was standing when the property sold.[15]

ArcGIS[16] was used to determine several location-specific characteristics. They include (1) the census tract in which each house is located, (2) the census block group in which each house is located, (3) distance to the nearest communication antenna, (4) distance to the nearest parkway/interstate, (5) distance to the nearest railroad, and (6) distance to the Fort Knox military base. Since the visual disamenity of communication antennas is the focus of this study, all proximity measures were calculated using straight-line distances. All antennas within a 10-mile radius of each property that were standing when the property was sold were identified. This information was used to determine the number of antennas located within specified distances from each property. In addition, using the Viewshed tool in ArcGIS, a variable was created that is distance to the nearest visible communication antenna for each house in the sample. This variable facilitates isolation of the impact of visual pollution (see Paterson and Boyle 2002; Jensen, Panduro, and Lundhede 2014). This variable is used along with (unconditional) distance for comparison.

Averages or shares for the housing characteristics are given in Table 1. The typical house sold for $183,609 (in 2011 dollars), has three bedrooms and two full bathrooms, is 1,655 square feet in size, has a lot size of about eight-tenths of an acre, and is 33 years old. 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. To check if antennas are located in areas where property values are low to begin with, Table 1 also shows averages for houses within and beyond 4,500 feet of an antenna.[17] Houses within 4,500 feet of an antenna sell for $32,991 (16%) less than houses more than 4,500 feet away, have slightly fewer bedrooms and bathrooms, are smaller, and are on smaller lots. The most notable difference is that houses within 4,500 feet of an antenna are about 18 years older on average than houses more than 4,500 feet away from an antenna. The differences in means between houses within and beyond 4,500 feet are statistically different from zero at usual levels for all characteristics except for Within 1 Mile Ft. Knox. It appears that communication antennas are in fact located in areas where properties are less valuable. While most of the difference in sales prices for houses within and beyond 4,500 feet of an antenna can be explained by differences in the types of houses, the primary focus of this study is controlling for differences that are unobservable. The precise location information for each house provided in the data is used to control for these unobservables.[18]

For the full sample of houses, the median distance to the nearest visible antenna when a house is sold is 4,459 feet, or approximately 0.84 miles. The mean distance is 5,959 feet (1.3 miles) with a standard deviation of 5,334

[13] Since the earliest construction year in the sample of antennas is 1927 and the latest 2011, it cannot be assumed that the absence of a construction date means the antennas with missing dates were built before the year 2000 and can be included in the final sample.

[14] See www.google.com/earth/ for access to images.

[15] This was a concern for only a handful of antennas. Multiple antennas were assigned the same coordinates, and it was determined that this corresponded to multiple antennas being mounted on the same structure. Some demolition dates indicated that an antenna was removed, and some demolition dates indicated that the actual structure was taken down. Being dismantled refers to the latter.

[16] See www.esri.com/software/arcgis.

[17] 4,500 feet is approximately the median value of distance to the nearest standing antenna in this sample. Distance in thousands of feet is used in the analysis that follows.

[18] A regression of the number of communication antennas in a census tract on the median sales price and census tract demographics suggests that the number of antennas in a census tract is negatively correlated with property values. However, even though the coefficient has the expected sign, the coefficient is not statistically different from zero at conventional levels, and the median sales price and demographics explain only 8% of the variation in the number of communication antennas in a census tract.

TABLE 1
Mean or Share for Structural Housing Characteristics

Variables	All	Less than 4,500 ft	Greater than 4,500 ft
Sales price (2011 dollars)	183,609	167,235	200,226
Bedrooms	3.241	3.161	3.323
Full bathrooms	1.811	1.687	1.937
Partial bathrooms	0.368	0.346	0.39
Square feet of living space	1,655	1,573	1,739
Lot size (acres)	0.82	0.383	1.263
Lot size missing	0.046	0.044	0.049
Has < in lot dimensions[a]	0.127	0.149	0.105
Has > in lot dimensions[a]	0.003	0.003	0.004
Age (years)	33.153	42.078	24.096
Age unknown	0.01	0.006	0.014
Fireplace	0.479	0.474	0.484
Basement	0.602	0.613	0.59
Finished basement	0.175	0.153	0.197
Central air	0.909	0.898	0.921
Brick exterior	0.346	0.322	0.37
Vinyl exterior	0.162	0.157	0.168
Metal roof	0.01	0.006	0.013
Composition roof	0.94	0.944	0.935
Ranch style	0.447	0.409	0.485
Modular style	0.014	0.004	0.024
Cape cod style	0.084	0.102	0.066
Carport	0.057	0.066	0.049
Garage	0.663	0.657	0.668
One-car garage	0.169	0.209	0.128
Multiple-car garage	0.563	0.494	0.632
Within 1 mile parkway/Interstate	0.485	0.629	0.338
Within 1 mile railroad	0.511	0.569	0.452
Within 1 mile Ft. Knox	0.014	0.014	0.014
Sample size	142,161	71,604	70,557

[a] The lot dimensions indicated the lot size was less (greater) than the listed size.

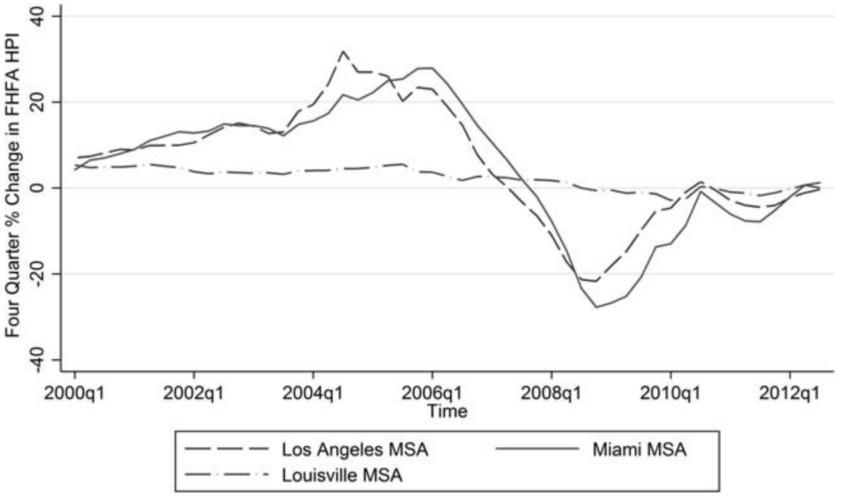
feet. Only 0.4% of houses are within 500 feet of the nearest visible antenna, while 9.5% of the houses in the sample have a visible antenna within 2,000 feet. Some houses are likely affected by the presence of multiple antennas. For example, there are 108 houses that have two visible antennas between 500 and 1,000 feet and 6 that have three antennas within that same radius. This variation in antenna density means that estimating the disamentity value caused by communication antennas using distance to the nearest antenna could be biased due to the presence of multiple antennas. Estimates would tend to be biased upward, because all the value of the disamenity would be attributed to the nearest antenna when it should be attributed to the combination of antennas.

Before moving to estimation of any disamenity value of antennas, it is worth addressing an overall concern about housing market analysis during the Great Recession. The concern is how an equilibrium framework such as that described by Rosen (1974) can produce misleading results during a period of disruption.[19] Without question, housing prices declined between 2006 and 2009, but as Carson and Dastrup (2013) report, there was considerable spatial variation. Across metropolitan areas, housing prices declined none at all to more than 60%. The four-quarter percentage change in the Federal Housing Finance Agency's housing price index[20] is shown in Figure 2 for the study area and the Los Angeles and Miami metropolitan statistical areas (MSAs). Even though the Louisville MSA was affected by the recent housing crisis,

[19] This issue is discussed in detail by Boyle et al. (2012).

[20] Federal Housing Finance Agency Housing Price Index data available at www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx.

FIGURE 2
Four Quarter Percent Change in the Federal Housing Finance Agency Housing Price Index in the Los Angeles, Louisville, and Miami Metropolitan Statistical Areas



house prices remained relatively stable compared to the larger MSAs that were affected the most. This stability alleviates concerns that the results presented below are being affected by a rapidly changing and unstable housing market.

Changes in census tract demographics[21] from 2000 and 2010 for the study area were also compared to changes for the entire United States. The only notable difference is that unemployment more than doubled nationally, while there was only a 62% increase in the study area. For the entire United States, the percentage change in the number of people who moved in from out of state fell by 71%, while it increased by 12% in the study area; since the study area contains the Fort Knox military base, the above average number of out-of-state movers is to be expected.[22]

Because there is a concern that antennas could be located in areas with not only lower property values but also disadvantaged populations, demographics for census block groups that contain antennas were compared to those within the same census tract that do not have any antenna structures, for the entire state of Kentucky in 2010. While small differences exist, none are significant at conventional levels. Table 1 shows that houses near these antennas sell for less than homes farther away; however, these differences do not appear to be driven by differences in demographic characteristics.[23]

IV. EMPIRICAL MODEL

To determine the impact proximity to an antenna structure has on property values, hedonic property value models and quasi-experimental methods are used. The first regressions rely on cross-sectional variation in distance to the nearest antenna and do not exploit the panel aspect of the data. The second

[21] Census data available at http://factfinder.census.gov.

[22] A regression of the change in the number of communication antennas in a census tract on the percentage changes in demographic characteristics in the same tract suggests that changes in demographics are not leading to significant changes in the number of communication antennas in an area. There were statistically significant coefficients for median income, unemployment, percentage of the population that owns their home, and the percentage of the population with a bachelor's degree or higher. However, the changes in these characteristics required to cause one additional antenna to be constructed or dismantled are extremely large. For example, it would take a 1,067% increase in unemployment to lead to the dismantling of one antenna.

[23] Note that this calculation is possible only for census tracts that have at least one block group without antennas.

set of regressions exploits the panel aspect of the data to reduce the potential bias caused by time-invariant unobservables. The data cover a period of 12 years, with communication antennas being built and dismantled throughout the period as well as in between sales of the same property. These changes allow for estimation of the traditional cross section specifications as well as the repeat sales and difference-in-differences specifications that are becoming more prevalent in the hedonic literature (Gayer, Hamilton, and Viscusi 2002; Linden and Rockoff 2008; Parmeter and Pope 2013; Haninger, Ma, and Timmins 2014; Muehlenbachs, Spiller, and Timmins 2014; Bajari et al. 2012).

Cross-Section Specification and Proximity Measures

Following Kuminoff, Parmeter, and Pope (2010) and Heintzelman and Tuttle (2012), a semilog specification with spatial fixed effects is used to address the potential bias caused by time-invariant, spatially correlated unobservables. The first specification is

$$\ln P_{ijt} = \mathbf{Z}_{ijt}\beta + \mathbf{X}_{ijt}\delta + \lambda_t + \gamma_j + \epsilon_{ijt}, \qquad [2]$$

where $\ln P_{ijt}$ is the natural log of the price of house i at location j at time t, $\mathbf{Z}_{ijt}$ is the set of variables describing proximity to the nearest antenna structures, $\mathbf{X}_{ijt}$ includes an extensive set of structural housing characteristics, λ_t are year-month time dummy variables, γ_j are spatial fixed effects, and ϵ_{ijt} is the error term. To demonstrate the importance of including the spatial fixed effects, equation [2] is estimated without spatial fixed effects and again with census tract or census block group fixed effects. If there are unobserved spatial characteristics that are correlated with the proximity variables, β in equation [2] should be more precisely estimated when smaller geographic fixed effects are used.

Distance to communication antennas is measured using a continuous quadratic measure of distance to the nearest visible antenna that was standing when the property sold.[24] The spatial fixed effects ensure that this continuous measure of distance is measuring the impact of a nearby antenna and not proximity to an area that may be a magnet for communication antennas. As a robustness check, the inverse of distance to the nearest antenna that was standing when the property sold is also used.

As an additional robustness check, proximity is measured using 500-foot distance rings that include a dummy variable equal to 1 if a communication antenna is located within some specified distance. The dummy variable method is the primary specification used by Heintzelman and Tuttle (2012) and allows for a high degree of nonlinearity in the disamenity caused by these antennas. A shortcoming of this method is that the size of the distance rings and the distance used as the omitted category is somewhat arbitrary. If properties are affected by the presence of multiple antennas, the dummy variable approach will overestimate the disamenity caused by communication antennas. Since multiple properties in the sample have more than one antenna nearby, proximity is also measured using the number of antennas within each ring. This is the method used by Mastromonaco (2014) to estimate the impact of Superfund sites on property values in Los Angeles.

Panel Analysis

One strategy for removing time-invariant unobservables is to exploit the variation in distance to the nearest antenna for properties that sell multiple times. During the study period, new antennas were constructed and old antennas were dismantled. These changes create variation in distance to the nearest antenna over time for the same property. This approach eliminates any time-invariant unobservables that may be correlated with the proximity variables and is the primary method used by Gayer, Hamilton, and Viscusi (2002), Heintzelman and Tuttle (2012), Mastromonaco (2014), and Bajari et al. (2012). The following regression is estimated:

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[24] Banfi, Filippini, and Horehájová (2008) and Bond (2007a, 2007b) estimate the impact of cell phone towers on property values, but their specifications do not fully account for endogeneity of tower location and correlated unobservables.

$$\ln P_{it} \quad \ln P_{it'} = (z_{it} \quad z_{it'})\beta + (\mathbf{X}_{it} \quad \mathbf{X}_{it'})\delta + \lambda_t + \epsilon_{it} \quad \epsilon_{it'}, \qquad [3]$$

where $\ln P_{it}$ is the natural log of the price of house i at time t, z_{it} is the distance to the nearest standing antenna at time t, and $\mathbf{X}_{it}$ are structural housing characteristics that may vary over time. Following Gayer, Hamilton, and Viscusi (2002), λ_t is a set of year variables equal to –1 if the year indicates the first year the property sold, 1 if the year indicates the year of the last sale, and 0 for all other sales.[25] This allows for appreciation in housing values over time. ϵ_{it} is the error term. This specification is different from the repeat sales model that is typically estimated. In the typical repeat sales model, only the proximity variables that measure distance to the nearest antenna would be allowed to vary over time, while the structural housing characteristics are assumed to be constant. Several recent studies use data from sources that do not record the structural housing characteristics each time a house is sold and make the assumption of constant structural characteristics (Heintzelman and Tuttle 2012; Mastromonaco 2014; Bajari et al. 2012). Equation [3] will be estimated with and without the changing structural housing characteristics to control for changes and determine how sensitive the estimate of β is to the assumption of constant structural characteristics.

There are shortcomings when using the repeat sales approach. There is the possibility that the unobservables are not time invariant. Kuminoff, Parmeter, and Pope (2010) show that when the omitted spatial characteristics are time varying, the bias in the first-differenced estimates increases substantially. Since not all properties are sold multiple times, the repeat sales approach leads to much smaller sample sizes. In addition, properties that sell multiple times may be systematically different than properties that sell only once. Properties that turn over multiple times may be repeatedly priced below market value, or more importantly, the local disamenity has an above-average effect on those properties. With an extensive list of housing characteristics at the time of all sales, the number of time-varying unobservables is smaller than in studies that do not have house characteristics at the time of sale each time the property is sold.[26]

V. RESULTS

Cross-Section Results

Results that use a continuous measure of distance to the nearest visible antenna are reported in Table 2, Panel A. In column (1), census tract fixed effects are included, and the results show that holding constant the characteristics of the house, the year, and month the property was sold, and the area in which the property is located, consumers are willing to pay a premium to be located farther away from a communication antenna. The estimates in column (1) show that the sales price of a house is increasing at a rate of approximately 0.74% at a distance of 1,000 feet and at a rate of about 0.68% at 2,500 feet. No effect is found beyond 21,093 feet (approximately 4.0 miles). Interestingly, specifications (not shown) that do not include any spatial fixed effects indicate that houses with communication antennas nearby sell for more, not less, than houses where the nearest antenna is farther away. Column (2) includes census block group fixed effects, which are more precise than the census tract fixed effects used in column (1). These estimates suggest that the sales price of a house increases at a rate of about 0.57% at a distance of 1,000 feet, and a rate of 0.53% at 2,500 feet. No effect is found beyond 21,583 feet (approximately 4.1 miles). Even though the effect of distance is identified by variation in distance within a smaller geographic area, the specification using census block group fixed effects provides

[25] Bailey, Muth, and Nourse (1963) introduce this method of estimating a price index using a repeat sales framework. The first period (year 2000) is the base year, and the remaining coefficients can be interpreted as the log price index.

[26] A difference-in-differences specification was also used to mitigate the effects of time-invariant unobservables. This technique is discussed in detail by Parmeter and Pope (2013) and used by Linden and Rockoff (2008), Muehlenbachs, Spiller, and Timmins (2014), and Haninger, Ma, and Timmins (2012) in difference-in-differences. Treatment and control groups were identified using the method of Linden and Rockoff (2008).

TABLE 2
Cross-Section Results for Antenna Impact Using Continuous Measures of Distance

Variable[a]	(1) ln(Sales price)	(2) ln(Sales price)
Panel A		
Distance to nearest visible antenna	0.00772*** (0.00150)	0.00600*** (0.00132)
Distance^2 to nearest visible antenna	− 0.000183*** (3.49e–05)	− 0.000139*** (2.99e–05)
Constant	10.51*** (0.0309)	10.24*** (0.0195)
Observations	141,208	141,208
R-squared	0.853	0.862
Panel B		
Distance to nearest antenna	0.0104*** (0.00187)	0.00888*** (0.00173)
Distance^2 to nearest antenna	− 0.000323*** (5.81e–05)	− 0.000284*** (5.74e–05)
Constant	10.50*** (0.0307)	10.23*** (0.0199)
Observations	142,161	142,161
R-squared	0.853	0.862
Panel C		
Inverse distance to nearest visible antenna	− 0.0359*** (0.00886)	− 0.0285*** (0.00743)
Constant	10.56*** (0.0299)	10.28*** (0.0187)
Observations	141,208	141,208
R-squared	0.853	0.862
Year-month dummies	Yes	Yes
Tract fixed effects	Yes	No
Block group fixed effects	No	Yes

Note: Distances to antennas are measured in thousands of feet. Standard errors are clustered at the level of included fixed effect.
[a] Also included in each regression are bedrooms, full bathrooms, partial bathrooms, square feet, square feet^2, lot size, lot size missing, age, age^2, age unknown, fireplace, basement, finished basement, central air, exterior type, roof type, style of home, garage, carport, within 1 mile parkway/interstate, within 1 mile railroad, and within 1 mile Ft. Knox.
*** $p < 0.01$.

estimates that are more precisely estimated than the census tract specification. This result provides further evidence that there are spatially correlated unobservables that are negatively correlated with distance to a communication antenna.[27]

Panel B uses the same quadratic distance specification but uses the more naive measure of distance to the nearest antenna that does not take into account whether the nearest antenna is visible from the house. While the effect is similar, it is estimated with less precision than the specification that accounts for visibility of the nearest antenna. For approximately 5% of the houses in the sample, the nearest antenna is not visible, and that fact produces measurement error in this specification.[28]

As a robustness check, the same specifications are estimated using the inverse of distance to the nearest visible antenna. These re-

[27] Regressions were estimated that included the percentage of rural residents in a census tract instead of census tract fixed effects. The results show that the sales price of a house is decreasing as the number of people living in rural areas increases, and that proximity to a communication antenna has a positive effect on the sales price of a house in highly urban areas, and a negative effect in more rural areas. This is consistent with the idea that antennas in more urban areas are more likely to be disguised than in rural areas, where the antennas structures tend to be much larger. Urban areas have multiple structures such as tall buildings, smoke stacks, clocks, and church steeples that antennas can be located on or around. The R^2 for the urban/rural specification was 0.72 compared to 0.85 in the census tract specification in Table 2.

[28] As an additional robustness check, a specification was estimated that uses distance to the nearest tower-type antenna. These structures are larger and are visible at greater distances than the smaller antenna structures and are expected to have a larger effect on property values and have an effect at greater distances if they are visible. If the estimated effect is larger than when all antennas are considered, this provided additional evidence that households are aware of this visual disamenity and respond rationally (Pope 2008; Currie et al. 2015). As expected, the results show that the tower-type antennas lead to a larger decrease in property values and have an effect farther away.

TABLE 3
Cross-Section Results of Antenna Impact Using 500-Foot Distance Rings: Any Antenna and Number of Antennas

Variable[a]	(1) ln(Sales Price) 1 if Within	(2) ln(Sales Price) Number Within
0 to 500	−0.0752*** (0.0232)	−0.0494** (0.0206)
500 to 1,000	−0.0613*** (0.0134)	−0.0390*** (0.0112)
1,000 to 1,500	−0.0630*** (0.0109)	−0.0417*** (0.00917)
1,500 to 2,000	−0.0620*** (0.00987)	−0.0417*** (0.00691)
2,000 to 2,500	−0.0512*** (0.00918)	−0.0289*** (0.00650)
2,500 to 3,000	−0.0450*** (0.00796)	−0.0286*** (0.00538)
3,000 to 3,500	−0.0428*** (0.00759)	−0.0288*** (0.00473)
3,500 to 4,000	−0.0343*** (0.00652)	−0.0248*** (0.00456)
4,000 to 4,500	−0.0128** (0.00593)	−0.0167*** (0.00425)
Constant	10.30*** (0.0194)	10.31*** (0.0208)
Observations	141,208	141,208
R-squared	0.862	0.863
Year-month dummies	Yes	Yes
Tract fixed effects	No	No
Block group fixed effects	Yes	Yes

Note: Standard errors are clustered at the census block group.
[a] Also included in each regression are bedrooms, full bathrooms, partial bathrooms, square feet, square feet^2, lot size, lot size missing, age, age^2, age unknown, fireplace, basement, finished basement, central air, exterior type, roof type, style of home, garage, carport, within 1 mile parkway/interstate, within 1 mile railroad, and within 1 mile Ft. Knox.
** $p<0.05$; *** $p<0.01$.

sults are shown in Table 2, Panel C. When census tract fixed effects are included, the estimates show that the sales price of a house is increasing at a rate of approximately 3.6% at a distance of 1,000 feet, and at a rate of about 0.57% at 2,500 feet. When census block group fixed effects are included, the estimates show that the sales price of a house is increasing at a rate of about 2.9% at a distance of 1,000 feet, and a rate of 0.46% at 2,500 feet. Again, the effect is estimated more precisely as more precise fixed effects are included. Overall, the results do not appear to be extremely sensitive to functional form when using a continuous measure of distance.

Results from an alternative specification that uses 500-foot distance rings are shown in Table 3. Column (1) indicates whether an antenna is located within a specified radius, and column (2) estimates the marginal effect of an additional antenna within the same radius by using the density of nearby antennas. The results suggest that houses located near an antenna sell for less than a comparable house farther away and that both distance to the nearest antenna and the density of nearby antennas have a significant effect on property values. In both specifications, the effect of communication antennas on property values diminishes almost monotonically with distance.[29]

[29] Bond and Wang (2005) and Bond (2007a) estimate the impact of cell phone towers on property values in New Zealand, but the studies have limitations. The first lacks precise location information for the houses and uses street name fixed effects as a proxy for distance to a tower. The second geocodes houses, but the model is misspecified. They use a continuous distance measure but set distance equal to zero if the house sold before the tower was constructed. Bond's (2007b) is the only study found that uses U.S. data. It is limited to sales from one area of Orange County, Florida, and includes the latitude and longitude of each property in each regression. Banfi, Filippini and Horehájová (2008) look at the impact of cell phone towers on rents in Zurich Switzerland and find a significant decrease in rents of about 1.5% on average. Filippova and Rehm's (2011) is the most recent study. They use data from the Auckland region of New Zealand and also use distance bands and a continuous distance measure. Their distance band specification yields insignificant results, and the coefficient of the continuous distance measure has a significant, but wrong-signed coefficient. They report a negative but insignificant impact on property values. The authors fail to consider the interaction terms between distance and their location variables. Given they use 50-meter increments for their distance bands, it is likely there is not enough variation within each band to identify any impact.

TABLE 4
Results Using Repeat Sales and a Continuous Measure of Distance: All Repeat Sales and Sold Only Twice

Variable	(1) Δ ln(Sold price)	(2) Δ ln(Sold price)
Panel A		
Δ Distance to nearest visible antenna[a]	0.00537*** (0.000924)	0.00200** (0.000941)
Constant	0.0543*** (0.00308)	0.152*** (0.00527)
Observations	29,759	20,871
R-squared	0.102	0.144
Panel B		
Δ Distance to nearest visible antenna[a]	0.00546*** (0.000869)	0.00254*** (0.000861)
Δ Bedrooms	0.0781*** (0.00562)	0.0613*** (0.00628)
Δ Full bathrooms	0.171*** (0.00802)	0.169*** (0.00912)
Δ Partial bathrooms	0.105*** (0.00959)	0.111*** (0.0114)
Δ Finished basement	0.0211*** (0.00385)	0.00992** (0.00458)
Δ Central air	0.255*** (0.00979)	0.243*** (0.0116)
Δ Carport	0.0585*** (0.0145)	0.0397*** (0.0151)
Δ Garage	0.0152* (0.00783)	0.0220** (0.00914)
Observations	29,759	20,871
R-squared	0.202	0.231
All repeats	Yes	No
Sold twice	No	Yes

[a] Distances to antennas are measured in thousands of feet. Standard errors are clustered at the property level.
* $p<0.1$; ** $p<0.05$; *** $p<0.01$.

The results that account for number of antennas (shown in Table 3, column (2)) are consistent with the argument made by Mastromonaco (2014) that considering only distance to the nearest site will lead to biased estimates if there are multiple sites that could adversely affect a property's sales price. As is expected, adding an additional antenna near a residential property has a smaller effect than an antenna being located near a property that did not previously have one nearby. Since the absolute value of the point estimate of almost every coefficient in column (2) of Table 3 is smaller than the corresponding coefficient in column (1), the estimates that measure proximity with distance to the nearest site are likely biased. To further explore this possible effect, a specification (not shown) was estimated that included both distance to the nearest visible antenna along with the density of nearby antennas, using 500-foot rings. Although the effect of density of nearby antennas remained significant, the effect of distance to the nearest antenna was not significant at conventional levels.

Panel Results

Results from the first repeat sales specification that assumes the structural housing characteristics are constant over time are shown in Table 4, Panel A. In this specification, the change in sales price is assumed to be a function of the change in distance to the nearest visible antenna and a set of year dummy variables that are equal to –1 if the year indicates the time of the first sale, 1 if the year indicates the year of the last sale, and 0 for all other sales. Comparing the change in sales price for houses that are sold more than once eliminates any bias that could be caused by time-invariant spatially correlated unobservables.

Comparing columns (1) and (2) for each cross-section specification in Table 2 shows that as more precise spatial fixed effects are used, the estimated effect of communication antennas on the sales price of a house is smaller and more precisely estimated. This indicates that the spatially correlated unobservables are negatively correlated with proximity to an antenna. If this is true, and the unobservables are time invariant, the repeat sales estimates of the impact communication antennas have on property values should be similar to the estimates using the more precise census block group fixed effects.

The results in each column of Table 4 are consistent with this hypothesis. Column (1) includes all houses that sold more than once during the sample period. For every 1,000-foot change in distance to the nearest antenna, on average, the sales price of a house increases by 0.54%. Column (2) includes the set of houses that sold only twice during the 12 years the data cover. Since repeat sales are identified by the standardized address that was assigned to each property, limiting the sample to houses that sold only two times reduces the chance of including houses that are being considered repeat sales due to a coding error. Even though the sample size is reduced by 8,888 observations compared to the sample of all repeat sales, the R^2 increases by 0.042, and the effect of distance is still precisely estimated. In this specification, for every 1,000-foot change in distance to the nearest antenna, on average, the sales price of a house increases by 0.20%.

Of the 29,886 houses that sold more than once, a nontrivial number experienced a change in a major structural characteristic between sales. For example, 4,316 (17%) of houses had a change in the number of bedrooms between sales. The repeat sales results in Table 4, Panel B are based on relaxing the assumption that structural housing characteristics are constant over time. As is expected, including the changes in structural housing characteristics leads to a higher R^2, increases in each characteristic lead to a larger positive change in sales price, and the effect of distance is more precisely estimated. This result suggests that the change in distance to the nearest antenna between sales of the same property is not completely orthogonal to the change in housing characteristics, an assumption that must be made when detailed sales data are not used. When changing structural housing characteristics are accounted for, the estimated impact is slightly larger than the estimate in Panel A. While these estimates are not statistically different at conventional levels, a larger effect when the changing structural housing characteristics are included is consistent with the results from Bajari et al. (2012) that show ignoring time-varying correlated unobservables leads to underestimates of the benefits of pollution reduction.[30]

VI. DISCUSSION AND CONCLUSIONS

Overall, the results from the preferred specifications that include spatial fixed effects show that houses located near communication antennas sell for less on average than comparable houses located farther away from an antenna. There are a few important points to note about these results. First, regardless of the specification, time-invariant spatially correlated unobservables bias the cross-sectional estimates of the disamenity associated with nearby communication antennas when no controls for neighborhood characteristics are included. When spatial fixed effects are not included, the results suggest that houses near communication antennas sell for more, not less, than a similar house farther away from an antenna. When spatial fixed effects are included to capture the effect of time-invariant spatially correlated unobservables, each specification used indicates that houses near communication antennas sell for less than a similar house located farther away from an antenna. When the more precise census block group fixed effects are included, the estimated reduction in sales price caused by a communication antenna becomes smaller and is estimated more precisely in each of the cross-section specifications. This effect reinforces the importance of carefully controlling for

[30] Estimates from the difference-in-differences specification show that houses within 2,000 feet of an antenna at the time they were sold sell for about 3.3% less than a comparable house more than 2,000 feet away from an antenna at the time it was sold. When the equilibrium price function with respect to structural housing characteristics is allowed to change over time, an effect of about 2.2% is found but is not statistically significant at conventional levels. Since many houses in the sample are affected by the presence of multiple antennas, defining treatment and control groups using the method of Linden and Rockoff (2008) that uses distances to the nearest standing and not-standing antennas may not be appropriate.

spatially correlated unobservables that are correlated with proximity to a localized disamenity.

Consistent with the conjecture made by Mastromonaco (2014), estimating the effect of communication antennas on property values using distance to the nearest antenna is likely biased due to the presence of multiple nearby antennas. The results in column (2) of Table 3 indicate that a house located within 500 feet of an antenna sells for 7.5% less than a similar house more than 4,500 feet away from its nearest antenna. The results in column (2) of Table 3 show that adding an additional antenna within 500 feet of a house leads to a smaller reduction in sales price of 4.9%.

The results also suggest that the omitted spatial characteristics correlated with proximity to a communication antenna are time invariant and are being captured by the census block group fixed effects. First, the effect communication antennas have on nearby properties is smaller and is estimated more precisely when census block group fixed effects are used compared to the census tract estimates. This confirms that there are unobservables spatially correlated with distance to a communication antenna. Second, the repeat sales method eliminates any bias caused by time-invariant unobservables and provides results that are smaller than the cross-sectional estimates that include census block group fixed effects. Since the antennas are located in areas where property values are lower, the repeat sales specification that eliminates all time-invariant unobservables should yield results with the smallest amount of bias. Since the sample of houses that are sold multiple times may not be a random sample of all houses, some bias could still exist.

The best estimate of reduction in sales price caused by communication antennas shows that the sales price of a house is increasing at a rate of about 0.57% ($1,047) at a distance of 1,000 feet from the nearest antenna (Table 2, Panel A, column (2)). This suggests that a property located within 1,000 feet of the nearest antenna at the time of sale will sell for 1.82% ($3,342) less than a similar house that is 4,500 feet from the nearest antenna. In this specification, time-invariant spatially correlated unobservables are controlled for with census block group fixed effects. The repeat sales results in Table 4 provide additional evidence that the spatially correlated unobservables are being captured by the fixed effects. These estimates of the disamenity associated with communication antennas controls for time-invariant unobservables at the property level and suggests that a property located within 1,000 feet of an antenna will sell for 0.89% ($1,634) less than a similar house that is 4,500 feet from the nearest antenna (Panel B, column (2)). However, since the repeat sales are identified by matching a standardized address, these results could be sensitive to measurement error.

This effect is smaller than the estimated reduction caused by similar disamenities. Kroll and Priestley (1992) provide a review of the literature concerning overhead transmission lines and property values through the early 1990s. They find that in studies where a significant decrease was found, the decrease in property values typically fell in the range of 2% to 10%, and the effect diminished beyond a few hundred feet. Hamilton and Schwann (1995) estimate the impact of high voltage electric transmission lines have on property values, but primarily focus on the importance of using the correct functional form. They find that properties adjacent to a line lose about 6.3% of their value, but more distant properties are hardly affected. Using a repeat sales model, Heintzelman and Tuttle (2012) find that having a wind turbine located 0.5 miles away leads to a reduction in sales price from 8.8% to 15.81%.

The preferred specification for estimating the disamenity associated with communication antennas is the continuous measure of distance using census block group fixed effects (Table 2, Panel A, column (2)). These results imply that a property with an antenna located within 1,000 feet at the time of sale will sell for 1.82% ($3,342) less than a similar house that is 4,500 feet from the nearest antenna. In this sample, there are 3,031 houses within 1,000 feet of an antenna structure. Using the preferred repeat sales specification as a lower bound, if each antenna within 1,000 feet of a property were moved to a distance of 4,500 feet, there would be an aggregate increase in sales price of $4.95 million. The best estimate suggests the aggregate increase would be $10.13 million. These values should be compared to the cost of camouflaging or disguising communication antennas near residential properties to mitigate the effect they have on property values.

In areas where antennas are highly visible (Figure 1, upper photo), there is a potential externality caused by these antennas. If antennas are constructed near residential properties after the homeowner purchases the property, those houses suffer a small but nontrivial decrease in their property value and their owners are unlikely to be compensated by the land owner where the antenna is located or the owner of the antenna. Camouflaging is one solution to this problem that has been implemented in some areas. Camouflaged towers blend in with the landscape or are constructed in already standing structures such as church steeples and clock towers. Such developments will mitigate the disamenity associated with communication antennas and reduce the cost of convenience.

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Reid Cummings Mar 1
to me, Ermanno, Huubinh

Dear Mr. and Mrs. Nicolai,

Thank you for your kind words. For academics, I think the highest form of compliment comes from someone who found value in our work. We are pleased to learn of your success.

Based on the photo alone an obvious externality variable is the short proximity distances to and from your home. For sightlines and straight lines, we would expect results to be similar. We cannot run analysis or test predictions needed to offer any economic measurement, because we have none of your market's micro-variables. However, we can say that in our analysis using our dataset, homes within the proximities as close as those depicted on your photo lost economic value.

Best to you both, and thank you again.

Reid

J. Reid Cummings, D.B.A.
Interim Assistant Dean for Financial Affairs
Associate Professor of Finance and Real Estate
Executive Director, SABRE

Mitchell College of Business, University of South Alabama

Secretary, American Real Estate Society
Editor, *Journal of Real Estate Practice and Education*

[redacted]

...

Ermanno Affuso Mar 2
to Reid, me, Huubinh

I concur with Dr. Cummings.

Good luck with the outcome of the intervention.

Ermanno

...

Gmail Roger Nicolai [redacted]

Checking in…

Locke, Stephen [redacted]
To: Roger Nicolai [redacted]

Tue, Mar 29, 2022 at 1:18 PM

Nicolai,

I have looked over the pictures and documentation you have provided. Results from my study and other similar studies have found a statistically and economically significant negative impact on property values for homes located in close proximity to a cell phone tower. Your property is close enough to the proposed location that previous research would suggest economic damages are likely to occur.

Thanks,

Stephen L. Locke, Ph.D.

Associate Professor

Department of Economics

Western Kentucky University

[redacted]