Viewshed Effects and House Prices: Estimating A Spatial Hedonic Model

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Abstract

We use GIS techniques to create variables for measuring the visibility value of coasts and natural open areas in a spatial hedonic model of house prices. Data come from repeated house sales for the city of Haifa (Israel), 1998-2016. As visibility of amenities often interacts with other variables such as location, we suggest approaches for dealing with this identification problem. We exploit the multi-level structure of the data to estimate spatial panel models with multi-level random effects for identifying viewshed effects conditioned on location. Our main finding suggests that the viewshed effect on house prices is overstated when using OLS estimation. The spatial econometric results show that visibility of coast and natural open space adds to the value of housing units regardless of their location even though view is determined by proximity to these visual amenities. Viewshed effects are also shown to be sensitive to different ranges of visibility.

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1. Introduction

A scenic view is a residential amenity associated with the location of a dwelling. Many studies show that buyers are willing to pay a premium for sites with a view, see for example, Paterson and Boyle, 2002; Benson, et al, 1998; Do and Sirmans, 1994; Rodriguez and Sirmans, 1994; Cassel and Mendelsohn, 1985; Gillard, 1981; Plattner and Campbell, 1978. However, visibility is a multi-dimensional concept, and no single metric can fully capture both the type of view and the range of vistas that if affords. Viewshed analysis offers a geometric approach to calculating visibility from a source point to a target point accounting for potential obstacles that might impede lines of sights such as differences in height, pointing angle, horizontal orientation etc.

Many studies measure the value of visibility but fail to separate the effects of the utility derived from pure view with that derived from proximity to the amenity[1]. In the case of viewsheds, the price difference of two similar apartments where one is close and the other distant to the amenity (for example a coast or a natural open space) can be explained by the view of the amenity and by the lower costs of access. Hamilton and Morgan (2010) distinguish between the effects of visibility and proximity. However, estimating proximity and viewshed variables separately does not help in identification due to missing variables. Neglecting this correlated effect causes at least two empirical problems. First, the estimate of distance to an amenity on a property price's elasticity cannot be identified since the distance coefficient does not include the effects of viewshed variables which in turn depend largely on proximity to amenities. Second, neighborhood variables such as proximity and visibility to amenities are often spatially correlated. For example, the visibility from a dwelling unit does not only depend on its height and shape, but also depends on the heights and shapes of the buildings around it. As a result, OLS estimates are often biased without controlling for spatial autocorrelation.

This paper makes two methodological contributions. As hedonic house price studies tend to confound utility derived from visibility (viewshed) with that derived from proximity, we suggest two approaches to solving this identification problem. The first is to utilize information on building elevation and floor level since these factors generally improve visibility but are independent of distance. We utilize the treatment effect by controlling different factors which may affect visibility like proximity to amenities, floor level and building elevation. The second approach is the application of a SAR (spatial autoregression) model. We control for neighborhood effects that could affect visibility using the spatial lag of the dependent variable. We illustrate that the

[1] A similar issue exists with respect to capitalizing the effect of schools into house prices (Gibbons and Machin 2008, Nguyen-Hoang and Yinger 2011). In this instance, the very different effects of proximity to a school and quality of a school tend to be confounded leading to diverse outcomes (see for example Fleishman et al 2017, Metz 2015).

visibility effect can be identified if we include the average value of housing units in the same location. As local house prices are highly clustered and spatially correlated due to historical, demographic and geographical reasons, it is important to capture their spillover effects. Our empirical strategy can identify viewshed effects even when proximity to amenities has a negative effect on prices, as will be shown below.

A second methodological contribution relates to using spatial panel econometrics to exploit the multi-level structure of the data and to estimate the effect of neighborhood and location (address) specific variables and viewshed effects in hedonic price models. In this way, viewshed effects can be identified even when they are correlated with other location variables such as the distance to amenities. Traditionally, hedonic price models have not paid much attention to spatial dependence. In this paper, we extend hedonic estimation by incorporating spatial lag effects and time fixed effects. As house prices are recorded by time and location, ignoring the spatial independence and heterogeneous temporal effects of the observation results in serious specification problem and biased estimation. We capture these concerns using concentrated maximum likelihood estimation, which is consistent when the sample is large. Like other neighborhood variables, viewshed effects are also spatially autocorrelated. Identifying the marginal effect of viewsheds conditioned on location is possible when the spatially correlated effect is controlled. This has not been applied in previous research on viewshed effects.

Amenity viewsheds are derived from different sources such as water, mountains, and open spaces. They are often measured by the quantity of view that is captured (Sander and Polasky 2009, Osland et al 2021). Mittal and Byahut (2019) use geographically weighted regression and a dichotomous 'visual accessibility variable' to create a gravity-inspired visibility index that is then used on a small number of cross-section transactions. However, their statistical approach does not use panel data or automated GIS techniques in order to generate building-by-building visibility measures.

Paterson and Boyle (2002) show that visibility measures are important determinants of prices and that their exclusion may lead to incorrect conclusions regarding the significance and signs of other environmental variables**.** Their research pioneered the use of GIS data to create variables representing the physical extent and visibility of surrounding land use/cover features in a hedonic model. Prior to this, amenity was invariably incorporated into hedonic estimation via the use of dummy variables. A review of over 30 view-amenity studies up to the early-2000's underscores the widespread influence of this approach (Bourassa et al 2004). In order to improve on best practice, the authors try to identify the multidimensional nature of views generating metrics for type of view, scope of view, distance to coast, and aesthetic quality of surrounding area for a small cross section of transactions in Auckland, NZ in the year 1996. In this study, the nature of different vistas is captured by qualitative appraiser data and GIS technology is harnessed only for distance measurement. The results of the hedonic estimation suggest that willingness to pay for views depends on the quality of this amenity. For example, highest-quality sea-front views are found to increase the

market price of an otherwise comparable home by almost 60% and lowest-quality ocean views are found to add about 8%. A later review (Mittal and Byahut 2016) extended the focus of marginal price effects to a wider selection of land uses/amenities (including golf course, parks, lake fronts and farms) but did not improve on the quality of the measurement of these vistas.

Previous viewshed-based research has also not fully exploited recent technical advances to refine the effect of pure, a- priori topographic features such as ocean-front or mountain views on prices. Even when GIS technology has been adopted, the impact of views and scenery on pricing has invariably been captured as a qualitative binary variable (Hui et al 2007.Jim and Chen 2009, Sander and Polasky 2009) and using laborious data collection methods such as site visits for small areas (Benson et al 1998, Luttick 2000, Hamilton and Morgan 2010).

The approach adopted by Baranzini, and Schaerer (2011) presents one of the first uses of GIS to calculate three-dimensional view variables in order to develop more precise viewshed measures at the dwelling unit level. In spirit, it is similar to the method presented below. They combine a topographical land cover with a surface cover data layer to construct a 3D layer for the city of Geneva, Switzerland that accounts for all the elements in the landscape that can impede views. They apply these metrics to a sample of 13,000 rentals in the city and find a significant view premium for both location in a neighborhood with a water-related view (3%) and for individual dwellings with large water-related vistas (up to 57%). Greenspace viewsheds such as agricultural land vistas however have much less dramatic effects. In contrast, our approach is not only able to identify viewshed effect of different amenities, but also detect the sensitivity of visibility range by dividing our viewshed variables into 0-1km and 1-5km ranges.

Our study presents the use of an automated GIS-driven method that generates a suite of viewshed measurements for every building. While we can potentially do this nationally, the current paper illustrates the method for the city of Haifa. We combine various sources to create a unique citywide data base and utilize a large-scale repeat sales data set (n=27,067), which greatly extends the scope of analysis beyond the neighborhood or district scale. Additionally, we take advantage of GIS technology in order to augment DEM (digital elevation model) elevation estimates with building obstruction and multi-aspect dimensions of visibility. Haifa is a good example of a city where building elevation, view obstruction and aspect are key components of viewshed measurement.

The paper proceeds as follows. Section 2 presents the data, study area and the approach for measuring viewshed quantity. In this respect we assume viewshed quality and quantity are synonymous. More view is better than less, and this capitalizes into higher house prices. Section 3 presents a theoretical analysis of the components of viewshed utility. This serves to disentangle viewshed utility from proximity utility. Given the unbalanced panel and multi-level nature of the data, we present the motivation for

adopting a spatial lag model with nested random effects. In section 4 the empirical results are discussed, and their robustness is addressed. Section 5 concludes.

2. Data Description

2.1 Data Sources

The data for this study comes from a variety of sources. The first is housing unit sales (transaction) data from the Israel Tax Authority (ITA). The original transactions database relates to over 800,000 sales nationally for the period 1998-2016. For each transaction, the file records sale price, date of sale, and a set of variables describing the property's characteristics such as year built, floor space area, type of asset (garden apartment, duplex cottage, single home etc.), floor number and address. We use the date of sale and year-built variables to calculate whether the transaction took place prior to construction.

A second source is the Survey of Israel (SoI) 3D GIS buildings layer which contains over 1.7m observations nationally and contains information on building height and areal footprint (length of perimeter). Of this, more than 480,000 observations relate to residential assets. Road and areal distances for reach residential building to a variety of amenities and dis-amenities are calculated (see Table 1 for variables and their sources). Other data relate to neighborhood or community attributes of the locales in which the dwelling unit is located. For example, we utilize data on school quality and proximity provided by Ministry of Education relating to the normalized level of proficiency and violence in each school for the years 2008-2013. Each asset is assigned the average proficiency and violence scores for elementary and junior-high schools within a 400m aerial distance or with the scores of the closest school if the nearest is more than 400m away. This produces four proxy variables relating to level of education (2 school types x 2 measures). Localized data on distance to polluting industries come from the national pollutant register. The elevation of each building comes from the national DEM (digital elevation model) model. Descriptive statistics for all variables are presented in Table 2.

Table 1. Distance variables: source and method of calculation

Variable	Data Sources	Calculation
Road network distance to the coast (m)	Road network layer, coast layer	Calculated using ArcGIS Network Analyst extension and automated using ArcPy. Maximum search radius for major highways: 10km
Road network distance to commercial centers (m) Road network distance to employment centers (m) Road network distance to train stations (m) Road network distance to parks (m)	Road network layer + relevant uses extracted from SoI's land-use complexes layer	
Road network distance to major highways (m)	Road network layer	
Aerial distance to cemeteries (m) Aerial distance to parks (m) Aerial distance to industrial complexes (m) Aerial distance to schools (m)	Land-use complexes layer from SoI	Distance of the most proximate location or complex Maximal search radius: 100m for schools, parks and highways; 250m for cemeteries and industry complexes; 500m for pollution sources
Aerial distance to major highways (m)	Road network layer	
Aerial distance to polluting complex (m)	The 2016 Pollutant Release and Transfer Register from the Ministry of Environmental Protection, documenting aerial pollution by factory, regardless of type of pollutant.	
Aerial distance to polluting complex (m), excluding complexes polluting below the registered level		

Community socio-economic data (amenities, crimes rates) come from the Israel Central Bureau of Statistics (CBS) and are available nationally for Statistical Areas (SAs). An SA is a uniform administrative census unit of roughly 3000 inhabitants and is the highest level of spatial resolution for which socio-economic data is available. The study area comprises the 110 SAs within the municipal boundaries of the city. The presence of missing data reduces the number of SA's for actual analysis to 85.

2.2 Study Area

Historically Haifa owes much of its urban development to British Mandate plans to make it a central port and hub for Middle East trade in crude oil. Under these plans, Haifa saw large-scale development and became an industrial port city. Its large and flat coastal bay area became colonized by industrial and infrastructure use. Residential area

is therefore limited and spreads over the elevated areas of Mount Carmel and the low-lying suburbs beyond the bay area (Fig 1). Consequently residential areas in the city are concentrated on the slopes of Mount Carmel and on the flatter areas close to the Mediterranean coast. Topography is a highly influential factor in Haifa's urban development. Residential building is invariably along ridges and slopes punctuated by thickly vegetated and afforested ravines that transect the urban area (Fig 2). These natural open spaces generate a network of corridors for wildlife that exists within the city boundaries and generates significant negative externalities (Toger et al 2016, 2018). Haifa is also a city potentially threatened by hazards. The primary natural hazard is the seismic Yagur fault (Levi et al 2015). The chief anthropogenic hazard is the cluster of heavy industry installations (petrochemical, chemical and oil refinery plants) in the low-lying Haifa Bay area (Portnov et al 2009).

The spatial distribution of house prices by SA's is depicted in Figure 1. Significant clustering can be observed suggesting the existence of spatial spillover. This will be tested more rigorously below. Also apparent is a visible relationship to elevation in that higher house price neighborhoods are concentrated in the higher elevation areas of the Carmel Mountain range.[2].

[2] Note however that elevation is not necessarily synonymous with the well-documented higher-floor premium. For example, Conroy et al (2013) find that an increase in floor level is associated with more than a 2 percent increase in price. However, this relationship is quadratic in price suggesting that above the mean floor level, house prices increase at a decreasing rate. Hui et al (2012) in contrast find no evidence that sea-views are directly related to transaction prices in high-rise apartment buildings.

Fig. 1: The Spatial Distribution of Average House Price Per sq m (in Israeli shekels 2009) by SA in Haifa.

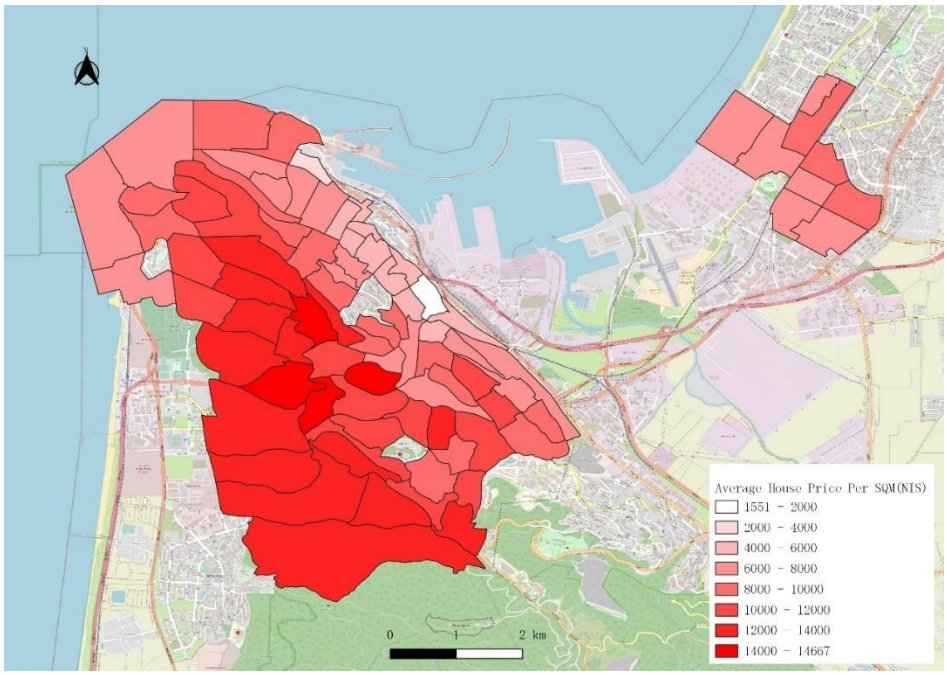


Fig 2: Natural Open Spaces in Haifa

To create a transactions level data base for the study area, the various data sources (transactions, assets and buildings) are integrated. Each transaction is assigned to an asset (unit) and from there to a building using an id and geographic coordinates. In the case of multi-story buildings each asset is also assigned a floor. The panel data of housing transactions is unbalanced (n=27067), i.e., there are missing observations for some units in some time periods. To make the panel data workable, arms-length transactions are removed if a unit is sold more than three times within a year (less than 1% of total observations). The descriptive statistics of this data set are presented in Table 2. Visibility measures (see below) are linked to the transaction data through the id of each individual asset. Each of the transactions in the study area is indexed by year and location and thus the grid coordinates of the asset yield the precise address of the location of the transaction (5601 distinct addresses). Addresses are also linked to one of the 85 SAs. The result is a multi-level, pseudo-panel dataset in the sense that there are repeated sales on the same assets (housing unit) over time. Frequently transacted units (sold more than 5 times during a year) are dropped (903 observations). These indicate the presence of adverse selection or statistical error in the unit likely to cause estimation bias.

Table 2: Descriptive statistics for variables in the study (N = 27,067).

Variable	Mean	Std.Dev.	Min	Max
Price per Square Meter (New Israeli Shekels 2009 prices	9478.456	4036.517	1008.869	94681.82
Structural Variables				
Number of Rooms	3.315	1.175	1	10
Floor space (Square Meter)	73.017	30.612	2	2000
Building Year	1970.475	18.774	1847	2017
Year of the Transaction	2008.235	5.224	1998	2016
Floor Level	2.462	2.394	0	22
Building Perimeter (meter, North)	23.521	16.523	3.577	238.89
Building Perimeter (meter, East)	25.566	17.828	0	213.698
Building Perimeter (meter, South)	23.381	15.635	3.759	223.036
Building Perimeter (meter, West)	25.636	18.626	5.276	248.105
Dummy=1 if Orientation is North-south	.477	.499	0	1
Dummy=1 if Orientation is Northeast-southwest)	.47	.499	0	1
Dummy=1 if Orientation is East-West	.485	.5	0	1
Elevation	135.524	112.107	-5.8	415
Dummy=1 if transaction is prior to construction date	.027	.161	0	1
Dummy=1 if type is apartment	.942	.234	0	1
Dummy=1 if closest elementary school is mixed	.036	.187	0	1
Dummy=1 if closest middle school is	.154	.361	0	1

mixed				
Visibility				
Coast (lines of sight, r=0-1km)	.054	.274	0	2.303
Nat. open space (lines of sight, r=0-1km)	.21	.383	0	2.079
Total visible area (m^2, r=0-1km)	5.736	1.705	0	7.472
Coast (lines of sight, r=1-5km)	1.271	1.534	0	4.898
Nat. open space (lines of sight, r=1-5km)	.441	.71	0	3.892
Total visible area (m^2, r=1-5km)	.852	.679	0	1.607
Neighborhood Variables				
Average proficiency scores at closest elementary school(s)	.307	.75	-2.573	1.91
Average proficiency scores at closest middle school(s)	.464	.737	-2.573	1.55
Average violence level at closest elementary school(s)	.343	.967	-1.784	5.691
Road distance to the coast (meter)	4390.903	2765.094	0	11320
Road distance to the commercial (meter)	346.661	315.51	0	2779
Road distance to the employment (meter)	728.788	452.593	0	3342
Road distance to the train station (meter)	3828.657	1985.44	23	10534
Road distance to the park (meter)	878.602	701.621	0	4096
Road distance to the main road (meter)	2696.364	1811.355	2	8948
Aerial proximity to nat. open area(meter)	196.144	202.243	0	1373.486
Aerial proximity to cemeteries (meter)	2306.491	1785.986	20	7179
Aerial proximity to industry (meter)	238.127	145.228	0	1143
Aerial proximity to the main road (meter)	503.969	444.68	0	2695
Aerial proximity to schools (meter)	166.892	108.336	0	760
Aerial proximity to severe air pollution	2513.552	938.187	526.737	5141.827

Notes: Distance to building perimeter is calculated from building centroid in 4 different directions: north, east, south and west. Orientation is determined by the direction that minimizes distance from the building centroid.

2.3 Calculating Viewsheds

Capturing visibility via 3D viewsheds is an approach that lends itself to GIS applications. Early studies in this genre (see for example Benson 1998, Lake et al 2000, Paterson and Boyle 2002) invariably used small samples and laborious data collection methods. While DEM-based, they also tended to ignore building obstructions and the multi-aspect nature of visibility. Sander and Polasky (2009) for example calculated top floor viewsheds with maximum view radii of 1000m for 5000 residential properties in Ramsey County Minnesota. They generated a bespoke raster DEM for the study area and integrated this with an existing 10m DEM for the wider Twin Cities region. This allowed them to identify 'best views' visible from top floors of properties in their sample. They incorporated the resultant view quality metrics such as the extent of the view and visible land covers, in their hedonic estimation. Barazani and Schaerer (2011) extended dwelling-level viewshed calculations using a DEM for the city of Geneva combined with complex queries to generate a 3D vista for a 1km radius around the central point of each building in their study area. Their viewshed areas however were limited in scope and scale. They calculated visibility metrics for 3 observer heights (ground floor, mid-building and top floor) relating to 7,700 buildings (18,500 dwelling units). Intersecting all visible cells with different land use covers allowed them to determine the visible land uses.

More recently, GIS techniques have combined with computerized geometrics to generate a Sky View Factor (SVF), i.e. a metric of the unobstructed area from buildings in cities. In highly dense urban areas with buildings of varying heights and complex DEMs, this presents a considerable challenge and calls on considerable computing resources. Yi and Kim (2017) for example present an automated grid-based approach that calls for extracting the relevant geometrical features from each cell estimating their SVF using a ray-based (vectorized) method and reprocessing the extracted geometry onto a panoramic 3D image of the city.

Our approach is inspired by these studies and utilizes the capabilities of readily available GIS extensions such as the ArcGIS Visibility toolset. We use these to calculate three measures of visibility, all computed for 1km and 5km visibility ranges: the total area visible from a given asset, the number of lines of sight to the coast and the number of lines of sight to natural open areas. The automated procedure for calculating these is implemented in Python using the ArcPy library (see Fig 3). It iterates over all assets in the study area and identifies obstructions within a 6km radius of the given asset (step 1 in Fig 3). The procedure then computes the visibility range, identifying all areas that are at least 200m away from the asset but no more than 5km away (step 2 in Fig 3).

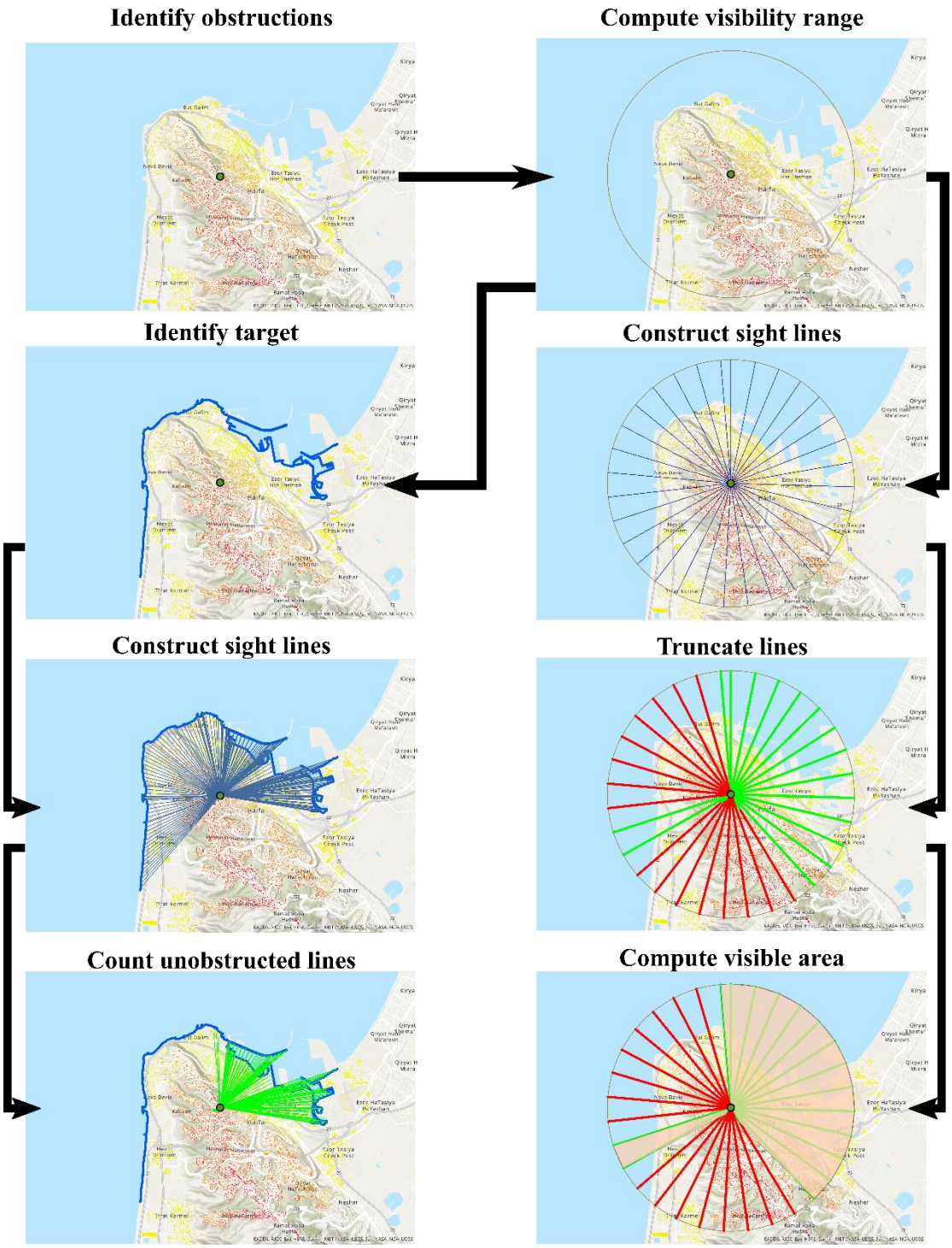
We compute two visibility measures. The first relates to total visible area. 3D lines emanating from the asset to the edge of the visibility range are constructed using the ArcGIS Lines of Sight tool such that the end points of two subsequent lines are 1km apart. This generates 32 Lines of Sight as depicted in step 3 on the right-hand path in Fig. 3. The effects of obstructions and the topographical shape of the surface are computed such that lines are truncated when they meet an obstacle (see step 4 on the right hand path). Finally, the end points of the truncated lines are connected to form a simplified polygon and its area represents the total visible area. This is represented as the final step on the right-hand side of Fig. 3 and yields a measure of viewshed quantity but not quality. The same procedure is adopted for the 1km radius case with the maximum length of truncated lines restricted accordingly.

This approach differs to other GIS-generated viewsheds that are based on much fewer targets. Osland et al (2020) for example position 4 buoys in the sea to generate vista metrics for buildings along the Oslo fiord. The resultant raster image generates buoy counts for each dwelling unit along the coastline which proxies for ground level view. However, this method cannot account for actual view limitations due to dwelling unit aspect (orientation), floors number in multi-floor buildings and view impediments due to trees etc.

The second visibility measure considers both quantity and quality. To this end we utilize target-based Visibility Analysis. This involves aiming and shooting sight lines to specific targets such as the coast or natural green areas and computing the number of uninterrupted lines that this yields. The 5km visibility range is intersected with a given target (step 3 in the left-hand path in Fig3) which can be either the coast (a polyline layer) or green spaces (polygons converted to points). Then the Construct Sight Lines and Line of Sight tools are used to count the number of sight lines reaching the target (steps 4 and 5, left hand side of Fig. 3).

For each visibility measure, we generate two variables representing range of viewshed. The first is the amount of visibility in the 0-1km range and the second is amount of visibility in the 1-5 km range, after subtracting amount of visibility in the 1 km range from the amount visible in the 5km range.

Figure 3: Visibility computation process.



3. Estimation Strategy

Hedonic methods are based on a theory of consumer behavior that suggests that commodities are valued for their individual "utility-bearing" attributes or characteristics (Rosen 1974). Two key assumptions are that the housing market is competitive, and the commodity is highly differentiated. Since the housing market satisfies these two conditions, the price in the equilibrium, P^*, is determined by the implicit vector prices of a dwelling's characteristics $\boldsymbol{x} = (x_1, \dots, x_K)$ which is the general form of the hedonic price model.

$$\frac{\partial logP^*}{\partial x_i} = \beta_i \frac{\partial U}{\partial x_i} \tag{1}$$

This characteristic vector consists of structural attributes (e.g., the number of rooms), accessibility (e.g., proximity to amenities), environmental quality (such as natural open spaces and air pollution), and neighborhood (e.g., education, demographic) variables. Hence, the empirical hedonic model in equation (2) is particularly useful for estimating the (implicit) value of a given landscape characteristic where demand and supply relations are complicated.

$$logP^* = \boldsymbol{x\beta} + \epsilon \tag{2}$$

When a dwelling's characteristics $x_1, \dots, x_K$ are strictly exogenous such as structural attributes, the coefficient $\boldsymbol{\beta} = (\beta_1, \dots, \beta_K)'$ in equation (2) can be estimated by OLS. However, when both the prices and dwelling characteristics are correlated with some common factors, for example, neighborhood variables that are correlated with locations, OLS estimates are biased. A well-known example relates to effect of schools on house prices (Gibbons and Machin 2008, Nguyen-Hoang and Yinger 2011).

Identification of the viewshed effect needs to distinguish between two effects: (a) spatially autocorrelated effects, where resident preference is related to the preferences of other residents in the same neighborhood (for example, with respect to the viewshed of natural open space) and (b) correlated effects, where residents in the same neighborhood tend to show similar taste for amenities since they are located in similar locations that have similar attributes such as distance to the amenity and building elevation. These two effects can be tested by regressing viewshed variables on location-specific variables using simple OLS. The results are shown in Table 3. Increasing building elevation by 1 meter adds 0.07%, -0.003%, 0.14% to the visibility of open natural spaces, coast, and open areas in a 1km range. Each additional floor adds 0.03%, 0.003%, 0.17% to the visibility for natural open space, coast, and total open areas in the 1km range. A positive relation between visibility ranges and viewshed effects can be seen. This is larger at r=1-5km than at r=0-1km, for all three viewshed variables. The proximity variables that correlate with viewshed variables in our regression are road distance to the coast and aerial distance to natural open space. The estimates show both the accessibility to the coast and natural open space is significantly and negatively correlated with the view of the coast and natural open space. Moreover, all six viewshed variables show strong spatial autocorrelation with the spatial autocorrelation (SAR)

coefficient greater than 1. The R-squares of OLS regressions using all the location variables to explain each of the 6 viewshed variables are all above 50%. This result confirms our concerns for the existence of multicollinearity when using both location variables and viewshed variables in OLS estimation.

Table 3. Spatial Autocorrelation and Correlation of Viewshed Variables

Correlated Covariates	**Distance to amenity**		**Elevation**		**Floor Level**		**Spatial Autocorrelation**
	Coeff.	T-stat.	Coeff.	T-stat.	Coeff.	T-stat.	Coeff.
Viewshed of natural open space (r=0-1km)	0.0230**	1.98	0.0763***	36.53	0.0344***	37.07	1.0631***
Viewshed of natural open space (r=1-5km)	-0.1464***	-6.74	0.0729***	18.67	0.0720***	41.42	1.0195***
Viewshed of coast (r=0-1km)	-0.0267***	-31.32	-0.0032	-1.55	0.0084***	12.55	1.2317***
Viewshed of coast (r=1-5km)	-0.1785***	-38.99	0.0342***	3.05	0.1835***	50.82	1.0381***
Total visible area (r=0-1km)			0.1437***	16.09	0.1715***	41.01	1.0018***
Total visible area (r=1-5km)			0.1564***	45.77	0.0740***	46.27	1.0034***

Notes: Regression results are estimated by OLS with time fixed effects. Statistical significance is as follows: * $p < .10$, ** $p < .05$, *** $p < .01$.

Ignoring spatial dependence can result in model misspecification and biased estimated parameters. In the literature, considerable attention has been devoted to the likely spatial dependence of error terms in estimating hedonic equations. In a well-known example, Pace and Gilley (1997) utilize data from Harrison and Rubinfeld's (1978) seminal study to compare ordinary least squares and spatial autoregressions and demonstrate the significant efficiency gains from the latter.

Given this, we explicitly test for spatial autocorrelation (Table 4). The univariate Moran's I statistic for both the SA and location levels suggests that spatial autocorrelation of both dependent and independent variables is indeed present. All the Moran’s I statistics are significant after standardization (conversion to Z-statistics).

Table 4. Univariate Moran's I statistics

	Unit Price	Year Built	Rooms	Transaction *Type*	Visibility of Coast	Visibility of Nat. open space	Total Visible Area	Air Pollution
Statistical Area (SA)	0.5249	0.3467	0.1626	0.3031	0.6444	0.2871	0.4122	0.6636
Location (x,y co-ordinates)	0.9001				0.5488	0.6083	0.9214	

Note: Moran's I for SA's measures the correlation of the variable and its spatial lag based on an inverse distance weight matrix of 85 Statistical Areas. Moran's I for location uses a contiguity matrix.

3.1 Identifying the Viewshed Effect Using SAR

Let S_i be a vector of structural variables including the number of rooms, the year of sale, year of building, floor space, and dwelling type. Let Z_j denote a vector of neighborhood variables such as distance to amenities and elevation. X_{ij} denotes the viewshed effect which is unit specific but correlated with Z_j, which can be written in the functional form,

$$X_{ij} = \delta Z_j + \tilde{X}_{ij}\,, E\left(\tilde{X}_{ij}|Z_j\right) = 0$$
$$E\left(X_{ij}|Z_j\right) = \delta Z_j$$

We are interested in estimating the marginal effect of $\mathrm{E}[\log\left(P_{ij}\right)|\tilde{X}_{ij}]$, which is denoted by coefficient β_2. Traditionally, viewshed effects and neighborhood variables appear on the right-hand side of the estimated (OLS) model as in equation (3) where estimate of β_2 is biased without controlling for spatial autocorrelation in dependent variable.

$$\log\left(P_{ij}\right) = \alpha + \beta_1 Z_j + \beta_2 X_{ij} + \beta_3 S_i + u_j + v_{ij} \qquad (3)$$

Additionally, collinearities exist between neighborhood variables such as distance to amenities and the amenity visibility (such as views of coasts and natural green area).
A consequence of this multicollinearity is that estimated viewshed effects on house prices β_2 tend to be contaminated by neighborhood variables Z_j even controlling for other independent variables.

To identify viewshed effects and decouple proximity from visibility, we adopt the approach used for analyzing peer effects in social networks (Lee 2007; Bramoulle et al. 2009). These are invariably riddled with endogeneity issues that impede determining the direction of causality between interacting agents and obscure the distinction between exogenous (contextual) influences, endogenous (peer) outcomes and correlated (similar environment) effects.

As a solution we can control for neighborhood effects that affect visibility using the spatial lag of the dependent variable. The intuition is straightforward and spatially lagged instruments have been used in prior hedonic studies (for example Cheshire and Sheppard 1998). If visibility increases the value of a housing unit, then a unit with better views will be more expensive than another unit in the same location, all other conditions equal. For example, a dwelling unit with a coastal view will be more expensive than one without a coastal view, given the proximity to the coast and other location conditions. Indeed, β_2 can be identified if we include the average value of housing units in the same location, denoted by $\log(\widetilde{Price_l})$ which is equivalent to a spatial lag that captures the average value of housing units in the neighborhood and can be expressed as follows:

$$E\left[\log\left(P_{ij}\right)\left|Z_j\right.\right] \approx \frac{\mathbf{1}}{N_t}\sum_{j=1}^{N_t} w_{ij}^t \, log(Price_{in})$$

where N_t is the number of units in the neighborhood, $w_{ij} = 1$ if unit i and j are neighbors. In each period, the spatial weights can be written in a matrix form $W_t = (w_{ij}^t)$. Therefore, we propose a model incorporating a spatial autoregressive regressor (SAR) by inserting $X_{ij} = \delta Z_j + \tilde{X}_{ij}$ into equation (3) as follows:

$$\log\left(P_{ij}\right) = \alpha + \rho E\left[\log\left(P_{ij}\right)\left|Z_j\right.\right] + \beta_1 Z_j + \beta_2(\delta Z_j + \tilde{X}_{ij}) + \beta_3 S_i + u_j + v_{ij} \qquad (4)$$

Assume $E\left(S_i\middle|Z_j, \tilde{X}_{ij}\right) = 0$, since $E\left(u_j + v_{ij}\right) = 0$, the conditional expected price in log on location and viewshed effect is given by

$$E\left[\log\left(P_{ij}\right)\left|Z_j, \tilde{X}_{ij}\right.\right] = \alpha + \rho E\left[\log\left(P_{ij}\right)\left|Z_j, X_{ij}\right.\right] + (\beta_1 + \beta_2\delta)E(Z_j|X_{ij}) + \beta_2\tilde{X}_{ij} \quad (5)$$

We are interested in discovering a unique linear expression of conditional expected price $E\left[\log\left(P_{ij}\right)\left|Z_j, \tilde{X}_{ij}\right.\right]$ on explanatory variables $Z_j, \tilde{X}_{ij}$. Given $\rho \neq 1$, reorganizing equation (5) yields

$$E\left[\log\left(P_{ij}\right)\left|Z_j, \tilde{X}_{ij}\right.\right] = \frac{\alpha}{1-\rho} + \frac{\beta_1 + \beta_2\delta}{1-\rho}E\left(Z_j\middle|X_{ij}\right) + \frac{\beta_2}{1-\rho}\tilde{X}_{ij} \qquad (6)$$

Neighborhood effect β_1 and viewshed effect β_2 can be identified if we impose the restriction $\beta_1 + \beta_2\delta \neq 0$. Further, the structure of the spatial weight matrix W_t satisfies the following condition: the matrices I, W_t, and W_t^2 are linearly dependent and no individual unit is isolated (Lee 2007; Bramoulle et al. 2009). This condition is obviously satisfied when we use pseudo-contiguity matrices, which will be discussed in the next section.

3.3 The Basic Econometric Model

We specify a series of hedonic models with the natural log of the sale price as the dependent variable and the variables in Table 1 as explanatory variables. The nonlinear form is consistent with Rosen's (1974) notion that individuals cannot repackage housing attributes to capture arbitrage opportunities without a cost (see also Graves et al. 1988). Our basic econometric model can be expressed as follows:

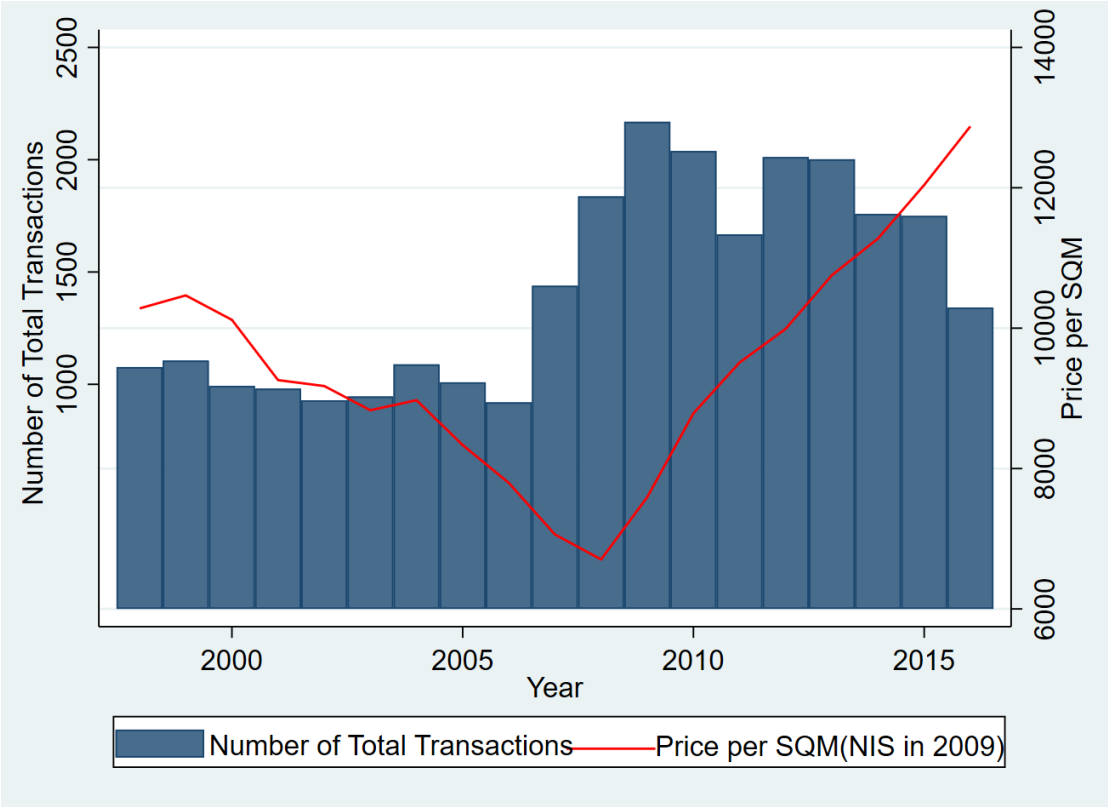
$$y_{trli} = \alpha_t + \lambda \widetilde{y_{trli}} + X_{trli}\beta + Z_{rl}\gamma + V_r\phi + u_{trli}, (\lambda < 1)$$

$$\widetilde{y_{trli}} = \frac{\mathbf{1}}{N_{it}} \sum_{j=1}^{N_{it}} w_{ij}^{t}\, y_{trlj} \qquad (7)$$

We denote the period $t = 1, \dots, T$; statistical area id $r = 1, \dots, R$; location id $l = 1, \dots, L$; transaction id $i = 1, \dots, I$. The dependent variable is transaction price (in logs) for a housing unit, denoted by y_{trli}. The time trend in average house prices in the study area is depicted in Figure 4 and shows the growth in house prices starting in 2009.

In our models, vector X_{trli} denotes the attributes of the transaction such as the number of rooms, floor number, visibility variables, and type of sale. These are time-variant variables, while all other variables are time-invariant. Vector Z_{rl} relates to the attributes of locations such as distance to amenities and air pollution, which are associated with an address and are identified by x,y coordinates. Vector V_r is the attributes of statistical areas, including crime rates and amenities. These observations are collected for the 85 statistical areas in Haifa for which data are available, where u_{trli} is the error term, which depends on the error component assumption and will be discussed in the following section. In the baseline model, u_{trli} is i.i.d and $\sim N(0, \sigma_\epsilon)$.

Fig.4: Housing Transaction Prices in Haifa and Volume by Year



3.4 Spatial Weights

We use contiguity for defining neighbors. We do not use a distance-based measure of connectivity due to the sheer size of such a matrix (27067×27067) over 19 years. Additionally, it is unnecessary to assume spatial correlation between each two transactions from different years. Instead, we use first-order pseudo-contiguity matrices within a radius of r km, i.e., all the transactions within a circle of radius r km in the same year. Two dwelling units are neighbors (with 1 assigned to a neighbor) if the geographic distance between them is lower than r km; otherwise, dwelling units are not considered as neighbors (with 0 assigned to a non-neighbor). We choose $r =$ 0.5km, so there are 20 neighbors for each unit on average.[3]

Following Baltgai et al (2015) we allow the spatial weight matrix to very over time. Since we have different observations (transactions) each year, this matrix differs in size for different years. For example, in 2006, W_{2006} is relatively small (920 by 920) whereas in 2009 W_{2009} it is relatively large (2169 by 2169).

[3] We do not impose a fixed number of neighbors for each unit. Proposition 2 in Bramoulle et al. (2009) points out if all groups have the same size, the group effect cannot be identified.

$$W = \begin{pmatrix} W_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & W_T \end{pmatrix}$$

For each period t, the entries of spatial weight matrix W_t satisfy the condition that $w_{ij}^t = 1$ if region j and region i are neighbors and $w_{ij}^t = 0$ if otherwise.

3.5 Model specifications

Since the data covers almost two decades (1998- 2016), our first model includes time fixed effects. These are nested in equation (4) where $\alpha_t \neq 0$ and β represents the coefficients on transaction-specific variables, γ is a feature of location, and ϕ characterizes the attributes of a statistical area. Although our panel data is unbalanced, we can still achieve a fixed effect by averaging the values of both the dependent and independent variables by different levels of spatial aggregation and time.

We utilize the multi- level structure of the data and the existence of spatial correlation to unravel these identification issues. Akin to social network analysis where interacting agents have their own specific reference groups defined by individuals whose mean attributes exert mutual influence on their outcomes, individual dwelling units are similarly nested within buildings that themselves are nested within locales. The error components of this structure can be exploited to separate exogenous from endogenous influences.

To exploit the multi-level random effects and nested error structure of the data we adopt an approach pioneered by Baltagi and Bresson (2011) who use maximum likelihood panel data estimation in order to incorporate spatial effects (via the error terms) and heterogeneity (via random effects).To fully control the correlation of unobserved error within different levels of spatial autoregression, Baltagi et al. (2015) extend this approach to an unbalanced spatial lag model with nested random effects and apply this method to estimate a hedonic housing model based on flats sold in the city of Paris over the period 1990-2003.

Earlier research in hedonic house price studies also uses a similar error structure to estimate the consumer's willingness to pay for different characteristics such as clean air and proximity to a hazardous waste site (see, for example, Baltagi and Chang 1994, Harrison and Rubinfeld 1978, Mendelsohn et al. 1992). Our unbalanced panel consists of three hierarchical levels with $r = 85$ statistical areas, each containing L_{tr} second level addresses. Each second-level address contains M_{trl} observations on the housing unit. Thus, the total number of observations N is

$$N = \sum_{t=1}^{T} \sum_{r=1}^{R} L_{tr} = \sum_{t=1}^{T} \sum_{r=1}^{R} \sum_{m=1}^{L_{tr}} M_{trl} \tag{8}$$

The error term is given by

$$u_{trli} = \delta_{tr} + \mu_{trl} + \epsilon_{trli} \tag{9}$$

where δ_{tr} is the SA- level random effect, μ_{trl} is the location level random effect, ϵ_{trli} is the random effect at the dwelling unit level. For the random specification, we assume that:

$$\begin{aligned} &\delta_{tr} \sim i.i.n.\left(0, \sigma_\delta^2\right), \\ &\mu_{trl} \sim i.i.n.\left(0, \sigma_\mu^2\right), \\ &\epsilon_{trli} \sim i.i.n.\left(0, \sigma_\epsilon^2\right) \end{aligned} \tag{10}$$

Further, let ρ_1, ρ_2 denote the proportion of random effects at the SA and location level on the individual error terms respectively, such that $\rho_1 = \frac{\sigma_\mu^2}{\sigma_\epsilon^2}, \rho_2 = \frac{\sigma_\delta^2}{\sigma_\epsilon^2}$. SAR Model (7) with error components (9), (10) can be estimated by ML (Maximum Likelihood) and relates to nested unbalanced panel data with spatial spillover effects as articulated by Antweiler (2001). The log likelihood function of this model is provided in Appendix 1.

4. Estimation Results

Given the structure of the spatial panel data, a series of estimations are presented with various combinations of temporal and spatial effects. We estimate three non-spatial models and three spatial models as follows:

A. Time fixed effect

$$y_{trli} = \alpha_t + \boldsymbol{X}_{trli}\boldsymbol{\beta} + \epsilon_{trli}$$

B. One-way random effect (statistical area) and time fixed effect

$$y_{trli} = \alpha_t + \boldsymbol{X}_{trli}\boldsymbol{\beta} + \delta_{tr} + \epsilon_{trli}$$

C. Multi-level random effect (statistical area, location) and time fixed effect

$$y_{trli} = \alpha_t + \boldsymbol{X}_{trli}\boldsymbol{\beta} + \delta_{tr} + \mu_{trl} + \epsilon_{trli}$$

D. Spatial time fixed effect (SAR model)

$$y_{trli} = \alpha_t + \lambda \widetilde{y_{trli}} + \boldsymbol{X}_{trli}\boldsymbol{\beta} + \epsilon_{trli}$$

E. Spatial one-way random effect (statistical area) and time fixed effect (SAR) model

$$y_{trli} = \alpha_t + \lambda \widetilde{y_{trli}} + \boldsymbol{X}_{trli}\boldsymbol{\beta} + \delta_{tr} + \epsilon_{trli}$$

F. Spatial multi-level random effect (statistical area, location) and time fixed effect (SAR) model

$$y_{trli} = \alpha_t + \boldsymbol{X}_{trli}\boldsymbol{\beta} + \lambda \widetilde{y_{trli}} + \delta_{tr} + \mu_{trl} + \epsilon_{trli}$$

Table 5 presents the results of the three non-spatial models (A-C) using full variables and all transactions respectively. Model A is estimated by OLS and Models B and C are estimated by restricted maximum likelihood (REML). In Table 5, the OLS estimation of Model A achieves a log-likelihood of -9582.18. Comparing Models A and B to C, the likelihood values are largely improved by introducing the random effect in the error terms. The likelihood values grow to -5123.85 and -1356.01 by adding regional random effect in location in Model B and both location and SA in Model C. The estimated nested random effects are $\hat{\rho}_1 = 0.46$, $\hat{\rho}_2 = 1.08$, which indicates the variance at the SA, location, and individual transaction scales accounts for 18.3%, 42.4%, and 39.2% of total variance according to the variance decomposition formula

provided in the Appendix 1.

For the viewshed variables, the naïve OLS estimation of Model A shows a positive viewshed effect of natural open spaces and a negative viewshed effect of total visible area for both range 0-1 and 1-5 km with high levels of significance. Model A also predicts a positive effect of a coastal view in the 1-5 km range instead of the 0-1 km range. After controlling regional random effects for both region and location in model C, total visible area shows a positive effect on house prices which gives an intuitive prediction compared with Model A and B. In model C, a one percent increase in visibility of natural open space within the 0-1km range adds around 1.6% percent to dwelling unit value. However, increase in the visibility of natural open space within the 1-5k range has a negative effect on unit value. This finding confirms our hypothesis that naïve OLS estimates are biased, predicting negative viewshed effects even after controlling for regional random effects.

Table 5. Estimation Results (Non-spatial)

	MODEL A		MODEL B		MODEL C	
Log price	Coef.	z	Coef.	z	Coef.	z
Visibility						
Natural Open space (r=0-1km)	0.0549***	10.1	0.0161***	2.87	0.0156**	2.14
Coast (r=0-1km)	-0.0195***	-2.62	0.0194**	2.38	0.0012	0.11
Total visible area (r=0-1km)	-0.0028*	-1.79	-0.0001	-0.08	0.0046***	3.07
Natural open space (r=1-5km)	0.0067*	1.94	-0.0111***	-2.98	-0.0085*	-1.94
Coast (r=1-5km)	0.0244***	11.55	0.0128***	5.97	0.0079***	3.18
Total visible area (r=1-5km)	-0.0465***	-9.15	-0.0096**	-1.96	-0.0177***	-3.19
Road Distance						
Coast	-0.0388***	-22.18	-0.0270***	-4.96	-0.0313***	-3.65
Commercial	0.0940***	12.93	0.0625***	7.13	0.0864***	6.4
Employment	-0.0987***	-17.21	-0.0497***	-6.37	-0.0342***	-2.81
Train station	0.0074**	2.1	0.0317***	4.06	0.0294**	2.35
Park	0.0075**	2.19	-0.0178***	-2.85	-0.0335***	-3.32
Main Road	0.0361***	8.73	0.0003	0.04	0.0155	1.22
Aerial Distance						
Cemeteries	0.0567***	31.24	0.0479***	5.77	0.0398***	3.55
Industry	0.0822***	5.18	-0.0228	-1.19	0.0162	0.55
Road	-0.0852***	-12.27	0.0519***	4.05	0.0753***	3.79
Schools	-0.0812***	-3.75	0.0797***	3.11	0.1096***	2.78
Natural Green Area	0.1314***	10.97	0.0807***	5.33	0.1153***	4.86
Air pollution	0.1335***	23.54	0.0881***	5.35	0.1176***	4.63
Structural						
Elevation	0.0021***	34.83	0.0021***	18.93	0.0022***	13.69
Year built	0.0032***	28.05	0.0024***	22.82	0.0015***	14.84
Rooms	-0.0018	-0.98	0.0001	0.04	0.0003	0.18
Floor level	-0.0075***	-8.72	-0.0025***	-3.05	-0.0024***	-2.65

Floor space	0.0115***	120.26	0.0105***	113.56	0.0096***	98.12
Square of floor space	-0.0005***	-54.33	-0.0045***	-52.59	-0.0040***	-50.41
Building Perimeter (North)	-0.0015***	-2.66	-0.0015***	-2.87	-0.0012	-1.4
Building Perimeter (East)	-0.0013**	-2.21	-0.0003	-0.49	0.0007	0.8
Building Perimeter (South)	0.0005	0.83	0.0010	1.8	0.0003	0.31
Building Perimeter (West)	0.0007	1.18	-0.0004	-0.82	-0.0019**	-2.42
Orientation (North-south, 0/1)	0.0023	0.55	0.0082**	2.2	0.0007	0.13
Orientation (Northeast-southwest, 0/1)	-0.0097**	-2.07	-0.0046	-1.07	-0.0053	-0.83
Orientation (East-West, 0/1)	-0.0042	-1.04	-0.0011	-0.29	0.0034	0.62
Apartment (0/1)	-0.0278**	-2.22	-0.0372***	-3.31	-0.0463***	-4.45
Sale prior to construction (0/1)	0.0749***	6.21	0.1166***	10.64	0.0516***	4.56
Closest Sch.=Elementary (0/1)	0.0696***	6.03	0.0614***	4.5	0.0895***	4.44
Closest Sch.=Middle (0/1)	0.0870***	13.93	-0.0012	-0.14	0.0062	0.5
Proficiency elementary school	0.0194***	5.12	0.0175***	3.42	0.0197**	2.39
Proficiency middle school	0.0281***	7.79	0.0220***	4.2	0.0245***	2.86
Violence elementary school	0.0180***	7.62	0.0210***	6.03	0.0304***	5.03
Random-effects Parameters						
Location-Address					0.1546	
Statistical Area			0.1819		0.2350	
Dwelling Unit	0.39210		0.2497		0.2261	
Log Likelihood	-9582.18		-5123.85		-1356.01	
LR test against Model A			4522.20		8841.01	
Observations	27067		27067		27067	
Statistical Areas	85		85		85	

Notes: Regression results are estimated by restricted maximum likelihood (REML), also known as residual maximum likelihood. Statistical significance is as follows: * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 6 presents the spatial counterparts of the models in Table 5. By adding the SAR coefficient, spatial Models D-F outperform Models A-C with respect to log likelihood; from -9582.18, -5123.85 and 1356.01 to -3202.96, -1774.97 and -637.16 respectively. The estimated nested random effects are $\hat{\rho}_1 = 0.47$, $\hat{\rho}_2 = 0.42$, which indicate the variance at the SA, location, and individual transaction scales accounts for 24.7%, 22.5%, and 52.8% of total variance according to the variance decomposition formula provided in Appendix 1. After controlling for spatial autocorrelation, the magnitudes of most location-based estimates are reduced. This supports the hypothesis of upward bias generated by the neighborhood effect. We find that spatial dependence does not replace the covariance within the unobserved errors. The standard errors of both statistical areas and locations are significantly different from zero. This indicates the existence of spatial autocorrelation in both the dependent variable and the error terms. Using the error component structure cannot therefore solely characterize the correlation of the house prices within a neighborhood.

With respect to viewshed effects, Table 6 illustrates that controlling for neighborhood effects reduces the magnitudes of the viewshed effect. In Model F, the estimates show that a 1 percent increase in visibility of the natural open space and the total visible area in the 0-1km range adds 1% and 0.4% to dwelling unit value, respectively. A one percent increase in visibility of coast in the 1-5km range adds to 0.8% to unit value. However, visibility of natural open space and total visible area from 1-5km have no significant effect on dwelling unit value, which show that the range of visibility matters. A coastal view only adds value when the range of visibility is above 1km. This indicates that the price premium for living close to the coast is possibly explained by the proximity rather than visibility.

In spatial models (D-F), almost all the road distance and aerial distance variables are consistent with intuition. Distances to amenities such as coast, employment, parks, and schools have negative coefficients. With respect to local schools, there is mixed evidence that both proximity and quality of local (elementary and middle) schools can impact house prices. Intuitively, the distance to dis-amenities such as cemeteries and sources of air pollution is positive with high statistical significance, namely, people would pay more to live far away from these places. The coefficient signs on distance to main road and industry are ambiguous since residents gain from the accessibility but are harmed by the noise and pollution from such proximity. An interesting finding is the negative effect of accessibility to commercial areas. This may be explained by separation of commercial and residential areas through planning controls.

Proximity to natural open spaces shows a significant negative effect on house prices. In the context of Haifa this counter-intuitive result is not so surprising. As noted earlier the residential areas of Haifa are transected by deep ravines with rocky slopes, thick vegetation and woodlands. These natural open areas are habitats for wild boars. The negative externalities associated with the infiltration of this wildlife into the urban fabric have been documented by Toger et al (2016, 2018). Most coefficients on distance are robust in spatial models D - F after controlling for spatial autoregression. The estimated elasticity on distance to school becomes negative as predicted by theory, but positive in non-spatial models B and C. This indicates that the endogenous effect δ outweighs the proximity effect β_2. Other factors such as spatial sorting have stronger effect in explaining the effect of school distance on house prices.

Most of the structural covariates are significant. Aside from number of rooms and type of middle school, all estimates are highly significant. Almost all transaction-specific variables are statistically significant and have the expected signs. In contrast to similar studies, floor number shows a negative sign suggesting that a higher-floor premium does not exist. This could either mean that the floor effect has a non-monotonic effect on prices or that urban topography (elevation) swamps-out the floor effect. Number of rooms is generally positively correlated with price since it is positively correlated with dwelling unit size. In our estimations, floor space overshadows number of rooms, and the t-statistic of the latter is not significant. Building size has a negative effect on prices,

as indicated by the negative signs associated with building perimeters. Some of these are not significant since perimeters for different orientations are almost perfect correlates. Finally, building orientation shows no significant effect on prices.

As noted, elevation is an important factor driving house prices. The city of Haifa is built on a mountain ridge and price is related to elevation with respect to topography and not with height of building. Consequently, higher buildings are prevalent in the flatter, low-lying and generally cheaper parts of the Haifa area. Our estimates in representative Model F indicate that every 10m of topographic elevation adds 1.5% to the value of the dwelling unit. Nevertheless, since elevation is strongly correlated with all the viewshed variables (see Table 3) it is included. Without this variable, the estimates of viewshed variables would be biased even when they are correctly identified, due to missing variables.

Table 6. Estimation Results (Spatial Regressions)

	MODEL D		MODEL E		MODEL F	
Log price	Coef.	z	Coef.	z	Coef.	z
Visibility						
Natural open space (r=0-1km)	0.0104***	2.09	0.0177***	2.95	0.0117*	1.66
Coast (r=0-1km)	0.0054	0.80	0.0120	1.36	0.0035	0.32
Total visible area (r=0-1km)	-0.0006	-0.43	0.0008	0.58	0.0043***	2.89
Natural open space (r=1-5km)	0.0010	0.33	-0.0005	-0.13	-0.0052	-1.23
Coast (r=1-5km)	0.0126***	6.58	0.0095***	4.47	0.0074***	3.08
Total visible area (r=1-5km)	-0.0178***	-3.85	-0.0136***	-2.70	-0.0170***	-3.14
Road Distance						
Coast	-0.0083***	-5.08	-0.0008	-0.35	-0.0306***	-4.13
Commercial	0.0415***	6.26	0.0782***	9.08	0.0714***	5.47
Employment	-0.0619***	-11.84	-0.0739***	-10.83	-0.0316***	-2.72
Train station	0.0005	0.15	-0.0025	-0.59	0.0356***	3.12
Park	-0.0091***	-2.93	-0.0261***	-6.51	-0.0364***	-3.82
Main Road	0.0285***	7.60	0.0295***	6.18	0.0035	0.3
Aerial Distance						
Cemeteries	0.0096***	5.44	0.0214***	9.22	0.0356***	4.17
Industry	-0.0039	-0.27	0.0584***	3.06	0.0165	0.58
Road	-0.0069	-1.09	-0.0160**	-1.91	0.0393**	2.1
Schools	-0.0540***	-2.76	-0.0555**	-2.17	-0.0579	-1.52
Natural Green Area	0.6539***	11.14	0.0700***	4.88	0.1197***	5.22
Air pollution	0.0986***	19.09	0.1439***	20.22	0.0729***	3.26
Structural						
Elevation	0.0001***	7.25	0.0005***	7.86	0.0015***	10.09
Year built	0.0024***	23.56	0.0019***	18.69	0.0014***	14.71
Rooms	-0.0035***	-2.02	-0.0020	-1.19	-0.0004	-0.27
Floor level	-0.0040***	-5.18	-0.0030***	-3.43	-0.0024***	-2.75
Floor space	0.0101***	111.80	0.0094***	104.82	0.0094***	98.94

Square of floor space	-0.0005***	-50.63	-0.0005***	-49.56	-0.0005***	-50.6
Building Perimeter (North)	-0.0006	-1.20	-0.0011	-1.57	-0.0007	-0.9
Building Perimeter (East)	-0.0011**	-2.18	-0.0004	-0.60	0.0006	0.7
Building Perimeter (South)	0.0002	0.41	0.0005	0.72	-0.0001	-0.08
Building Perimeter (West)	0.0004	0.80	-0.0010	-1.53	-0.0018**	-2.35
Orientation (North-south, 0/1)	0.0093**	2.52	0.0042	0.90	0.0020	0.37
Orientation (Northeast-southwest, 0/1)	-0.0043	-1.01	-0.0057	-1.10	-0.0055	-0.88
Orientation (East-West, 0/1)	-0.0052	-1.43	-0.0022	-0.48	0.0014	0.27
Apartment (0/1)	-0.0251**	-2.21	-0.0369***	-3.47	-0.0429***	-4.24
Sale prior to construction (0/1)	0.0834***	7.64	0.0423***	3.78	0.0372***	3.37
Closest Sch.=Elementary (0/1)	0.0673***	6.44	0.0564***	4.35	0.0740***	3.81
Closest Sch.=Middle (0/1)	0.0250***	4.38	0.0350***	4.94	0.0022	0.19
Proficiency elementary school	-0.0094***	-2.72	-0.0075	-1.56	0.0170**	2.14
Proficiency middle school	0.0332***	10.16	0.0380***	8.82	0.0338***	4.14
Violence elementary school	0.0120***	5.61	0.0210***	6.41	0.0233***	4.05
SAR Coefficient	0.4992***	74.30	0.5250***	67.33	0.3900***	53.26
Random-effects Parameters						
Location-Address			0.1348		0.1508	
Statistical Area					0.1439	
Dwelling Unit			0.2390		0.2205	
Log Likelihood	-3202.96		-1774.97		-637.16	
LR test			2697.20		5496.95	
Observations	27067		27067		27067	
Statistical Areas	85		85		85	

Notes: Regression results are estimated by restricted maximum likelihood (REML), also known as residual maximum likelihood. Statistical significance is as follows: * $p < .10$, ** $p < .05$, *** $p < .01$.

4.2. Robustness Tests

We begin by testing the consistency of the panel data. Specifically, we test for the existence for systematic bias in the missing observations in the unbalanced panel. Since the panel data are incomplete, this means that if a dwelling unit is considered an observation, we cannot observe the transaction price in each year. ML and OLS assume that the data is missing randomly. In contrast, even though these estimators can also be modified for unbalanced panels due to missing observations, their asymptotic properties, in the event of missing observations, may become problematic if the reason why data are missing is not known. To test this, we calculate the correlation of average house price and number of transactions per year. It turns out there is almost no correlation between them with a correlation coefficient of -0.01786 and $R^2 = 0.0003$.

To test the robustness of the estimation results two tests are invoked. The first relates to a local differences model where samples are kept only if there are comparable

observations in the same location or year. The price premium between them and their comparable units is explained by the features of the transaction such as viewshed variables. Specifically, let $\log(\widetilde{Price_i})$ be the average price of units within same location. Which is given by the conditional expectation of $\log(Price_i)$ given the location variables.

$$\log(\widetilde{Price_i}) = E\left[\log\left(P_{ij}\right)\left|Z_j\right.\right] \tag{10}$$

$$= \alpha + \beta_1 Z_j + \beta_2 E(X_{ij}\left|Z_j\right.) + \beta_3 S_i \ = \alpha + \beta_1 Z_j + \beta_2 \delta Z_j + \beta_3 S_i$$

Subtracting (3) from (10), the local first differenced regression is:

$$\log\left(Price_{ij}\right) - \log\left(\widetilde{Price_{ij}}\right) = \widetilde{\beta_2}\tilde{X}_{ij} \ + u_j + v_{ij} \tag{11}$$

Since the neighborhood variables Z_j cancel out, there are only structural and visibility variables in equation (11). This specification is equivalent to a panel fixed effect for unbalanced panel data if we set location as our panel indicator. The estimation results are presented in Table 7. Since the locations are controlled in Models G-I and there is no spatial autocorrelation and OLS estimation is unbiased. When the number of panels is large, as we group our data by location and year of transaction the number of observations drops remarkably. As shown in Table 7 a smaller sample is used as Model G uses the filtered sample of 25,885 transactions when location is controlled. The other 2,116 transactions are dropped since they are the only observations at their locations. Model H has 20,964 observations after location and year of transaction are both controlled. Model I has only 3,043 observations when floor level is also controlled. The more location variables are controlled, the more the estimates of the viewshed effect are free of the influence of location. The prediction of viewshed effects in Model G-I is in line with hedonic spatial Model F. This suggests that our representative model F is well-specified. Natural open space and total open area have positive effects on house prices within a 1km range. Specifically, Model I predicts that the marginal value of increasing natural open areas view by 1 percent is 3% given the same location, same floor number and all other conditions unchanged. Viewshed effects of the three amenities have a positive effect on price within the 1-5km range but they do not show any statistical significance.

The second robustness test involves comparing different time intervals in the dataset. Since proximity variables are treated as time-invariant, the amenities used for distance variables are recorded as recent observations. As city infrastructure changes, so does the location of air pollution, schools etc. Although our regressions contain time fixed effects, theoretically, the dependent and independent variables are more consistent in time in the later periods. This test repeats the regression for different time intervals, from 2011-2017, 2015-2017. Results show that the signs of the main variables of interest are stable (see Appendix 2, Tables 9-10).

Table 7: Local Differenced Regression

	MODEL G		MODEL H		MODEL I	
Log price	Coef.	z	Coef.	z	Coef.	z
Visibility						
Natural open space (r=0-1km)	0.04032***	4.55	0.03340***	4.94	0.03328***	4.92
Coast (r=0-1km)	-0.00195	-0.13	-0.00242	-0.22	0.00261	0.23
Total visible area (r=0-1km)	-0.01426***	-7.35	0.00399***	2.67	0.00318**	2.14
Natural open space (r=1-5km)	0.00198	0.36	-0.00142	-0.34	0.00095	0.23
Coast (r=1-5km)	0.00343	1.10	0.00079	0.33	0.00253	1.06
Total visible area (r=1-5km)	0.00464	0.67	-0.00681	-1.29	0.00089	0.17
Structural						
Year of built	0.00191***	14.00	0.00186***	17.80	0.00189***	18.13
Rooms	0.00138	0.63	-0.00181	-1.09	-0.00194	-1.16
Floor level	0.00126	1.07	-0.00083	-0.93		
Floor space	0.00979***	77.56	0.00995***	103.36	0.00993***	103.34
Square of floor space	-4.230E-06***	-50.48	-4.210E-06***	-38.38	-4.220E-06***	-50.54
Building Perimeter (North)	-0.00082	-1.07	-0.00005	-0.08	-0.00003	-0.05
Building Perimeter (East)	0.00142*	1.77	0.00062	1.02	0.00083	1.35
Building Perimeter (South)	0.00026	0.33	-0.00044	-0.71	-0.00048	-0.79
Building Perimeter (West)	-0.00143*	-1.83	-0.00093	-1.57	-0.00105	-1.77*
Orientation (North-south, 0/1)	0.01058*	1.93	0.00292	0.70	0.00229	0.55
Orientation (Northeast-southwest, 0/1)	-0.00455	-0.70	-0.00283	-0.57	-0.00268	-0.54
Orientation (East-West, 0/1)	-0.00504	-0.95	-0.00594	-1.46	-0.00644*	-1.59
Apartment (0/1)	0.04468***	5.08	-0.04482***	-4.10	-0.04383***	-4.02
Sale prior to construction (0/1)	0.06352***	4.35	0.09202***	8.21	0.09219***	8.25
Closest Sch.=Elementary (0/1)	0.13440***	3.68	0.13549***	4.87	0.13633***	4.91
Closest Sch.=Middle (0/1)	0.04470**	2.35	0.01044	0.72	0.01322	0.91
Proficiency elementary school	0.05596***	4.33	0.04926***	4.99	0.04972***	5.06
Proficiency middle school	0.02025	1.18	0.03216**	2.46	0.03683***	2.82
Violence elementary school	0.05169***	5.26	0.04243***	5.66	0.04434***	5.93
Observations	25,885		20,964		3,043	

5. Conclusions

This paper attempts to extend current practice in viewshed analysis and incorporates this into hedonic house price modeling. We develop a new automated, GIS-based method for quantifying the viewshed effect of amenities such as visibility of coast, natural open spaces and total open space and test their impact on repeat sales for house prices in Haifa.

The paper makes two contributions. First, from a theoretical perspective, we highlight the tendency in hedonic house price studies to confound utility derived from visibility (viewshed) with that derived from proximity and suggest a strategy for dealing with this. Second, in the realm of spatial econometrics we illustrate how the effect of neighborhood and location (address) specific variables and viewshed effects can be estimated separately in a hedonic model. The viewshed effect of amenities can be identified even when they are correlated with other location variables such as the distance to amenities. We compute precise measures for the visibility of coast, natural open space and total visible open areas and test both spatial and non-spatial hedonic models with multilevel random effects.

Our main empirical finding suggests the viewshed effect on house prices is overstated with OLS estimation. Moreover, without controlling for spatial effects, naïve OLS specification produces biased estimates for viewshed effects. This is because these effects often cannot be distinguished from possible proximity to these areas. After controlling for spatial effects, the magnitudes of the viewshed effect decreases. We also exploit the multi-level structure of the data using the SAR model to disentangle spatial autocorrelation and the identification issues that this implies. In our representative model F, a 1 percent increase in visibility of natural open spaces and total visible area in 1km range add 1% and 0.4% to dwelling unit value respectively. A one percent increase in visibility of the coast in a 1-5km range adds o 0.8% to a dwelling unit's value all other variables (such as location) equal. Range does matter and visibility of natural open space and total visible area within a 1-5 km range do not have a significant effect on house prices. .

The role of natural topography is underscored in the analysis. Our results for the city of Haifa seem to suggest that for cities characterized by hilly landscapes, visibility of an amenity can outweigh proximity in determining prices. Visibility seems to be a key determinant of house prices when proximity (accessibility) is constrained. Topography may also serve to distort the effect of the higher-floor premium prevalent in many cities with flat natural landscapes. In those cities, such as Tel Aviv or Chicago, accessibility rather than visibility is key. The latter can be constricted very easily through bad planning. This calls for the judicious use of land regulation and proactive public-sector intervention to preserve viewsheds and their eventual capitalization in house prices.

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Appendix.1 The Estimation Procedure of Multilevel Error Random Effect Spatial Lag Model

Due to the data's multilevel structure, we use a 2-stage process for maximizing the likelihood function. If we pool the observations, the loglikelihood is given by:

$$lnl = -\frac{1}{2}Nln(2\pi) - \frac{1}{2}\ln|\Omega| + \ln|A| - \frac{1}{2}u'\Omega^{-1}u \quad (5)$$

where

$$A = I_N - \lambda W$$

The variance-covariance matrix of the disturbance is defined as follows:

$$\Omega = E[uu'] = \sigma_\epsilon^2\left[I_N + \rho_\mu J_\mu + \rho_\delta J_\delta\right]$$

Let $\boldsymbol{X}_{trli} = (X_{trli}\ Z_{rl}\ V_r)'$ be a vector of all the independent variables and $\boldsymbol{\beta} = (\beta, \gamma, \phi)$ be its coefficient. Let $e = \Omega^{-\frac{1}{2}}u,\ e = y^* - \boldsymbol{X}^*\boldsymbol{\beta}^*,\ y^* = (I_N - \lambda W)y - (1-\theta_1)\,\bar{y} - (1-\theta_2)\bar{\bar{y}}$

$$\boldsymbol{X}^* = (I_N - \lambda W)\boldsymbol{X} - (1-\theta_1)\,\bar{\boldsymbol{X}} - (1-\theta_2)\bar{\bar{\boldsymbol{X}}}$$

With $\theta_1 = 1 - \frac{\sigma_\epsilon^2}{\sigma_\mu^2}, \theta_2 = \frac{\sigma_\epsilon^2}{\sigma_\mu^2} - \frac{\sigma_\epsilon^2}{\sigma_\delta^2},\ \bar{y}, \bar{\bar{y}}, \bar{\boldsymbol{X}}, \bar{\bar{\boldsymbol{X}}}$ are group averages of the dependent and independent variables at the regional and location levels.

Following Antweiler (2001) $|\Omega|$ can be written as follows:

$$|\Omega| = (\sigma_\epsilon^2)^N \prod_{r=1}^{R} \theta_1 \prod_{l=1}^{L_r} \theta_2 \quad (6)$$

$$ln|A| = \sum_{t=1}^{T}\sum_{r=1}^{R} ln|1 - \lambda\omega_{tr}| \quad (7)$$

where ω_{tr} is the rth largest eigenvalue of weight matrix of W_t.

At the first stage, the parameters $\boldsymbol{\beta}$ and σ_ϵ^2 can be solved from their first order maximizing conditions:

$$\boldsymbol{\beta}^* = (\boldsymbol{X}^{*\prime}\boldsymbol{X}^*)^{-1}(\boldsymbol{X}^{*\prime}y^*)$$

$$u'\Omega^{-1}u = \hat{e}'\hat{e} = (y^* - \boldsymbol{X}^*\boldsymbol{\beta}^*)'(y^* - \boldsymbol{X}^*\boldsymbol{\beta}^*) \quad (8)$$

At the second stage, we can write the loglikelihood function as a function of three parameters $(\lambda, \theta_1, \theta_2)$ by replacing the components (6) (7) (8) as follow:

$$lnl = -\frac{1}{2}Nln(2\pi) - \frac{1}{2}\ln[(\sigma_\epsilon^2)^N \prod_{r=1}^{R}\theta_1 \prod_{l=1}^{L_r}\theta_2] + \sum_{t=1}^{T}\sum_{r=1}^{R} ln|1-\lambda\omega_{tr}|$$
$$-\frac{1}{2}(y^* - \boldsymbol{X}^*\boldsymbol{\beta}^*)'(y^* - \boldsymbol{X}^*\boldsymbol{\beta}^*)$$

The iterative two-stage procedure needed to estimate the parameters of the random effects spatial error and spatial lag model bears similarities to the non-spatial random effects model (Breusch 1987). The difference is that the concentrated loglikelihood function must be maximized for three parameters ($\lambda, \theta_1, \theta_2$) instead of only one ($\theta_1$).

Appendix.2

Table 9: The Estimation of Non-Spatial Hedonic Models for 2011-2017

	MODEL D		MODEL E		MODEL F	
Log price	Coef.	z	Coef.	z	Coef.	z
Visibility						
Natural open space (r=0-1km)	0.05402***	6.47	0.01169	1.38	0.01065	1.06
Coast (r=0-1km)	-0.02376**	-2.12	0.02658**	2.21	0.00401	0.27
Total visible area (r=0-1km)	0.00029	0.14	0.00427**	2.18	0.00685***	3.40
Natural open space (r=1-5km)	0.02100***	4.05	0.00105	0.19	-0.00394	-0.66
Coast (r=1-5km)	0.02207***	6.85	0.01255***	3.96	0.01155***	3.36
Total visible area (r=1-5km)	-0.05371***	-6.89	-0.02684***	-3.65	-0.03202***	-4.06
Road Distance						
Coast	-0.00005***	-16.88	-0.00003***	-4.21	-0.00004***	-3.86
Commercial	0.00007***	6.50	0.00006***	4.69	0.00008***	4.69
Employment	-0.00007***	-8.29	-0.00004***	-3.51	-0.00003**	-2.07
Train station	0.00002***	3.17	0.00004***	3.91	0.00004**	2.54
Park	-0.00001	-1.25	-0.00004***	-3.97	-0.00004***	-3.26
Main Road	0.00005***	7.90	0.00001	0.52	0.00002	1.22
Aerial Distance						
Cemeteries	0.00006***	22.05	0.00005***	4.98	0.00005***	4.14
Industry	0.00013***	5.37	0.00000	-0.01	0.00002	0.66
Road	-0.00008***	-7.54	0.00002	1.17	0.00005**	2.04
Schools	-0.00012***	-3.57	0.00008**	2.09	0.00007	1.34
Natural open space	0.00017***	9.38	0.00013***	5.79	0.00014***	4.70
Air pollution	0.15319***	18.07	0.06994***	3.12	0.09950***	3.47
Structural						
Elevation	0.00186***	20.24	0.00224***	14.32	0.00231***	11.94
Year built	0.00244***	15.53	0.00175***	12.33	0.00119***	8.88
Rooms	-0.01154***	-4.20	-0.01017***	-4.16	-0.00672***	-2.87
Floor level	-0.00771***	-6.00	-0.00226*	-1.85	-0.00221*	-1.76
Floor space	0.01637***	55.28	0.01472***	53.31	0.01410***	49.59
Square of floor space	-0.00003***	-25.02	-0.00003***	-22.80	-0.00003***	-21.51
Building Perimeter (North)	-0.00183**	-2.26	-0.00203***	-2.76	-0.00155	-1.55
Building Perimeter (East)	-0.00058	-0.70	0.00019	0.25	0.00109	1.08
Building Perimeter (South)	0.00129	1.51	0.00189**	2.44	0.00110	1.06
Building Perimeter (West)	-0.00004	-0.05	-0.00087	-1.21	-0.00214**	-2.19
Orientation (North-south, 0/1)	0.00048	0.08	0.00843	1.53	0.00312	0.44
Orientation (Northeast-southwest, 0/1)	-0.00169	-0.24	-0.00125	-0.19	-0.00087	-0.11
Orientation (East-West, 0/1)	0.00065	0.11	0.00727	1.34	0.00948	1.35
Apartment (0/1)	-0.24598***	-5.35	-0.23369***	-5.66	-0.20729***	-5.16
Sale prior to construction (0/1)	0.11806***	4.54	0.16448***	6.99	0.10345***	3.97

Closest Sch.=Elementary (0/1)	0.06688***	3.59	0.06432***	3.03	0.09201***	3.48
Closest Sch.=Middle (0/1)	0.08737***	9.05	0.01155	0.89	0.01518	0.94
Proficiency elementary school	0.02074***	3.68	0.01657**	2.21	0.02892***	2.87
Proficiency middle school	0.03653***	6.93	0.02277***	2.95	0.02436**	2.35
Violence elementary school	0.00789**	2.26	0.01272***	2.58	0.02513***	3.64
Random-effects Parameters						
Location-Address			0.2075		0.1484	
Statistical Area					0.2094	
Dwelling Unit			0.2432		0.2011	
Log Likelihood	-3202.96		-487.77		-10.93	
LR test			2359.32		3313.00	
Observations	10553		10553		10553	
Statistical Areas	85		85		85	

Table 10: The Estimation of Non-Spatial Hedonic Models for 2015-2016

	MODEL D		MODEL E		MODEL F	
Log price	Coef.	z	Coef.	z	Coef.	z
Visibility						
Natural open space (r=0-1km)	0.05667***	3.86	0.02381	1.57	0.01474	0.91
Coast (r=0-1km)	-0.05847***	-3.02	-0.01507	-0.71	-0.03582	-1.58
Total visible area (r=0-1km)	-0.00117	-0.37	0.00191	0.63	0.00374	1.22
Natural open space (r=1-5km)	0.03074***	3.45	0.01936**	2.05	0.01228	1.28
Coast (r=1-5km)	0.02162***	3.93	0.01507***	2.77	0.01480***	2.65
Total visible area (r=1-5km)	-0.06446***	-4.76	-0.04337***	-3.31	-0.04653***	-3.49
Road Distance						
Coast	-0.00003***	-6.91	-0.00003***	-3.16	-0.00003***	-3.04
Commercial	0.00004**	2.30	0.00003	1.55	0.00005**	2.07
Employment	-0.00005***	-3.43	-0.00003*	-1.65	-0.00003	-1.55
Train station	0.00001	1.47	0.00004**	2.17	0.00004*	1.89
Park	-0.00001	-1.32	-0.00002	-1.45	-0.00002	-1.38
Main Road	0.00003**	2.69	0.00001	0.37	0.00001	0.56
Aerial Distance						
Cemeteries	0.00005***	11.92	0.00006***	5.28	0.00006***	5.17
Industry	0.00012**	2.76	0.00001	0.13	0.00002	0.27
Road	-0.00003**	-1.96	0.00002	0.50	0.00003	1.00
Schools	-0.00011*	-1.89	0.00010	1.43	0.00008	1.11
Natural Green Area	0.00013***	4.10	0.00010***	2.64	0.00010**	2.35
Air pollution	0.21565***	14.85	0.16953***	5.32	0.18372***	5.35
Structural						
Elevation	0.00162***	10.18	0.00192***	8.07	0.00187***	7.32
Year built	0.00206***	7.10	0.00160***	5.91	0.00137***	5.24
Rooms	0.00038	0.07	-0.00069	-0.14	0.00085	0.18
Floor level	-0.01126***	-5.28	-0.00790***	-3.82	-0.00744***	-3.63
Floor space	0.01935***	29.52	0.01787***	28.21	0.01792***	27.75
Square of floor space	-0.00005***	-16.67	-0.00005***	-15.61	-0.00005***	-15.95
Building Perimeter (North)	-0.00222*	-1.59	-0.00186	-1.41	-0.00105	-0.70
Building Perimeter (East)	0.00036	0.25	0.00042	0.31	0.00051	0.33
Building Perimeter (South)	0.00136	0.92	0.00111	0.79	0.00034	0.22
Building Perimeter (West)	-0.00067	-0.48	-0.00087	-0.66	-0.00108	-0.71
Orientation (North-south, 0/1)	0.01017	0.97	0.01197	1.24	0.00809	0.74
Orientation (Northeast-southwest, 0/1)	0.01575	1.30	0.01911*	1.67	0.01887	1.48
Orientation (East-West, 0/1)	0.01566	1.52	0.02076**	2.17	0.01833*	1.69
Apartment (0/1)	-0.26554**	-2.81	-0.23098***	-2.66	-0.23395***	-2.75
Sale prior to construction (0/1)	-0.04380	-0.83	0.06693	1.31	0.07621	1.37
Closest Sch.=Elementary (0/1)	0.07528**	2.18	0.08479**	2.07	0.09577**	2.13
Closest Sch.=Middle (0/1)	0.07461***	4.47	0.03337	1.50	0.03859	1.58

Proficiency elementary school	0.01256	1.30	0.02131*	1.68	0.03157**	2.21
Proficiency middle school	0.03243***	3.62	0.01677	1.30	0.02457*	1.69
Violence elementary school	-0.00180	-0.31	0.00692	0.82	0.01407	1.45
SAR Coefficient	0.00162***	10.18	0.00192***	8.07	0.00187***	7.32
Random-effects Parameters						
Location-Address			0.1609		0.1529	
Statistical Area					0.1508	
Dwelling Unit			0.2309		0.1809	
Log Likelihood	-502.96		-189.53		-103.01	
LR test			403.40		576.43	
Observations	3,092		3,092		3,092	
Statistical Areas	85		85		85	