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Working Paper 2009:10

Department of Economics

The Effects of a Refinery on Property Values – The Case of Sweden

Jakob Winstrand

The Effects of a Refinery on Property Values - The Case of Sweden

Jakob Winstrand*

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Abstract

This study estimates the impact of the non-aesthetic view and odor caused by Preemraff, a refinery on the Swedish west coast, on house values in the surrounding area. To carry out the analysis a spatial hedonic house price model was applied to transaction data for the period 1994 - 1996, enriched with information whether Preemraff was visible or not from the property. The results indicate that house prices increase as distance to Preemraff increases, but that the effect is small. The estimated price elasticity with respect to distance in the direction the prevailing wind blows is 0.071 and 0.162 in the opposite direction. This suggests that there is an effect of the odor on house prices, though the magnitude of the effect is small. Further estimates indicate that the negative effect of a view of Preemraff from a house is relatively strong in the proximity of the refinery, -24.6 % at a distance of 1000 meters. However, at larger distances the visibility of Preemraff declines and already 2000 meters from Preemraff the positive effect of having a view overshadows the negative effect of the visible refinery. The estimates also imply that the premium for a sea front in a parish non-adjacent to Preemraff is about 139.6 % whereas in an adjacent parish the premium is 47.7 %. The corresponding premiums for a sea view are 69.0 % and 23.7 %.

Keywords: Refinery, hedonic house price model, spatial correlation, heterogeneous directional effects.

JEL-codes: Q51, Q53.

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1 Introduction

Preemraff is a refinery that was built on the west coast of Sweden in 1975. The refinery is located north of Lysekil in Brofjorden, an area known for its beautiful coastline. Among Swedes, the municipality of Lysekil is an attractive area in which to own a summer residence and the price for a house with a sea front or a sea view is very high. In some areas, however, the otherwise overwhelming view is distorted by the refinery's two large chimneys and vessels making port at the refinery jetty. In addition to the non-aesthetic view house owners living east to north-east of the refinery, the direction in which the prevailing wind blows, complain about "the odor of crude oil".

In an area known for its beautiful surroundings, a direct view of the refinery is likely to have a negative effect on house prices. Owners of houses located in the direction in which the prevailing wind blows are likely to experience an even larger reduction in prices since the wind carries the odor in their direction. Furthermore, prices of all houses in the area, even those without a direct view of the refinery or located in the direction of the prevailing wind, are likely to be affected by the risk inherent in the transportation of crude oil to the refinery and reduced attractiveness of ocean front amenities. If so, the refinery constitutes a cost to the neighborhood by lowering house prices. On the other hand, the neighborhood also benefits from the refinery since job opportunities increase.

To make well-founded decisions whether odorous, non-aesthetic, and possibly dangerous projects such as the Preemraff refinery should be carried out or not, decision makers need knowledge about the willingness to pay for environmental goods. For marketed goods such prices are easily observed. Environmental goods such as clean air or a sea view are, however, not traded at a market and hence prices are not readily available. A commonly used method to estimate prices for non-traded environmental goods is the hedonic house price model. In hedonic house price models it is assumed that a house can be seen as a bundle of attributes characterizing the house and these characteristics determine the price of the house. Thus, the transaction price of a house reflects not only the structural characteristics of the building, but also the environmental characteristics such as a sea view. Under these assumptions, the marginal contribution of each characteristic to the total house price can be estimated and an implicit price for a single characteristic can be calculated.

This study estimates the impact of Preemraff on house values. The objective is to measure the impact of the non-aesthetic view, the odor, and the impact of the reduced attractiveness of ocean front amenities in the surrounding area.

To carry out the analysis, a hedonic house price model is used. The data set was collected by Statistics Sweden for assessment by the Swedish tax authorities. It contains data on transaction prices and structural characteristics on all single-family houses sold in the municipality of Lysekil (as well as adjacent municipalities) for the period 1994 - 1996 (430 observations). All sales are geocoded. A physical inspection of each house enriched the data set with information on the visibility of Preemraff.

The results suggest that prices increase with distance to Preemraff in all directions, though slowly. The price elasticity with respect to distance is smallest towards approximately north-east, which is the direction the prevailing wind carries the odor. The estimated price elasticity with respect to distance is 0.071 in the direction of the prevailing wind and 0.162 in the opposite direction. This suggests that there is an effect of the odor on house prices, but the size of the effect is marginal. Further estimates indicate that the negative effect of having a view of Preemraff is relatively strong in the proximity of the refinery, -24.6 % at a distance of 1000 meters. However, at larger distances the visibility of Preemraff declines and already 2000 meters from Preemraff the positive effect of having a view overshadows the negative effect of the view of the refinery. Generally, the premium paid for a sea front or a sea view is large, but the results indicate that there is a large difference in premiums if the house is located in a parish adjacent to Preemraff or not. The premium for a sea front in a non-adjacent parish is about 139.6 % whereas in an adjacent parish the premium is 47.7 %. The corresponding premiums for a sea view are 69.0 % and 23.7 %.

In the following section previous studies on assessment of environmental externalities are presented. Section 3 describes the methodological approach. In section 4, data and estimation procedure are described. Results are presented in section 5, and section 6 concludes.

2 Previous studies

The use of hedonic house price models to assess the impact of environmental externalities has a long tradition. Some early articles where the effect of air pollution on house prices was studied are Ridker and Henning (1967), Anderson and Crocker (1971), and Harrison and Rubinfeld (1978), and an early study of the effect of an electric power plant is Blomquist (1974). A survey by Boyle and Kiel (2001) covers more recent articles (and some of the articles mentioned above) where hedonic models are used to estimate the willingness to pay for environmental goods such as air quality, water quality and distance from toxic sites. To our knowledge, the only article where the

impact of proximity to a refinery on house values is studied is Flower and Ragas (1994). Flower and Ragas studies the impact of two refineries located in the parish of St. Bernard, New Orleans, on values of neighboring properties. Flower and Ragas first model includes dummies for different sub-markets around the two refineries. The results are, however, quite inconclusive and it is difficult to determine whether the dummies capture differences in the sub-markets, rather than the intended differences in exposure to the refineries. In their second model the data is divided into sub-sets depending on the location relative to the refineries and, instead of using sub-market dummies, Flower and Ragas include measures of distance to the refineries. They find that property values decline as distance increase for one of the refineries and the opposite for the other refinery. The relatively inconclusive results might be a result of a failure to control for neighborhood effects, but this cannot be verified since there are no tests for spatial autocorrelation.

The vast majority of studies concerning toxic and potentially toxic sites (and other undesirable land uses) use sales price as dependent variable and distance to the particular site as one of the explanatory variables. It is rare to find an article where visibility of the site is included as explanatory variable, and the only study covered in Boyle and Kiel (2001) where the impact of visibility of an environmental externality is included is Gamble and Downing (1982). The scarcity of such studies may be due to difficulties acquiring the proper data, or simply because the site is a landfill that does not interfere with the view. That an aesthetic view affect house prices is common knowledge, it has also been confirmed in hedonic models by, amongst others, Gillard (1981), Benson et al. (1998), Bourassa et al. (2004), and Bourassa et al. (2005). However, the bulk of studies where the impacts of views are examined only consider the effect of aesthetic views such as an ocean view, not a non-aesthetic view such as the visibility of an industrial park. One exception is the article mentioned above, Gamble and Downing (1982), where visibility of nuclear reactors is included in the hedonic model, but the estimate is not significant. More recently GIS (Geographical Information System) has been used to determine the visibility of different environmental externalities, e.g.; Lake et al. (1998) found that a road visible from the front of a property decrease the property value with, on average, 2.5 %: Lake et al. (2000a) examines several view variables constructed with GIS, however, according to the authors, the model probably suffers from too many correlated variables and, hence, the results are unreliable¹: Lake et al. (2000b) found that a view of roads or industries, or an “obstructed view” all had negative impacts on property prices, though the effect of an obstructed view was very small and

¹The subject of the article is how GIS can be applied to hedonic house price modeling.

statistically significant at the 10 % level².

A common problem with hedonic house price models is spatial autocorrelation. This problem arises mainly due to omitted neighborhood characteristics in the specification of the hedonic model, and these omitted variables may cause inconsistent and biased estimates (this is explained further in section 3.1). Numerous studies have shown that when the residuals are spatially correlated, spatial models can improve estimates of hedonic house price schedules. As an example, Pace and Gilley (1997) use the same data set as Harrison and Rubinfeld (1978) and show that when accounting for the spatial structure inherent in the data, the estimated errors fell by 44 % relative to the OLS. More examples of how models designed to account for the spatial structure can improve estimation are: Case et al. (2004); Dubin (1992); Wilhelmsson (2002).

Spatial models were originally developed in geology and geography and explicitly accounts for the spatial structure inherent in the data. Models developed by geologists are based on an assumption about the functional form of the covariance matrix. These types of models are referred to as geostatistical models. Models developed by geographers are usually referred to as lattice models and requires an exogenously determined spatial weight matrix. (Cressie, 1993) According to Pace et al. (1998) the structure of lattice models is well suited to the characteristics of the housing market and therefore they recommend lattice models for house price modeling. The spatial models considered in this paper are all lattice models.

Despite the relatively long history of applying spatial models for assessment and prediction of house prices, spatial models have gained little attention in environmental studies. None of the articles covered in Boyle and Kiel (2001) considers the use of models that explicitly accounts for spatially correlated errors, which is probably due to the scarcity of such studies. In addition to the article by Pace and Gilley (1997) some examples of applications of spatial models in studies of the effects of environmental externalities on house prices are: Beron et al. (2003) where the demand for air quality in southern California is examined. Kim et al. (2003) use spatial models to measure the marginal willingness to pay for improvements in air quality in Seoul. Day et al. (2007) applies spatial techniques to identify the implicit prices for noise pollution from road, rail and air traffic sources in the city of Birmingham. Wilhelmsson (2000) examines the effect of noise pollution on house prices in Stockholm.

²All three studies where GIS is used are based on data from Glasgow, Scotland.

3 Method

3.1 The hedonic house price model

As mentioned in the introduction, the underlying assumption in the hedonic house price model is that the service a house provides can be decomposed into a set of different attributes that characterize the house. Each attribute carries an implicit price and the transaction price is a function of the implicit prices for all the attributes. This implies that the transaction price of a house for which some of the attributes are non-marketed goods include the implicit prices for these non-marketed goods. Using observed transaction prices of houses, it is possible to estimate implicit prices for non-marketed goods.

Denote the hedonic price function as $P(Z)$ such that the price of house i ($i = 1 \dots n$) is a function of its k characteristics $Z_i = (z_{i,1} \dots z_{i,k})$. Though there is no theoretical support for the choice of functional form for the price function many empirical applications in the housing literature utilize the semi-log specification (Sirmans et al., 2005). One reason for this might be that the estimated parameters are easily interpreted. All estimates in this paper are based on the semi-log specification and the choice is supported by a Box-Cox test³. The hedonic price schedule in semi-log form is given by

$$P(Z) = e^{Z\beta + \varepsilon},$$

where β is a $(k \times 1)$ vector with unknown parameters, and ε is a $(n \times 1)$ vector with residuals. Assuming that the residuals are $\varepsilon \sim N(0, \sigma^2 I)$ (zero mean with constant variance and zero covariance) OLS can be applied to the transformed price schedule

$$p = \ln(P(Z)) = Z\beta + \varepsilon. \tag{1}$$

As long as the residuals are *iid*, OLS yields unbiased, efficient, and consistent estimates. Unfortunately, using house price as dependent variable, the residuals are often spatially correlated. In general there are two sources for spatial dependency; omitted variables and measurement errors.

House prices are strongly related to the location of the house. Characteristics of the neighborhood that have an impact on the price of a house will also have an impact on prices of neighboring houses. If any of these characteristics are measured with error or omitted, then the residuals in Eq. (1) will be spatially correlated and thus violating the *iid*-criteria. Since there is an abundance of neighborhood characteristics it is very likely that some of

³The estimated Box-Cox parameter is $\lambda = 0.10$ but we cannot reject the null of $\lambda = 0$ at the 5 %-level.

the characteristics are unobservable or omitted. For example, an intangible variable like area (neighborhood) reputation may affect property prices.

The structural characteristics of houses in a neighborhood are often homogeneous, i.e. living area, age, building materials, etc. are usually quite similar within a neighborhood. The composition of residents in a neighborhood is also relatively homogeneous. Socioeconomic characteristics such as income, education, religion, and crime rates tend to cluster. Social services (e.g. schools, stores, public transportation, and recreational facilities) and environmental characteristics (e.g. air and water quality, and undesirable land uses) are also features of the neighborhood that many houses share. (Militino et al., 2004) In empirical studies some of these characteristics are included in Eq. (1), but it is usually impossible and/or too costly to acquire data on all characteristics. Sometimes proxies are used for unobservable characteristics but these proxies are usually measured with errors themselves and, hence, will not eliminate the problem with spatial correlation (Dubin, 1992). Consequently, it is quite likely that an estimation of Eq. (1) is affected either by omitted variables or measurement errors, or both, and using OLS may result in spatially correlated residuals and biased and inconsistent estimates. This might be a rather serious problem when the results are to be used as guidance for policy decisions since both magnitude and inference could be erroneous, which may result in a socially inefficient allocation of funds. One way to improve estimation in presence of spatial dependency is to use dummies for different sub-markets (e.g. parish). However, the sub-market approach is relatively coarse and may not reduce the problem with spatially correlated residuals⁴. Another issue with the sub-market approach related to this study is that if we use sub-market dummies based on geographical areas, such as parishes, those dummies will be correlated with variables describing location relative to Preemraff (distance and direction). Hence, using dummies for parishes, estimates will be affected by multicollinearity and we will not be able to distinguish the effect of Preemraff from the effect of the parishes. A more suitable approach is to use spatial models in which the spatial dependency is modeled explicitly.

3.2 Spatial models

In hedonic house price modeling, spatial correlation is most frequently handled by applying the spatial autoregressive model (SAR) or the spatial error

⁴The first test in Table 7 in appendix A.2 is the basic Morans-I for the model including sub-markets defined by parish. As can be seen, in this case the sub-market approach does not solve the problem with spatial correlation.

model (SEM). Both types use an exogenously determined spatial weight matrix to account for the spatial dependency, and the weight matrix determines the degree of potential spatial dependency. The SAR model is an extension of Eq. (1) analogous to an $AR(1)$ model in time series econometrics and can be expressed as

$$p = \rho W_1 p + Z\beta + \varepsilon, \quad (2)$$

where ρ is an unknown scalar spatial parameter and W_1 is the $(n \times n)$ spatial weight matrix. The SEM is also an extension of Eq. (1), but the spatial dependency is specified as an autoregressive error process as

$$\begin{aligned} p &= Z\beta + \varepsilon \\ \varepsilon &= \lambda W_2 \varepsilon + u, \end{aligned} \quad (3)$$

where λ is an unknown scalar spatial parameter, W_2 is the spatial weight matrix, and $u \sim N(0, \sigma^2 I)$.

The choice between the SAR and the SEM specification can either be purely ad hoc or guided by a sequence of tests described in Anselin (2001), Anselin and Bera (1998), and Anselin et al. (1996). In practice, however, the most frequently used model is the SEM, perhaps because it allows more freedom in the choice of weight matrix.

Each weight w_{ij} in W_1 and W_2 is exogenously determined and specifies the spatial relationship between house i and house j . There are numerous ways to assign values to each weight but usually some measure of distance between the houses is used⁵. Usually the weight matrix is row-standardized such that all rows sum to unity and, hence, the process is filtered spatially. All elements of W_1 and W_2 must always be non-negative and all elements on the main diagonal have to be zero such that a house price cannot predict it self. For the SAR model in Eq. (2) the covariance matrix for the disturbance terms is $\Sigma = \sigma^2 (I - \rho W_1)^{-1}$, where I is the identity matrix, and consequently W_1 must be symmetric to ensure that Σ is symmetric. The corresponding covariance matrix for the SEM specification in Eq. (3) is $\Sigma = \sigma^2 [(I - \lambda W_2)'(I - \lambda W_2)]^{-1}$ which does not restrict W_2 to be symmetric. More details of the applied weight matrices are given in section 4.2.

3.3 Heterogeneous directional effects

Since this paper is concerned with the effect of Preemraff on prices of nearby houses, and the effect is very likely to be correlated with the distance to the refinery, one of the explanatory variables should be some measure of

⁵See Dubin (1998) for more details and examples of how to specify the weights.

the distance between the refinery and the houses. A straightforward way of defining this measure is to simply use the Euclidean distance to the refinery. If we denote the Euclidean distance as $D = [d_1 \dots d_n]'$ we can expand Eq. (1) as

$$p = Z\beta + \gamma_1 D + \varepsilon, \quad (4)$$

where γ_1 is an unknown parameter. This specification would however imply that we implicitly assume that the effect is equal in all directions. As Cameron (2006) shows, failure to allow for directional heterogeneity can result in “larger-than-necessary standard errors and apparent heteroscedasticity” and biased estimates of distance parameters.

In the case of Preemraff, it is very unlikely that the distance gradient has the same slope in all directions. There are two main reasons for why the directional effect is likely to be heterogeneous; prevailing winds and topography. In the area where Preemraff is located, prevailing winds blows towards east to north-east. These winds cause the odor of crude oil to proliferate towards east to north-east of the refinery and decrease towards west to south-west of the refinery. Thus, though the odor exist in all directions close to the refinery, the effect of the odor on house prices is likely to be more pronounced east to north-east of the refinery. The topography of the area surrounding the refinery is also likely to cause directional heterogeneity in distance effects. The coastal area is full of small islands and fjords, features that may cause the distance gradient to differ between directions.

A straightforward approach to model heterogeneous directional effects is to use dummies for different directions, or simply one dummy for the direction in which we might assume that the effect is most prominent. These modeling strategies are, however, relatively crude and Cameron (2006) suggests a more harmonious specification which enables directional heterogeneity to be modeled continuously. This is achieved by transforming xc, yc -coordinates into polar coordinates such that the longitudinal xc -coordinate for house i becomes $xc_i = d_i \cos(\theta_i)$ and the latitudinal yc -coordinate $yc_i = d_i \sin(\theta_i)$, where d_i is the Euclidean distance from house i to the site of interest (in our case Preemraff) and θ_i is the direction measured in radians. Then we can expand Eq. (4) as follows

$$p = Z\beta + \gamma_1 D + \gamma_2 \cos(\Theta)D + \gamma_3 \sin(\Theta)D + \varepsilon, \quad (5)$$

where γ_1, γ_2 , and γ_3 are unknown distance parameters, $D = (d_1 \dots d_n)'$, and $\Theta = \text{diag}(\theta_1 \dots \theta_n)$ ⁶. The parameter γ_1 measures the effect of distance in all directions, γ_2 and γ_3 can loosely be interpreted as measuring the effects in

⁶As Cameron (2006) describes, sometimes it may also be appropriate to let the intercept vary with direction. This can be achieved by including the terms $\delta_1 \cos(\Theta) + \delta_2 \sin(\Theta)$

the east-west (longitude) and north-south (latitude) direction, respectively⁷. One advantage using polar coordinates is that we can get an estimate, on a continuous scale, of the direction in which the distance gradient is steepest. We can rewrite Eq. (5) by collecting terms as

$$p = Z\beta + (\gamma_1 + \gamma_2 \cos(\Theta) + \gamma_3 \sin(\Theta)) D + \varepsilon.$$

From this expression we see that the total distance effect for house i is $\gamma_1 + \gamma_2 \cos(\theta_i) + \gamma_3 \sin(\theta_i)$ and we can calculate the directions in which the predicted maximum and minimum distance effect occurs. The direction (measured in radians) in which the maximum effect occurs, i.e. the direction in which the distance gradient is steepest, is $\theta^* = \arctan(\gamma_3/\gamma_2)$, which implies that the expression for the direction in which the distance gradient is flattest is $\theta^{**} = \theta^* + \pi = \arctan(\gamma_3/\gamma_2) + \pi$.⁸ It is straightforward to include the heterogeneous distance effect in the spatial models. The SAR model (Eq. (2)) with heterogeneous distance effects is given by

$$p = \rho W_1 p + Z\beta + \gamma_1 D + \gamma_2 \cos(\Theta) D + \gamma_3 \sin(\Theta) D + \varepsilon, \quad (6)$$

and the corresponding SEM (Eq. (3)) is given by

$$\begin{aligned} p &= Z\beta + \gamma_1 D + \gamma_2 \cos(\Theta) D + \gamma_3 \sin(\Theta) D + \varepsilon \\ \varepsilon &= \lambda W_2 \varepsilon + u. \end{aligned} \quad (7)$$

4 Data and estimation

4.1 Data

The data set used in this paper was collected by Statistics Sweden for assessment by the Swedish tax authorities. It contains data on transaction prices and structural characteristics on all single-family houses sold in the municipality of Lysekil (as well as adjacent municipalities) for the period 1994 - 1996. All sales are geocoded using RT90⁹ and the location of Pre-

in Eq. (5). However, several specifications were tested but the parameters associated with the heterogeneous intercept were never significant. Model 3 in Table 4 includes the heterogeneous intercept.

⁷For example, if we are interested in the distance effect to the north ($\theta = 0.5\pi$) we can calculate the effect as $\gamma_1 + \gamma_2 \cos(0.5\pi) + \gamma_3 \sin(0.5\pi) = \gamma_1 + \gamma_3$, since $\cos(0.5\pi) = 0$ and $\sin(0.5\pi) = 1$.

⁸Note that by construction, the maximum and the minimum effects are always diametrically opposed.

⁹RT90 is the *Swedish grid* which is used by the National Land Survey of Sweden.

emraff was found manually¹⁰. The number of observations in the sample is 430.

In addition to almost 40 variables describing the structural characteristics, the data set also includes a quality variable created for assessment purposes. The quality variable is an index that reflects the structural qualities of houses and it is based on a mandatory survey where each household answered 25 questions about the structural quality of their house. One attractive feature of this index is that it accounts for renovations, i.e. if the kitchen is renovated the index for the house will increase. The index does not, however, account for living area, lot size, age, neighborhood characteristics, or environmental characteristics. Depending on availability, hedonic house price models usually include a relatively large set of variables describing structural attributes of the dwellings. In this paper the number of characteristics is reduced due to the use of the quality variable, and thus creating a more parsimonious model. Another advantage is that, though we are not interested in the parameter estimates for the structural characteristics as such, the potential problem with multicollinearity among structural characteristics is reduced.

Further, to complement data on structural characteristics, for all houses in the data set we have gathered data on whether Preemraff is visible or not. The visibility data was attained by physical inspection of the houses and the variable is a dummy denoted *Visual*. One thing to note here is that there are some houses located relatively far from Preemraff, from which the refinery's chimneys are barely visible. These houses are regarded as if Preemraff is not visible due to the large distance (the chimneys are barely visible and does not distract the view and, thus, we assume that there is no effect on house values). Effectively, all houses from which Preemraff is considered visible are located in the parishes adjacent to Preemraff.

Table 1 presents descriptive statistics and Table 2 presents correlation coefficients for the dependent variable and the explanatory variables. The sample includes transaction prices for houses located within an area of $10 \text{ km} \times 30 \text{ km}$ around Preemraff.

As can be seen from the correlation coefficients in Table 2, most of the variables have the expected signs. *Price* and *Distance* to Preemraff are positively correlated which implies that prices tend to increase with distance to Preemraff. The correlation coefficient for *Price* and *Visual* is negative suggesting that houses from which Preemraff is visible carries a lower price. The correlation between *Age* and *Price* is positive but very small and not

¹⁰It should be noted that the refinery covers a relatively large area and the coordinates used represent the center of the industrial park. Moving the point where distance is measured from, within the industrial park, does not change the results notably.

Table 1: Descriptive statistics

Variable	Mean	Median	Max	Min	Std
Price	627.567	575.000	4075.000	125.000	389.268
Distance	8056.663	7498.545	15417.197	973.471	3674.738
Lot size	1726.244	869.000	54760.000	63.000	4399.876
Living area	93.486	85.000	264.000	30.000	39.993
Sea front	0.019	0.000	1.000	0.000	0.135
Sea view	0.049	0.000	1.000	0.000	0.216
Quality	22.816	22.000	50.000	7.000	6.804
Age	48.628	41.500	215.000	3.000	31.666
Degrees	-24.960	-80.580	175.147	-127.467	82.572
Visual	0.079	0.000	1.000	0.000	0.270
Number of observations					430

Note: Price is measured in thousands of SEK. Distance is measured in meters. Living area and Lot size are measured in m^2 . Sea front, Sea view and Visual are dummy variables. Degrees is measured on $[-180, 180]$ counting counter clockwise from west.

significant. The correlation table also include *Degrees*, which is measured counter clock wise from east such that *East* = -180 (or 180), *South* = -90 , *West* = 0 , and *North* = 90 degrees. The negative correlation coefficient for *Degrees* suggests that, on average, houses located south of Preemraff are more expensive.

Originally the model included year dummies but these were not significant and therefore excluded from the final specification. The decision to exclude the year dummies (and not adjusting prices) was also based on Figure 1 in appendix, which plots average monthly prices over the period 1994 - 1996¹¹.

4.2 Estimation procedure

Estimates of hedonic house price models are very likely to be burdened with spatial autocorrelation and it is important to test the model to determine whether spatial correlation constitutes a problem or not. As mentioned in section 3.2, Anselin (2001), Anselin and Bera (1998), and Anselin et al. (1996) have derived a group of tests for this purpose. Another feature of these tests is that the results can give some guidance in the choice between the SAR

¹¹As is clear from Figure 1 in the appendix there is no seasonal pattern, which the initial (not presented) estimates verified. The two peaks are caused by sales of the most expensive houses in the data set.

Table 2: Correlation coefficients

	Price	Distance	Lot Size	Living Area	Sea Front
Price	1.000				
Distance	0.267*	1.000			
Lot Size	0.065	0.054	1.000		
Living Area	0.520*	0.060	-0.033	1.000	
Sea Front	0.289*	-0.010	0.128*	-0.000	1.000
Sea View	0.331*	0.014	-0.022	0.008	-0.031
Quality	0.434*	0.054	0.024	0.606*	0.034
Age	0.030	0.038	-0.029	-0.186*	0.084
Degrees	-0.338*	-0.321*	0.114*	-0.265*	0.029
Visual	-0.181*	-0.346*	0.007	-0.175*	0.151*
	Sea View	Quality	Age	Degrees	Visual
Sea View	1.000				
Quality	0.036	1.000			
Age	0.115*	-0.104*	1.000		
Degrees	-0.067	-0.207*	-0.068	1.000	
Visual	-0.026	-0.209*	-0.030	0.331*	1.000

Note: *Significant at 5 %.

model and the SEM. Most of the tests for spatial autocorrelation require that we specify the weight matrices W_1 and W_2 used in the spatial models.

As mentioned in section 3.2 there are different ways to specify the weight matrices and, depending on the choice of model, some restrictions have to be met. Regardless of model, all elements must be non-negative and all elements on the (main) diagonal must be zero. Ideally, we would like to account for the temporal dimension such that weights are non-zero only for transactions at a previous date. This would, however, cause the weight matrix W_1 to be non-symmetric, which implies that the covariance matrix in the SAR model (Eq. (2)) will not be symmetric. Further, specifying the weights using nearest neighbors also yields a non-symmetric weight matrix. Hence two different weight matrices will be used; W_1 , which is symmetric, non-temporal, and not row-standardized; W_2 , which is non-symmetric, row-standardized, and accounts for the temporal dimension.

W_1 is created based on Delaunay triangulation, which is a method to create “a net of triangles” for a set of points in a plane such that each point represents a vertex and none of the points are contained within a triangle. This implies that each point has a set of lines connecting the point to other “adjacent” points (though not necessary the nearest points). These connect-

ing lines can be used to form a symmetric weight matrix¹². Another approach to create W_1 in which the weights were constructed by specifying a maximum distance at which house prices were assumed to be spatially dependent was also tried. Several threshold values for the distance were tested, but irrespective of the threshold value the results were very similar to when the weights were created using the Delaunay triangulation. The draw-back using a threshold distance is that in areas where houses are scattered, some houses may not have any neighbor within the specified maximum distance.

For W_2 each weight is calculated as

$$w_{ij} = \frac{\delta_{ij}^t}{\sum_{j=1}^m \delta_{ij}^t}, \quad (8)$$

where $\delta_{ij} = 1/d_{ij}$, d_{ij} is the Euclidean distance between house i and house j , m is the number of nearest neighbors, and t is a distance decay parameter. Further, if house i was sold previous to house j then $w_{ji} = 0$. As can be seen in Eq. (8), the weights in W_2 declines with distance and as t increases the quicker the weights decline.

Using Delaunay triangularization we cannot assign weights to a specific number of nearest neighbors, the number of neighbors depends on how dense the area is. A house on the perimeter might only have three neighbors with assigned weights, whereas a house in a central area may have many more. For W_2 , on the other hand, the number of neighbors is determined exogenously. For all estimations presented in section 5, where W_2 is used, weights are assigned to the 20 nearest neighbors ($m = 20$) and $t = 1$ in Eq. (8)¹³.

The spatial weight matrices determine the degree of potential spatial correlation and cause the spatial models to depart from the linear models in Eqs. (4) and (5). Thus, the SAR and SEM cannot be estimated with OLS and maximum likelihood is used. All models and tests are carried out in MATLAB.

In addition to the visibility variable *Visual*, we have also included the interaction variable *Visual* \times *Distance* to account for the fact that the price effect of being able to see Preemraff from a house is likely to decline with distance¹⁴. It is quite important to include the interaction variable to measure the visual effect accurately (Benson et al., 1998). Even though all houses in parishes adjacent to Preemraff are located relatively close to the refinery,

¹²The weight matrix is constructed using the MATLAB code “fdelw2” provided by Kelley Pace on www.spatial-statistics.com.

¹³Several different numbers of nearest neighbors and values for the decay parameter t were tested and all results were fairly similar. The choice of 20 neighbors and $t = 1$ was supported by the error of regression and the spatial autocorrelation tests.

¹⁴In all regressions *Distance* is in logarithmic form.

there will still be differences in the effect on house prices depending on how close a house is located.

As mentioned earlier in section 4.1, houses in non-adjacent parishes are regarded as if Preemraff is not visible, even if it is. Houses in non-adjacent parishes from which Preemraff is visible also have the feature of a wide and/or deep view of the coastal area. Within such a view the presence of the refinery is barely noticeable due to the distance and other, more pronounced, objects dominating the view. In fact, these wider and deeper views will most likely increase the value of the house, irrespectively of whether Preemraff is visible or not. It is also reasonable to assume that the difference in premiums paid for such wide and deep views with and without the visible refinery is negligible. This was partially verified in early regressions where visibility for houses in parishes not adjacent to the refinery was included as a separate dummy. The coefficient of this dummy was not significant.

Another issue to consider in this particular case is how the presence of a refinery in a neighborhood affects the value of ocean front amenities. It is reasonable to assume that it is not as attractive to go for a swim, fish, or ride boats in the area surrounding the refinery as it is in other areas. Unfortunately we have no way of measuring access to ocean front amenities (or the distance to the ocean). However, ocean front amenities are likely to be more important for those living close to the ocean and, thus, we have included *Sea front* and *Sea view* separately for houses in parishes adjacent to Preemraff. It is reasonable to assume that such locations provide ocean front amenities with a lower standard compared to similar locations in non-adjacent parishes.¹⁵

5 Results

Table 3 present results from tests for spatial dependency and Table 4 present the regression results. The tests have different null hypotheses, either $\rho = 0$ or $\lambda = 0$, or both, where ρ is the spatial parameter in the SAR model and λ is the spatial parameter in the SEM. As we can see in Table 3 there is a problem with spatial autocorrelation¹⁶. All tests of the null $\lambda = 0$ are significant at 5 %, which indicate that the residuals are spatially dependent.

¹⁵Regressions with dummies for the adjacent parishes was also tested, but the coefficients were not significant when the heterogeneous distance measure was included.

¹⁶The tests are based on models including the heterogeneous distance effects, i.e. Model 2 in Table 4. The qualitative results were similar for Model 1 and 3. As mentioned, Table ?? in appendix A.2 display the results when sub-markets (parish) are included in the model. As can be seen, including sub-markets does not eliminate the problem with spatial correlation.

However, the null $\rho = 0$ is only significant when we assume that $\lambda = 0$, and when we estimate the SEM and test the null $\rho = 0$ we find that we cannot reject the null. This tells us that using the SAR model does not solve the problem with spatial correlation whereas the SEM does. Hence the test results indicate that the spatial error model (SEM) is preferred.

Table 3: Test for spatial dependency

Null	Restriction	Estimated	
		statistic	p-value
$\lambda = 0$	$\rho = 0$	11.579 †	0.000
$\lambda = 0, \rho = 0$	$W_1 = W_2$	101.088 ‡	0.000
$\lambda = 0$	$\rho = 0$	99.753	0.000
$\lambda = 0$	ρ is unrestricted but estimated	104.957	0.000
$\lambda = 0$	ρ is unrestricted and not estimated	97.303	0.000
$\rho = 0$	$\lambda = 0$	4.382	0.036
$\rho = 0$	λ is unrestricted but estimated	0.016	0.898
$\rho = 0$	λ is unrestricted and not estimated	1.932	0.165

Note: †The statistic is distributed as $N(0, 1)$. ‡The symmetric W_1 is used and the statistic is distributed as χ_2^2 with a critical value of 5.99 at 5 %. All other statistics are $\sim \chi_1^2$ with a critical value of 3.84 at 5 %.

The regression results presented in Table 4 includes results for three different versions of the SEM; Model 1 with homogeneous distance effect, Model 2 with heterogeneous distance effect, and Model 3 with heterogeneous distance effect and intercept. However, even though results from all models are included in the table, only results from Model 2 will be commented on to economize on space. Results for the other models are included for the interested reader¹⁷.

As can be seen in Table 4 all parameters of the heterogeneous distance measure are significant. In Table 5 maximum and minimum effects are presented along with the corresponding directions. The effects in the four directions north, south, east, and west are also calculated and shown in the Table 5. We can see that house prices increase with distance to Preemraff in all directions. The smallest effect (prices increase slower with distance than in other directions) is at 32.8 degrees, which is in the north-east direction (the direction in which the prevailing wind blows). The estimates

¹⁷Additional results are presented in the appendix. The tables in appendix A.2 show the results when sub-markets, defined by parishes, are included in the model. Table 11 in appendix A.3 show the results when Model 2 in Table 4 is estimated with OLS and the SAR specification.

Table 4: Estimation results (Dependent variable is $\ln(\text{Price})$)

	Model 1	Model 2	Model 3
Constant	4.325*	4.552*	4.576*
	[6.688]	[9.588]	[9.540]
<i>D</i>	0.146*	0.117*	0.113*
	[2.051]	[2.215]	[2.124]
$\cos(\Theta)D$.	-0.038*	-0.161
	.	[-5.399]	[-1.392]
$\sin(\Theta)D$.	-0.025*	-0.083
	.	[-6.770]	[-1.529]
$\cos(\Theta)$.	.	1.037
	.	.	[1.059]
$\sin(\Theta)$.	.	0.521
	.	.	[1.075]
Lot size	6.1e-6	6.8e-6*	7.0e-6*
	[1.938]	[2.213]	[2.283]
Living area	0.005*	0.005*	0.005*
	[10.289]	[10.488]	[10.452]
Sea front	0.830*	0.874*	0.885*
	[6.093]	[6.693]	[6.745]
Sea front \times Adjacent parish	-0.391	-0.484*	-0.481*
	[-1.763]	[-2.258]	[-2.241]
Sea view	0.516*	0.525*	0.525*
	[6.345]	[6.721]	[6.721]
Sea view \times Adjacent parish	-0.265	-0.312*	-0.287*
	[-1.929]	[-2.363]	[-2.166]
Quality	0.015*	0.015*	0.015*
	[5.790]	[5.950]	[6.026]
Age	-0.005*	-0.005*	-0.005*
	[-4.317]	[-4.463]	[-4.500]
Age²	2.8e-5*	2.8e-5*	2.9e-5*
	[3.659]	[3.908]	[3.921]
Visual	-2.865	-3.168*	-3.071*
	[-1.804]	[-2.132]	[-2.033]
Visual \times Distance	0.373	0.418*	0.402*
	[1.891]	[2.260]	[2.141]
$W_2\varepsilon$	0.784*	0.558*	0.559*
	[12.933]	[7.631]	[7.649]
R_{adj}^2	0.697	0.721	0.721
Log-likelihood	57.202	84.622	85.788
Error variance	0.083	0.076	0.075

Note: *Significant at 5 %. t-values in square brackets.

suggest that prices increase more than twice as fast in the south-west direction (0.162) than in the north-east direction (0.071). Since distance is in logarithmic form, these estimates represent the price elasticity with respect to the distance to Preemraff. Thus, if the distance from Preemraff increases with 1 % towards north-west the price is expected to increase with 0.071 %.

Table 5: Magnitude of Distance Effects

	<u>Max</u>		<u>Min</u>		North	South	East	West
	Effect	Direction	Effect	Direction				
Model 1	0.146	.	0.146
Model 2	0.162	-147.186	0.071	32.814	0.092	0.141	0.078	0.155
Model 3	0.295	-152.712	-0.068	27.288	0.030	0.196	-0.048	0.274

Note: Direction in which the maximum and minimum effects occurs measured in degrees on $[-180, 180]$, with $0 = East$. Since we are interested in the distance effect the anisotropic intercept in Model 3 is not considered. These distance effects are calculated for houses without a view of Preemraff.

The structural variables *Lot size*, *Living area*, *Quality*, *Age*, and *Age*² are all significant and with the expected signs.

The coefficients for *Visual* and *Visual* \times *Distance* are both significant. In Table 6 total effects of *Visual* at different distances from Preemraff are presented¹⁸. The percentage effects at different distances range from -43.6 % at 500 meters to 10.5 % at 2500 meters. The positive effect at larger distances confirms that when the distance to the refinery is large enough, the positive effect of having a view overshadows the negative effect of the visible refinery.¹⁹

As mentioned in section 4.2 *Sea front* and *Sea view* are included separately for houses in parishes adjacent to Preemraff to capture the effect of the refinery on ocean front amenities. As can be seen in Table 4 the difference between the premiums paid for *Sea front* and *Sea view* in adjacent

¹⁸Note that coefficients corresponding to dummy variables cannot be interpreted as for continuous variables. If β is the estimated coefficient corresponding to a dummy variable then the relative effect is $\exp(\beta) - 1$ (Halvorsen and Palmquist, 1980). The effect of both a dummy variable and an interaction variable, such as for *Visual* and *Visual* \times *Distance*, is $\exp(\beta_1 + \beta_2 \times (\text{Visual} \times \text{Distance})) - 1$, where β_1 is the coefficient on the pure dummy and β_2 is the coefficient on the interaction variable (Benson et al., 1998). All values in Table 6 are calculated in this manner.

¹⁹Ideally, the model should include a polynomial in distance, but unfortunately inclusion of such a polynomial caused (near) singularity of the characteristic matrix.

Table 6: Effect of Visual

	500 m	1000 m	1500 m	2000 m	2500 m
Model 1	-0.422	-0.252	-0.130	-0.031	0.053
Model 2	-0.436	-0.246	-0.107	0.007	0.105
Model 3	-0.435	-0.254	-0.121	-0.014	0.079

Note: Some of the effects might be calculated based on non-significant estimates.

parishes and non-adjacent parishes is large. The premium for a sea front in a non-adjacent parish is about 139.6 % ($\exp(0.874) - 1$) whereas in an adjacent parish the premium is 47.7 % ($\exp(0.874 - 0.484) - 1$). The corresponding premiums for a sea view are 69.0 % and 23.7 %.

6 Conclusions

This study estimates the impact of Preemraff on house values. The objective was to measure the impact of the non-aesthetic view, the odor, and the impact of the reduced attractiveness of ocean front amenities in the surrounding area.

To carry out the analysis, a spatial hedonic house price model was applied to transaction data on all single-family houses sold in the area during the period 1994 - 1996 (430 observations). To complement the transaction data, each property was site-inspected to determine whether Preemraff is visible or not from the house.

To measure the distance effect, Euclidean distance was used and the coordinates were transformed into polar coordinates. The transformation enabled estimation of the distance effect in different directions on a continuous scale. The results indicate that house prices increase as distance to Preemraff increase, and that the smallest increase was in the direction prevailing winds that carry the odor blow. In the opposite direction, i.e. towards the direction prevailing winds blow, prices increase at twice the rate. However, the effect of distance is weak. The estimated price elasticity with respect to distance in the direction the prevailing wind blows is 0.071 and 0.162 in the opposite direction. This result suggests that an effect of the odor exist, though the magnitude of the effect on house prices is marginal.

The visual impact of Preemraff on prices was estimated using a dummy variable whether Preemraff was visible or not, and, since the effect is likely

to decline as distance increase, the interaction variable $Visual \times Distance$ was also included. The estimates indicate that the negative effect of being able to see Preemraff from a house is relatively strong in the proximity of the refinery. At a distance of 1000 meters the effect is -24.6 %. However, at larger distances the visibility of Preemraff declines and other elements in the view becomes more pronounced. The results suggest that this effect is very strong, and already at 2000 meters from Preemraff the positive effect of having a view overshadows the negative effect of the visible refinery.

To measure the impact on house values of from the reduced attractiveness of ocean front amenities in the surrounding area the dummy variables *Sea front* and *Sea view* were included separately for houses in parishes adjacent to Preemraff. The result was striking. Generally, the premium paid for a sea front or a sea view is large, but the results indicate that there is a large difference in the premium if the house is located in an adjacent parish. The premium for a sea front in a non-adjacent parish is about 139.6 % whereas in an adjacent parish the premium is 47.7 %. The corresponding premiums for a sea view are 69.0 % and 23.7 %. A part of the large difference in premiums between adjacent and non-adjacent parishes might be due to fewer beaches and boat docks in the adjacent parishes, but it seems unlikely that such factors can account for the entire difference. Even if it was the case, it may also be that the presence of Preemraff is the reason to why there are fewer facilities.

References

- R. J. Anderson, Jr. and T. D. Crocker. Air pollution and residential property values. *Urban Studies*, 8(3):171–180, 1971.
- L. Anselin. Rao's score test in spatial econometrics. *Journal of Statistical Planning and Inference*, 97:113–139, 2001.
- L. Anselin and A. K. Bera. *Handbook of Applied Economic Statistics*, chapter Spatial Dependence in Linear Models with an Introduction to Spatial Econometrics. Marcel Dekker, New York, 1998.
- L. Anselin, A. K. Bera, R. Florax, and M. J. Yoon. Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics*, 26:77–104, 1996.
- E. D. Benson, J. L. Hansen, A. L. Schwartz, Jr., and G. T. Smersh. Pricing residential amenities: The value of a view. *Journal of Real Estate Finance and Economics*, 16(1):55–73, 1998.

- K. J. Beron, Y. Hanson, J. Murdoch, and M. Thayer. *Advances in Spatial Econometrics*, chapter Hedonic Price Functions and Spatial Dependence: Implications for the Demand for Urban Air Quality. Springer-Verlag, Berlin, 2003.
- G. Blomquist. The effect of electric utility power plant location on area property value. *Land Economics*, 50(1):97–100, 1974.
- S. C. Bourassa, M. Hoesli, and J. Sun. What’s in a view? *Environment and Planning A*, 36(8):1427–1450, 2004.
- S. C. Bourassa, M. Hoesli, and J. Sun. The price of aesthetic externalities. *Journal of Real Estate Literature*, 13(2):167–187, 2005.
- M. A. Boyle and K. A. Kiel. A survey of house price hedonic studies of the impact of environmental externalities. *Journal of Real Estate Literature*, 9(2):117–144, 2001.
- T. A. Cameron. Directional heterogeneity in distance profiles in hedonic property value models. *Journal of Environmental Economics and Management*, 51:26–45, 2006.
- B. Case, J. Clapp, R. Dubin, and M. Rodriguez. Modeling spatial and temporal house price patterns: A comparison of four models. *Journal of Real Estate Finance and Economics*, 29(2):167–191, 2004.
- N. A. C. Cressie. *Statistics for Spatial Data. Revised Edition*. Willey, New York, revised edition, 1993.
- B. Day, I. Bateman, and I. Lake. Beyond implicit prices: Recovering theoretically consistent and transferable values for noise avoidance from a hedonic property price model. *Environmental Resource Economics*, 37(1):211–232, 2007.
- R. A. Dubin. Spatial autocorrelation and neighborhood quality. *Regional Science and Urban Economics*, 22:433–452, 1992.
- R. A. Dubin. Spatial autocorrelation: A primer. *Journal of Housing Economics*, 7:304–327, 1998.
- P. C. Flower and W. R. Ragas. The effects of refineries on neighborhood property values. *The Journal of Real Estate Research*, 9(3):319–338, 1994.
- H. B. Gamble and R. H. Downing. Effects of nuclear power plants on residential property values. *Journal of Regional Science*, 22(4):457–478, 1982.

- Q. Gillard. The effect of environmental amenities on house values: The example of a view lot. *Professional Geographer*, 33(2):216–220, 1981.
- R. Halvorsen and R. Palmquist. The interpretation of dummy variables in semilogarithmic equations. *The American Economic Review*, 70(3):474–475, 1980.
- D. Harrison, Jr. and D. L. Rubinfeld. Hedonic housing prices and the demand for clean air. *Journal of Environmental Economics and Management*, 5(1):81–102, 1978.
- C. W. Kim, T. T. Phipps, and L. Anselin. Measuring the benefits of air quality improvement: A spatial approach. *Journal of Environmental Economics and Management*, 45:24–39, 2003.
- I. R. Lake, A. A. Lovett, I. J. Bateman, and I. H. Langford. Modelling environmental influences on property prices in an urban environment. *Computers, Environment and Urban Systems*, 22(2):121–136, 1998.
- I. R. Lake, A. A. Lovett, I. J. Bateman, and B. Day. Using GIS and large-scale digital data to implement hedonic pricing studies. *International Journal of Geographical Information Science*, 14(6):521–541, 2000a.
- I. R. Lake, A. A. Lovett, I. J. Bateman, and B. Day. Improving land compensation procedures via GIS and hedonic pricing. *Environment and Planning C*, 18(6):681–696, 2000b.
- A. F. Militino, M. D. Ugarte, and L. Garcia-Reinaldos. Alternative models for describing spatial dependence among dwelling selling prices. *Journal of Real Estate Finance and Economics*, 29(2):193–209, 2004.
- R. K. Pace and O. W. Gilley. Using the spatial configuration of the data to improve estimation. *Journal of Real Estate Finance and Economics*, 14(3):333–340, 1997.
- R. K. Pace, R. Barry, and C. F. Sirmans. Spatial statistics and real estate. *Journal of Real Estate Finance and Economics*, 17(1):5–13, 1998.
- R. G. Ridker and J. A. Henning. The determinants of residential property values with special reference to air pollution. *Review of Economics and Statistics*, 49(2):246–257, 1967.
- G. S. Sirmans, D. A. Macpherson, and E. N. Zietz. The composition of hedonic pricing models. *Journal of Real Estate Literature*, 13(1):3–43, 2005.

- M. Wilhelmsson. The impact of traffic noise on the values of single-family houses. *Journal of Environmental Planning and Management*, 43(6):799–815, 2000.
- M. Wilhelmsson. Spatial models in real estate economics. *Housing Theory and Society*, 19:92–101, 2002.

Appendix

A.1 Figures

Figure 1: Average monthly transaction prices 1994 - 1996

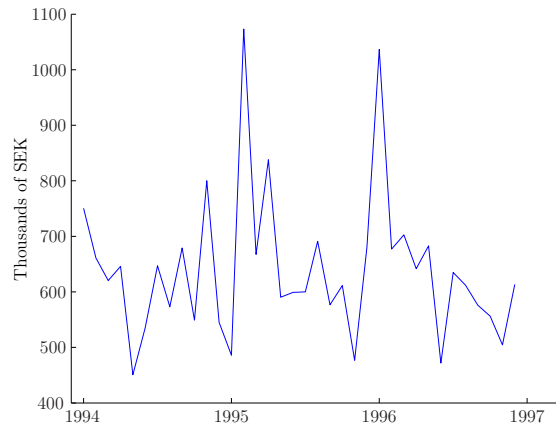
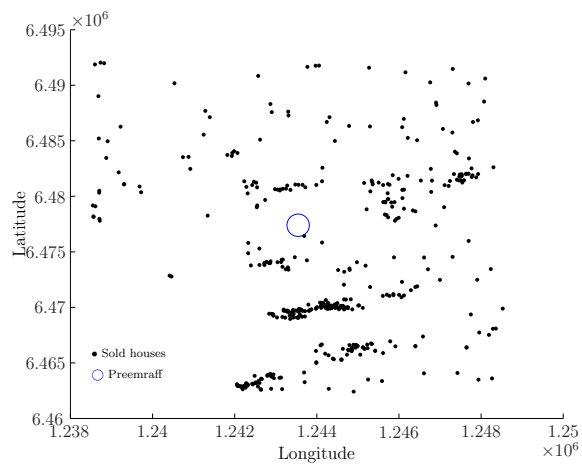


Figure 2: Spatial distribution of sold houses



A.2 Sub-markets

All results in this section are based on estimates where sub-markets have been included.

Table 7: Test for spatial dependency (sub-markets)

Null	Restriction	Estimated statistic	p-value
$\lambda = 0$	$\rho = 0$	11.022 †	0.000
$\lambda = 0, \rho = 0$	$W_1 = W_2$	72.139 ‡	0.000
$\lambda = 0$	$\rho = 0$	70.273	0.000
$\lambda = 0$	ρ is unrestricted but estimated	71.869	0.000
$\lambda = 0$	ρ is unrestricted and not estimated	68.091	0.000
$\rho = 0$	$\lambda = 0$	4.761	0.029
$\rho = 0$	λ is unrestricted but estimated	0.016	0.898
$\rho = 0$	λ is unrestricted and not estimated	2.580	0.108

Note: †The statistic is distributed as $N(0, 1)$. ‡The symmetric W_1 is used and the statistic is distributed as χ_2^2 with a critical value of 5.99 at 5 %. All other statistics are $\sim \chi_1^2$ with a critical value of 3.84 at 5 %.

Table 8: Magnitude of Distance Effects (sub-markets)

	<u>Max</u>		<u>Min</u>		North	South	East	West
	Effect	Direction	Effect	Direction				
Model 1	-0.082	.	-0.082
Model 2	0.020	-158.402	-0.039	21.598	-0.021	0.001	-0.037	0.018
Model 3	0.106	-176.881	-0.111	3.119	-0.009	0.003	-0.111	0.106

Note: Direction in which the maximum and minimum effects occurs measured in degrees on $[-180, 180]$, with $0 = East$. Since we are interested in the distance effect the anisotropic intercept in Model 3 is not considered. These distance effects are calculated for houses without a view of Preemraff.

Table 9: Effect of Visual (sub-markets)

	500 m	1000 m	1500 m	2000 m	2500 m
Model 1	-0.552	-0.358	-0.206	-0.078	0.036
Model 2	-0.518	-0.323	-0.174	-0.050	0.060
Model 3	-0.527	-0.333	-0.185	-0.060	0.050

Note: Some of the effects might be calculated based on non-significant estimates.

Table 10: Estimation results (sub-markets)

	Model 1	Model 2	Model 3
Constant	6.448*	5.729*	5.692*
	[9.947]	[7.628]	[7.349]
<i>D</i>	-0.082	-0.010	-0.003
	[-1.120]	[-0.121]	[-0.033]
$\cos(\Theta)D$.	-0.028*	-0.108
	.	[-2.415]	[-0.758]
$\sin(\Theta)D$.	-0.011	-0.006
	.	[-0.558]	[-0.074]
$\cos(\Theta)$.	.	0.667
	.	.	[0.563]
$\sin(\Theta)$.	.	-0.028
	.	.	[-0.041]
Lot size	5.0e-6	5.9e-6	6.1e-6*
	[1.619]	[1.917]	[1.965]
Living area	0.005*	0.005*	0.005*
	[10.557]	[10.612]	[10.539]
Sea front	0.794*	0.807*	0.808*
	[5.489]	[5.623]	[5.632]
Sea front × Adjacent parish	-0.377	-0.391	-0.380
	[-1.683]	[-1.759]	[-1.687]
Sea view	0.459*	0.470*	0.471*
	[5.604]	[5.779]	[5.785]
Sea view × Adjacent parish	-0.233	-0.234	-0.229
	[-1.706]	[-1.729]	[-1.686]
Quality	0.014*	0.015*	0.015*
	[5.750]	[5.912]	[5.937]
Age	-0.004*	-0.005*	-0.005*
	[-3.798]	[-4.024]	[-4.070]
Age ²	2.6e-5*	2.7e-5*	2.7e-5*
	[3.609]	[3.749]	[3.765]
Visual	-4.045*	-3.770*	-3.832*
	[-2.687]	[-2.499]	[-2.390]
Visual × Distance	0.521*	0.489*	0.496*
	[2.789]	[2.616]	[2.497]
$W_2\varepsilon$	0.471*	0.493*	0.504*
	[6.099]	[6.467]	[6.656]

Continued on next page...

Note: *Significant at 5 %. t-values in square brackets.

Table 10 continued

	Model 1	Model 2	Model 3
Morlanda	0.213 [1.236]	0.201 [1.163]	0.219 [1.162]
Tossene	-0.223* [-2.372]	-0.109 [-0.299]	-0.158 [-0.421]
Hunnebostrand	-0.300 [-1.051]	-0.259 [-0.581]	-0.332 [-0.714]
Askum	-0.167 [-1.552]	-0.151 [-0.441]	-0.205 [-0.575]
Malmö	0.303 [1.904]	0.218 [0.740]	0.176 [0.579]
Brastad	-0.564* [-6.936]	-0.236 [-0.764]	-0.261 [-0.824]
Bro	-0.468* [-5.715]	-0.274 [-0.785]	-0.294 [-0.829]
Skaftö	0.223* [2.811]	0.169* [2.003]	0.167 [1.676]
Lyse	-0.209* [-2.566]	-0.132 [-1.429]	-0.130 [-1.263]
Dragsmark	0.098 [0.679]	0.154 [1.059]	0.178 [1.140]
R^2_{adj}	0.715	0.719	0.718
Log-likelihood	87.337	90.552	90.707
Error variance	0.076	0.074	0.074

Note: *Significant at 5 %. t-values in square brackets.

A.3 Results from other specifications

Table 11: Estimation results (Different estimates of Model 2)

	OLS	SAR	SEM
Constant	4.055*	3.919*	4.552*
	[12.519]	[12.120]	[9.588]
<i>D</i>	0.164*	0.165*	0.117*
	[4.636]	[4.780]	[2.215]
$\cos(\Theta)D$	-0.031*	-0.030*	-0.038*
	[-6.125]	[-6.195]	[-5.399]
$\sin(\Theta)D$	-0.021*	-0.021*	-0.025*
	[-9.858]	[-9.844]	[-6.770]
Lot size	4.8e-6	4.4e-6	6.8e-6*
	[1.407]	[1.328]	[2.213]
Living area	0.005*	0.005*	0.005*
	[10.233]	[10.413]	[10.488]
Sea front	0.998*	0.994*	0.874*
	[7.180]	[7.310]	[6.693]
Sea front ×Adjacent parish	-0.600*	-0.590*	-0.484*
	[-2.574]	[-2.588]	[-2.258]
Sea view	0.651*	0.630*	0.525*
	[7.732]	[7.620]	[6.721]
Sea view ×Adjacent parish	-0.448*	-0.422*	-0.312*
	[-3.108]	[-2.982]	[-2.363]
Quality	0.015*	0.015*	0.015*
	[5.477]	[5.546]	[5.950]
Age	-0.004*	-0.004*	-0.005*
	[-3.543]	[-3.879]	[-4.463]
Age ²	2.8e-5*	3.1e-5*	2.8e-5*
	[3.872]	[4.248]	[3.908]
Visual	-2.636	-2.673	-3.168*
	[-1.718]	[-1.782]	[-2.132]
Visual ×Distance	0.351	0.356	0.418*
	[1.830]	[1.901]	[2.260]
W_1p	.	0.023*	.
	.	[2.080]	.
$W_2\varepsilon$.	.	0.558*
	.	.	[7.631]
R _{adj} ²	0.676	0.676	0.721
Log-likelihood	.	63.748	84.622
Error variance	0.091	0.087	0.076

Note: *Significant at 5 %. t-values in square brackets.