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# Relationships between housing prices and commuting flows<sup>1</sup>

Arnstein Gjestland, Liv Osland<sup>2</sup> and Inge Thorsen

**Work in progress. Please, do not cite.**

In relation to housing prices, gravity based accessibility measures have been suggested as a generalisation of polycentric labour market structures (Heikkila et al. 1989). Applications of gravity based accessibility variables can, however, be demanding with respect to data requirements and computation. This paper studies whether simpler accessibility indicators could be used. In contrast with gravity based measures the indicators introduced in this paper is based on actual commuting patterns. By using data from a Norwegian region, this paper shows that the relationship between housing prices and patterns of commuting is also fairly complex. The simpler measures cannot replace the gravity based approach. They add to the explanatory power of the hedonic model, however, and probably capture the effect of excluded zonal characteristics relevant for housing prices.

## 1. Introduction

The relation between house prices and access to work places is a central theme in both theoretical and empirical housing market research. There are many reasons why this relationship is important. Travelling to work is a regular and bounded trip. According to the Norwegian Travel Survey, travelling to work constitute approximately one fifth of all travels and approximately one third of all travels during the weekdays in Norway. Most commuters travel at the same point in time every day, which also creates congestions and pollution, and many transport investments are realized in order to cope with this type of travelling. Parallel to this, the house constitute a major part of households' wealth, and labour income constitutes the largest source of income, so understanding the relation between house prices and access to work is important for households. In order to reduce many of the transportation problems related to the home-work travelling, planners may seek to locate houses in areas where access to jobs are assumed to be good. One related issue is how to identify where job-accessibility is high. This issue is also connected to the question of how we should measure job-accessibility in relation to household location or housing.

There exists a relatively large amount of literature on how to measure accessibility, but there is no consensus on what is a good measure (Handy and Niemeier, 1997). In relation to housing prices, however, gravity based accessibility measures have been suggested as a generalisation of modern polycentric labour market structures (Heikkila et al. 1989). More

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recently, Osland and Thorsen (2008) and Osland and Pryce (2009) also found that gravity based accessibility measures significantly explain variation in housing prices.

As shown in Handy and Niemeier (1997) gravity based type of measures is not the only indicators that could be used to model the relationship between housing prices and job accessibility. Other weighted average measures could also be used to capture the job-opportunity density of a given area. In this paper we introduce such an indicator which is based on actual commuting in each zone, rather than the potential for commuting which forms the basis of gravity based accessibility measures as used in Osland and Thorsen (2008) or Osland and Pryce (2009). One measure is origin-specific, the other is destination specific. The origin-specific measure is the percentage of the total working population living in one zone and working in a different zone. The destination-specific measure is simply the percentage of people working in the zone that are living in another zone. These measures could easily be explained to non-experts in the field. They are less demanding when it comes to data requirements. Finally, they are computationally simpler than the gravity based measures, which involves non-linear methods of estimation and necessitate relatively detailed information on distances between zones.

According to Handy and Niemeier (1997) *“The fundamental issue is that an accessibility measure is only appropriate as a performance measure if it is consistent with how residents perceive and evaluate their community. In other words, a practical definition of accessibility must come from the residents themselves”* (page 1176). In view of the citation above, hedonic house prices estimation could be a useful tool. This method could be characterised as revealed preference approach. It enables measurements of the implicit prices of a range of non-traded goods which values may capitalize into house prices. Access to workplaces is one important example. By using this method it is possible to get a market-based and econometric evaluation of the proposed measures of accessibility. Together, these two features, simplicity and market evaluation, constitute potential strengths if they are going to be applied by for instance planners and policy makers.

This paper is outlined as follows: Section 2 contains a short literature review. Thereafter we present the study area an explicit formulation of hypotheses. In Section 4 we present the data, and in Section 5 we present the empirical analysis and results. Finally, we make conclusions based on our findings.

## **2. Short literature review**

The most widely accepted theory that links residential location to the price of housing is given by urban economic theory represented by the monocentric city model. The main spatial attribute of the theory is distance from the central business district (cbd). The relevant prediction of the monocentric model is that households that live far from the center of employment are compensated for higher costs of commuting by way of lower price of a unit housing. In this way, the model provides an important justification of the relationship between housing prices and workplaces.

In the housing market literature, accessibility has traditionally been accounted for by the simple measure of distance to cbd (Ball and Kirwan 1977, Dubin 1992). It is, however, well known in the housing market literature that this model has not consistently been supported by the empirical evidence. Many reasons have been suggested for the mismatch between theory and empirics; see for instance Osland and Pryce (2009). One obvious suggestion is the polycentric pattern of employment (Arnott et al. 1998). In spite of this, there are in fact

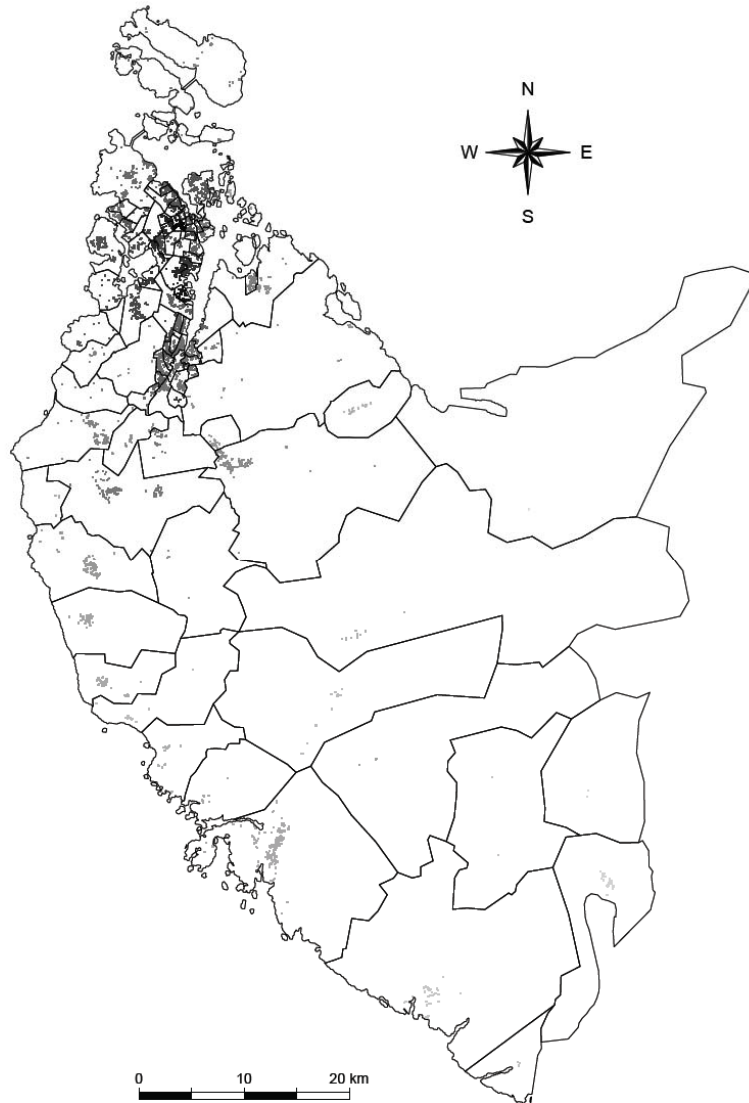
relatively few papers that focus on how polycentrism may affect property values (Heikkila et al. 1989) and how the relationship between housing values and a polycentric labour market should be modelled. One natural suggestion to cope with polycentrism is the one found in Waddell et al. (1993). This paper includes both distance to cbd and distance to secondary employment centers. One potential problem with this approach is that the researcher has to choose which employment centers to include. Due to problems with multicollinearity and interpretation of partial effects, it may not be straightforward to include distances to many employment nodes as separate variables in an empirical hedonic house price model.

A range of accessibility measures which could be characterised as polycentric, are frequently used in the literature of spatial interaction problems. One important type of accessibility measure in this case is the gravity-based measures or potential variables (Hansen, 1959). To cite Anselin (2002), these variables are specified so that “the potential for interaction between an origin  $i$  and all destinations  $j$  was formulated as a sum of “mass” terms in the destination, suitably downscaled by a distance decay function”, (page 250). In this way we include a weighted average of other destinations in our measure. In relation to housing prices, gravity based accessibility measures have been suggested as a generalisation of modern polycentric labour market structures (Heikkila et al. 1989). In spite of this, we are only aware of relatively few papers that relate gravity-based accessibility measures to housing prices, see Jackson (1979), Adair et al. (2000), Osland and Thorsen (2008) and Osland and Pryce (2009).

Jackson (1979) does not find evidence of dominance of neither the cbd-gradient nor the gravity based employment index. The main result in Adair et al. (2000) is that gravity based accessibility measures were not significant. One important reason for this could be that this study was based on data from the urban area of Belfast. By using a regional approach and Norwegian housing price data, the variable was clearly significant in Osland and Thorsen (2008). Osland and Pryce (2009) uses housing price data from Glasgow. The employment data were from all Scottish datazones. They found a highly significant non-monotonic relationship between house prices and access to employment. As we move very close to an employment node, house prices would fall if there are relatively potent negative externalities, according to this research. The result that there are negative externalities related to high levels of accessibility is in line with results found in Li and Brown (1980), although this paper measure access to employment by way of distance to the cbd.

### **3. Study area and hypotheses to be tested**

Our study area is situated in the south western part of Norway. The population is approximately 230 000, most of it concentrated in the north western corner in the twin-cities Stavanger and Sandnes. To the north a wide fjord acts as a natural barrier and delimits the study area. In the northeast fjords and mountains inhibits direct travels east-west and forces the traffic to take a southward detour. In the west the landscape is rather flat farming country, with a quite extensive network of local roads. Moving east the landscape gets rougher with topological barriers. The most southern and eastern areas are thinly populated and represents a border zone between our study area and the most southern region of Norway. Based on commuting flows and natural barriers, the area is characterised as one housing and labour market. This is important, given that a study of the effect of labour market accessibility on housing prices probably necessitate a connected regional housing and labour market area, rather than just an urban area.



**Figure 1: Map of the study area.** The postal zones are drawn and all the observations are marked with a colour indicating the mean price of houses in that postal zone. Black signifies respectively the highest and light grey the lowest mean prices.

This paper attempts to estimate a regression model that relates the price of homogenous housing at a given location to a range of variables. These variables are either related to the house itself or to its specific location in the geography:

$$(1) \quad P_{it} = f(z_{sit}, z_{lit}),$$

$P_{it}$  = the price of house  $i$  in year  $t$ ,

$z_{sit}$  = the value of dwelling-specific structural attribute  $s$  for house  $i$  in year  $t$ ;  $s = 1, \dots, S$ ,  $i = 1, \dots, n$ .

$z_{li}$  = the value of location-specific attribute  $l$  for house  $i$ ;  $l = 1, \dots, L$ ,  $i = 1, \dots, n$ .

Our focus is on some of the location-specific attributes. First we study the effect of a gravity based labour market accessibility measure (Hansen, 1959). The formulation of the measure is also based on Osland and Thorsen (2008) and is given by:

$$(2) \quad S_j = \sum_{k=1}^{98} E_k \exp(\sigma d_{jk})$$

In the above expression  $E_k$  represents employment in postal zone  $k$ ,  $d_{jk}$  represents minutes driving time between zone  $j$  and  $k$ ,  $\sigma$  is a parameter to be estimated by way of Maximum Likelihood estimation. We could alternatively have used a non-linear least squares estimator. The reason one of these estimators must be used is that the formulation of the accessibility measure makes the hedonic price function non-linear in its parameters. The estimated value of  $\sigma$  is imputed into (2) so that it subsequently is possible to use the resulting variable in an ordinary least squares regression. This procedure of estimating the distance deterrence parameter  $\sigma$  simultaneously with the other parameters is in contrast with the general approach in the transport literature, where one normally would use a pre-estimated value.

One problem with these types of estimations is that it may be difficult to converge on a solution, and in our experience a solution also rest on the fact that one needs good starting values on the parameters to be estimated. Sometimes this type of information is not available, and the estimation of a gravity based accessibility index can in this way be time-consuming and sometimes convergences are not found. The data requirements are also relatively comprehensive, given that we need a distance matrix that includes distances between all zones in the given study area.

As an alternative to this measure we suggest the following intuitive indicator of labour market accessibility in relation to housing prices: Let  $X$  be a commuting matrix where a typical element  $x_{ij}$  denotes the number of people living in zone  $i$  and working in zone  $j$ . We define the variable OUT-COM as the proportion of people living in zone  $i$  and working in another zone in the study area:

$$(3) \quad \text{OUT-COM}_i = \left( \frac{(\sum_{j=1, j \neq i}^N x_{ij})}{(\sum_{j=1}^N x_{ij})} \right) \cdot 100$$

The variable IN-COM is defined as the proportion of people working in zone  $j$  and living in one of the other zones:

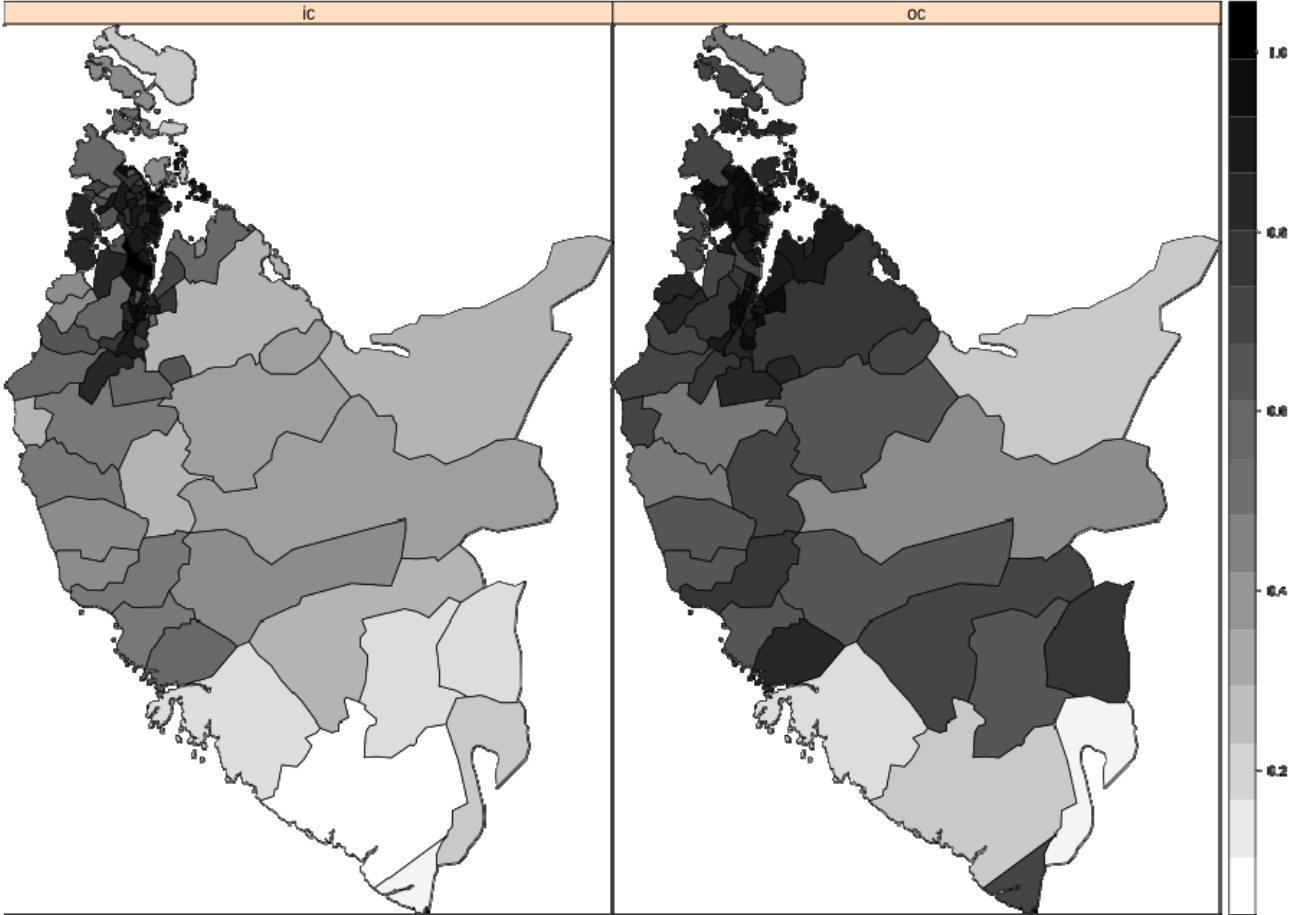
$$(4) \quad \text{IN-COM}_i = \left( \frac{(\sum_{i=1, i \neq j}^N x_{ij})}{(\sum_{i=1}^N x_{ij})} \right) \cdot 100$$

These measures can be included so that the hedonic price function is linear in its parameters and we need no information on distances between all zones.

An illustration of the variation of these measures in the study area is found in Figure 2. The general tendency is a high degree of in-commuting in Stavanger and surrounding zones in the north. The further south and away from the central business district we move, the lower the degree of in-commuting. The percentage out-commuting is also high in the most central cities

and a smaller but still high level in the postal zones surrounding these cities. One has to move to the most eastern and southern postal zones to find low levels of out-commuting.

It should be noted that the zones vary in size, and the largest postal code-zones are located in rural areas. In such zones, it is should be expected that the percentage of commuting will be lower due to the fact that significant distances must be travelled before the boundaries of these zones are crossed.



**Figure 2:** The IN-COM (map to the left) and OUT-COM (map to the right) variables depicted in a map of the study area. Darker areas signify high levels of commuting.

The idea that forms the basis of introducing these variables is that the percentage of in- and out-commuting represents a way of characterising zones in relation to house prices. A zone with high in-commuting is a zone where the number of jobs is high, and accessibility should, hence, also be high. According to standard urban economic theory, the higher the value of this variable, the higher will then the price of a unit price of housing be, all else equal. If a zone has a high value of out-commuting, this zone has fewer jobs available, and labour market accessibility in this zone is low. The tendency is that one has to travel out of the zone to find relevant jobs. It is, hence, assumed that this variable will exert a negative effect on house prices.

This way of characterising a zone could be particularly relevant for more rural areas. When analysing the effect of these variables on house prices, one should study whether the effect of the variables on house prices vary or interacts with the degree of centrality in the area.

#### 4. Overview of Data

We use housing price data from the second half of 2003 to 2007. The sample consists of 4392 observations, and only privately owned single family houses are included. One important reason is that this is about the only house type available on the market in the rural areas.

The housing data comes from two sources: finn.no, (Finn) a web based service used by the main real-estate franchises in Norway, and GAB the National Building Register. The data from Finn are used to compute the national housing price index. It includes the actual selling price, the year and month of sale, a measure for the size of the house, type of house, the year the house was build, and an identification code for each property.

Statistics Norway started collecting these data in 2002<sup>3</sup> and the completeness of the information available for each observation improves over time. Complete identification codes are for instance missing from all observations in 2002 and the first half of 2003. By 2007 the identification codes are nearly complete. According to Statistics Norway the Finn-data cover about 40% of the house sales in Norway. From 2004 this percentage is probably higher since data from one of the largest real-estate franchises (Notar AS) was added.

The GAB register is a combination of three registers, the official land property register, an address register and a building register. For buildings build before 1983 much information about the buildings are missing. For buildings and additions erected after 1983 information is quite extensive and accurate.

The GAB register plays a central part in the formal registration of a property transaction in Norway. This formal registration is not compulsory. Statistics Norway reports that about 94% of the house sales that are formally registered are registered within six months. GAB and Finn contains different information about housing characteristics. In order to achieve as much information as possible on housing attributes, we have combined the two sources. Matching is based on property identification code and selling price. The implication is that the prices come from both sources<sup>4</sup>. In GAB, only the last selling price of a house appears in the register. In cases were a house has been sold more than once in the study period, we have to rely on price information from the Finn-database only. Houses on leased grounds (ca 2-3% of the houses) have been excluded.

The hedonic, or micro variables, we were able to obtain is presented in Table 1 below. Table 1 also shows quite a big dispersion in lot-size. Observations with lot-size equal to zero have been excluded. We have also excluded observations with a useful floor space below 30 m<sup>2</sup>. Observations with missing exogenous variables are not included in the regressions.

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<sup>3</sup> Up until 2002 Statistics Norway used a survey based on a questionnaire sent out to house buyers that had registered their transaction in GAB.

<sup>4</sup> Only the last selling price of a house is registered in GAB. This means that if a house has been sold more than once, previous sales prices will not appear in this register.



**Table 1:** Descriptive Statistics

Variable	n	Mean	Median	Std. Dev.	Min	Max	Source
Price (in 1000 NOK)	4392	2630,7	2450	1188,1	280	16100	Finn and GAB
Age	4392	41,1	34	32,2	0	307	Finn (GAB)
Livarea	4392	166,8	160	56,9	33	714	Finn
Landarea	4392	656,4	573	679	8,9	24700	GAB
Garage dummy	4392	35,50 %	-	-	-	-	GAB

**Note:** The variable Age relies primarily on data from Finn, but is supplemented with information from GAB. The living area (defined as useful floor space) is calculated in accordance with “Norsk Standard, NS 3940 Areal- og volumberegninger av bygninger”.

The process of matching the two registers brings forth questions about sample selection bias. Statistics Norway writes the following about the Finn sample: “The statistics (...) cover a majority of all used dwellings sold in Norway. Nonetheless it is possible that to some degree there is systematic sample skewness with regard to geography.”<sup>5</sup> To be more specific the sample seems to be relatively smaller in the most rural areas. This comes in addition to the fact that the population of sold houses is smaller in the rural zones. In spite of this the Finn data is used to compute the official national price index for used dwellings. To our knowledge these data are the best information available in Norway.

To sum up we have information from two different sources. There might be some undetected spatial sample selection bias in our data, since a lower proportion of house sales in the most rural areas are registered on Finn. We also lose some observations through the matching with GAB. The missing observations might be regarded as the cost of acquiring more information about housing characteristics.

In addition to the micro data described above we use some variables that are grouped on the postal zone level. There are a total of 98 post zones in the area. For these zones we have defined travel time to central business district, travelling distances between all zones in the area and the number of jobs in each zones. These variables are all based on data delivered by Statistics Norway.

**Table 2:** Descriptive statistics for variables given on postal zone level.

Variable	Mean	Median	Std. Dev.	Min	Max
Num. Obs.	44,82	33,5	41,93	1	216

<sup>5</sup> Reference: “Average price per meter, detached houses”;  
 URI:[http://www.ssb.no/english/subjects/08/02/30/kvadenebol\\_en/](http://www.ssb.no/english/subjects/08/02/30/kvadenebol_en/)  
[http://www.ssb.no/english/subjects/08/02/30/kvadenebol\\_en/](http://www.ssb.no/english/subjects/08/02/30/kvadenebol_en/)

MinCBD	19,07	12,58	19,43	1	92,54
IN-COM	0,67	0,7	0,24	0,1	0,99
OUT-COM	0,81	0,87	0,17	0,12	0,97
DISTCBD	19,07	12,58	19,43	1	92,54

## 5. Empirical Analysis

There exist many empirical papers that use the hedonic methodology. An overview of some of these papers are found in Anselin and Lozano-Gracia (2009) and Chin and Chau (2003). In spite of this, there is no agreement on what is the correct specification of hedonic house price models, and the question of functional form remains an empirical question that must be determined for each market under scrutiny. Based on previous research from the study area (see Osland et al. 2007 and Osland and Thorsen 2008), we start off with the following empirical hedonic price model:

$$(5) \quad \ln(P) = a_0 + a_1 \ln(\text{MinCBD}) + a_2 (\ln(\text{MinCBD}))^2 + \mathbf{b} \cdot \mathbf{A} + c \text{TIME}_{it} + \varepsilon,$$

where  $P$  = observed real selling price of house  $i$  (1998 is base year),  $\mathbf{A}$  is a vector of dwelling attributes as explained in Table 1. CBD is the distance to the central business district measured in minutes car drive, accounting for speed limits, and  $t$  represents year of sale. All variables appear in logarithmic form except for the dummy variables.

In order to estimate the housing-price gradient, it is necessary to identify the center of the geography. According to Plaut and Plaut (1998) much of the empirical literature in the field assumes that the location of the center is known in advance. In our study the zone that should represent the CBD is found endogenously, however. We have experimented with a range of centrally located zones and used the descriptive measures of  $R^2$  and SRMSE/APE to choose the zone distance should be measured from. The inclusion of a quadratic term of the CBD-variable is based on results from Osland et al. (2007). The variable is interpreted as the effect of urban attraction. The formulation of the gravity based accessibility measure as shown in (2) is based on Osland and Thorsen (2008) as described in Section 3.

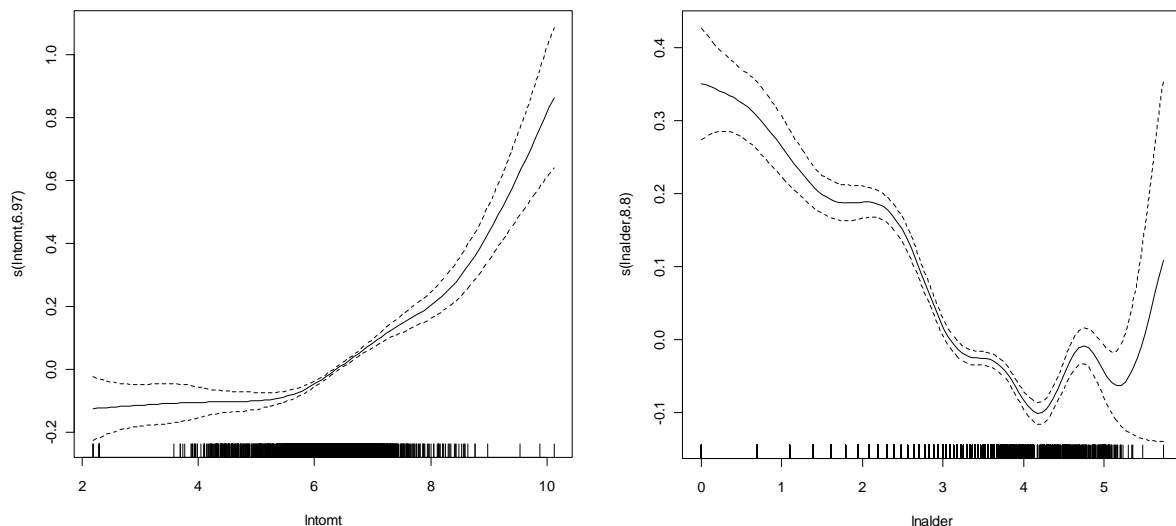
As mentioned above, we started the modelling procedure by applying previous estimation results from the same study area. The new data used in this paper is, however, from a more recent period in time, and we have less information when it comes to housing attributes compared to the studies referred to above. To avoid model misspecifications we therefore initially apply a semiparametric approach, the RESET test (Ramsey, 1969) and tests for spatial effects (Anselin, 1988). The RESET test is a misspecification test related to the functional form of the variables included in the model. In this case the test is based on powers of the fitted values. We test the null hypothesis that the model has no omitted variables. The alternative hypothesis is that the model is misspecified. According to Wooldridge (2003, page 294) the test has no power to detect unobserved omitted variables, see also Vaona (2009) for

more details on this test. The estimations are mainly performed by using Stata. We also use the program R<sup>6</sup> combined with related packages, see Bivand et al. (2008).

The semiparametric regression analysis is a flexible approach which is used as an exploratory tool to detect non-linearity in the data. There exist some hedonic studies which uses similar approaches. See for instance Coulson (1992), Pace (1998) and Bao and Wan (2004). In this paper a variant of generalized additive models based on Hastie and Tibshirani (1990) is applied in combination with iterative penalized regression smoothing splines. The method is explored in detail in Wood (2006). We estimate model (5) and include each continuous variable in turn into the smooth function  $s(z)$ , so that  $z$  is a variable vector not included in  $\mathbf{A}$ .

By way of example, the inclusion of the variable  $\ln(\text{LOTSIZE})$  in the smooth function gave the graphical result as shown in Figure 3. This graph is based on thin plate regression spline. The number in the legend of the y-axis is efficient degrees of freedom of the plotted term. The interpretation is that the equivalent of 6.97 degrees of freedom is used in estimating the smooth. A precise definition of efficient degrees of freedom can be found in Wood (2006, pages 170-172). The solid line in Figure 3 represents the variation around the mean predicted value of the dependent variable. The dashed lines represent approximately 95% confidence regions of the predicted values. What this figure illustrates is that the square of the variable  $\ln(\text{LOTSIZE})$  should be included in the model. The inclusion of this quadratic term increases the  $p$ -value of the RESET test from 0.1251 to 0.3690. The same line of arguing forms the basis of including the square of  $\ln(\text{AGE})$ .

**Figure 3:** The lotsize (to the left) and age-variable (to the right) is in turn included in the semiparametric smooth-function.



The number in the legend of the y-axis is efficient degrees of freedom of the plotted term.

The most important question in this paper is how to represent labour market accessibility. In this case we apply traditional specification tests such as Wald-tests and log-likelihood ratio tests in addition to the other tests described above. Finally, we include a range of descriptive measures, as shown in Table 3. By and large, we therefore follow the classical modelling strategy, as recommended by Florax et al. (2003). We start with relatively parsimonious

<sup>6</sup> R is available at: <http://www.R-project.org>

model formulations. Whether we should continue with more comprehensive model specifications are based on the results of a range of tests and descriptive measures.

The initial model-variants presented in Table 3 are based on various specifications of (5).

Model M0: In this model we estimate (5) as stated above.

Model M1: We estimate (5) and include a gravity based accessibility indicator (2).

Model M2: We estimate (5) and the new alternative accessibility measures (3) and (4).

Model M3: We estimate (5) and include the gravity based accessibility indicator (2) in addition to (3) and (4).

As expected, the estimated results from M1 and M3 show that the ACCESS-variable is significant and its coefficient takes a positive value (see Table 3). When it comes to M2 and the variable IN-COM, the results are not in line with a priori expectations. When the amount of in-commuting in a zone is increasing, the result is a decrease in housing prices. The variable OUT-COM, takes a positive value, but does not prove to be significant in M2. The value of the log-likelihood function is clearly higher in M1 compared to M2, and all the other reported descriptive statistics goes in favour of M1.

**Table 3:** Estimated results from alternative hedonic house price models.

Variable Name	M0	M1	M2	M3	M4
<b>Constant</b>	12.9697 (71.89)	12.4172 (63.52)	12.9424 (71.75)	12.2379 (61.87)	12.4415 (64.68)
<b>Lotsize</b>	-0.1725 (-3.00)	-0.2044 (-3.62)	-0.1673 (-2.91)	-0.2024 (-3.53)	-0.1987 (-3.61)
<b>Lotsize<sup>2</sup></b>	0.0222 (4.62)	0.0249 (5.27)	0.0219 (4.55)	0.0249 (5.20)	0.0248 (5.37)
<b>RurLotsize</b>	-0.0253 (-10.28)	-0.0212 (-8.83)	-0.0265 (-10.15)	-0.0228 (-9.49)	-0.0191 (-7.51)
<b>Age</b>	-0.2017 (-11.75)	-0.1924 (-11.38)	-0.2054 (-11.84)	-0.1994 (-11.73)	-0.1957 (-11.70)
<b>Age<sup>2</sup></b>	0.0173 (5.75)	0.0155 (5.23)	0.0179 (5.92)	0.0169 (5.65)	0.0158 (5.39)
<b>Garage</b>	0.0416 (7.21)	0.0428 (7.44)	0.0404 (6.93)	0.0418 (7.19)	0.0403 (6.95)
<b>Size of house</b>	0.5103 (42.77)	0.5051 (42.69)	0.5102 (42.80)	0.5028 (42.63)	0.5025 (42.52)
<b>YearDum04</b>	0.0970 (8.89)	0.0981 (9.03)	0.0968 (8.90)	0.0975 (9.07)	0.0974 (9.12)
<b>YearDum05</b>	0.2059 (18.75)	0.2069 (18.92)	0.2051 (18.68)	0.2054 (18.92)	0.2047 (19.01)
<b>YearDum06</b>	0.3701 (33.55)	0.3706 (33.67)	0.3699 (33.49)	0.3701 (33.83)	0.3700 (34.06)
<b>YearDum07</b>	0.5584 (53.95)	0.5579 (54.17)	0.5581 (53.85)	0.5570 (54.43)	0.5565 (55.14)
<b>Distance CBD</b>	-0.0558 (-3.14)	-0.1044 (-5.36)	-0.0429 (-2.28)	-0.1078 (-5.57)	-0.0870 (-4.14)
<b>Distance CBD<sup>2</sup></b>	-0.0464 (-13.18)	-0.0273 (-5.84)	-0.0510 (-12.22)	-0.0251 (-4.89)	-0.0326 (-6.06)
<b>ACCESS</b>		0.0643 (4.78)		0.0879 (4.29)	0.0626 (4.22)
<b><math>\sigma</math></b>		-0.1189 (-6.51)		-0.1287 (-4.06)	-0.1395 (-4.21)

<b>IN-COM</b>			-0.0295 (-2.06)	-0.0841 (-4.91)	0.0233 (0.51)
<b>OUT-COM</b>			-0.0005 (-0.03)	0.0552 (2.86)	0.2017 (3.93)
<b>IN-COM<sup>2</sup></b>					0.1203 (1.80)
<b>IN-COM<sup>3</sup></b>					0.0435 (3.08)
<b>OUT-COM<sup>2</sup></b>					0.3269 (2.93)
<b>OUT-COM<sup>3</sup></b>					0.1382 (3.08)
<b>n</b>	4392	4392	4392	4392	4392
<b>R2</b>	0.8222	0.8241	0.8225	0.8257	0.8268
<b>R2(adj)</b>	0.8217	0.8235	0.8219	0.8250	0.8260
<b>Log-likelihood</b>	1184.02	1207.05	1187.48	1227.12	1242.79
<b>VIF</b>	16.36	17.56	16.06	17.34	69.91
<b>Ramsey Reset</b>	0.7670	0.7603	0.4640	0.2528	0.7788
<b>APE</b>	510405	508469	510366	507889	506449
<b>SRMSE</b>	0.2891	0.2875	0.2895	0.2875	0.2865
<b>RLMlag</b>	1.70	0.86	1.38	0.24	0.39
<b>RLMerror</b>	323.59	313.09	324.15	305.78	290.79

The dependent variable is  $\ln(P)$ ,  $P$ =real house prices, 1998 is base year. White-adjusted robust  $t$ -values appear in parentheses. The RLM-tests for spatial effects asymptotically follow a  $\chi^2(1)$  distribution, with a critical value of 3.84 at the 5% level. VIF denotes the average value of the variance of inflation factor for all variables; see for instance Greene (2003). The Average Prediction Error (APE) is based on a comparison between predicted and the observed housing

prices;  $APE = \frac{\sum_i (\hat{P}_i - P_i)}{n}$ . Here  $n$  is the observed number of observations.

In M3 we include the gravity based accessibility variable in addition to the commuting variables. In this case both commuting-variables (IN-COM and OUT-COM) are significant. When comparing M1 and M3 the likelihood ratio test statistic is 40 which clearly exceed the critical value of the chi-square distribution ( $\chi^2_{0.05}(2) = 5.991$ ). The p-value of a Wald test is 0.000, given a null hypothesis of no joint significance of these two variables. This means that when including the gravity based accessibility variable the commuting variables become significant and contributes to the explanation of housing prices. The signs of the estimated parameters of the commuting variables are unchanged in comparison with results from M2.

All the models have been tested for spatial effects in accordance with for instance Anselin (1988). In Table 3 we report the robust Lagrange-multiplier tests (RLM), see Florax and Nijkamp (2003). The RLM-tests asymptotically follow a  $\chi^2(1)$  distribution, with a critical value of 3.84 at the 5% level. The RLM-error test, tests the null hypothesis of no significant spatial error correlation, correcting for presence of local spatial lag dependence in the dependent variable. Similarly the RLM-lag statistics test the null hypothesis of no spatial autocorrelation in the dependent variable, correcting for presence of local spatial error dependence. We also apply  $k$ -nearest neighbour-structure on the weights. The  $k$ -nearest neighbour is chosen on the basis of metric distances, so that distances between neighbours vary. Based on the log-likelihood values from the spatial error model, we have chosen to use  $k=3$  for the spatial error model. This means that each observation will have at least three neighbours. As is commonplace in econometrics we use row-standardized weight matrices ( $\mathbf{W}$ ). The weights

have been forced to be symmetric in the sense that if house  $m$  is a neighbour to house  $n$ , the reverse is also true.

The results from the tests for spatial effects in all model formulations indicate that the spatial error model is the correct model. As a consequence, the ordinary least squares model is consistent (Anselin, 1988). The spatial error model is formulated as follows:

$$(6) \quad \ln(P) = a_0 + a_1 \ln(\text{MinCBD}) + a_2 (\ln(\text{MinCBD}))^2 + \mathbf{b} \cdot \mathbf{A} + c \text{TIME}dum_t + \varepsilon$$

$$(7) \quad \varepsilon = \lambda \mathbf{W}\varepsilon + u,$$

where  $\mathbf{W}$  is the weight matrix and the spatial autoregressive parameter,  $\lambda$ , estimated simultaneously with all the other regression coefficients found in (6). The spatial error models have been estimated by using a sparse matrix approach (see Bivand et al. 2008, page 284).

The estimation of the spatial error model-variants of M0-M3 does not change any of the results. We report the results from the spatial error models in Appendix 1.

How should we interpret the non-expected results related to IN-COM and OUT-COM? Given the negative sign in relation to IN-COM and the positive sign of the parameter related to OUT-COM, these variables do probably not capture the effect of access to labour markets. There are important differences between the ACCESS-variable and the commuting variables. The ACCESS-variable is the weighted sum of all jobs in the area. The commuting variables, on the other hand, reflect the percentage of commuting in each zone, respectively. It is common knowledge that a high percentage of in-commuting in an area could denote congestion and other negative externalities which have negative and significant effects on house prices, see for instance Hughes and Sirmans (1992). The fact that accessibility could also be connected with negative externalities is also a major point in for instance Li and Brown (1980) and Osland and Pryce (2009).

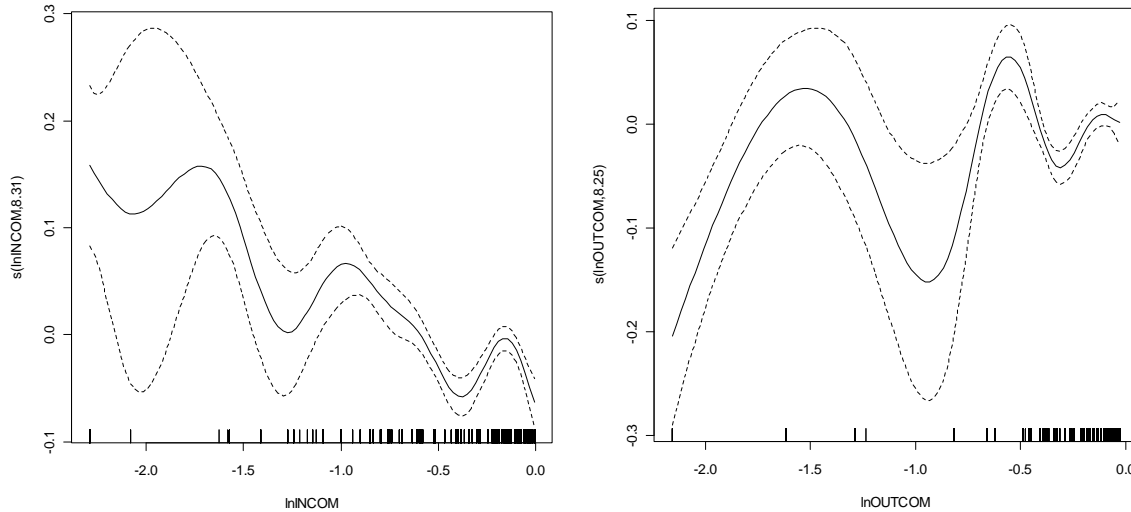
A high level of out-commuting could indicate that the zone is attractive for residential purposes. In this way the commuting variables could capture some neighbourhood characteristics which are otherwise not included in the models. If this is the case, these variables could not replace the gravity based accessibility variable.

As mentioned in Section 3, characterising a zone by way of commuting levels could be particularly relevant for more rural areas. When analysing the effect of these variables on house prices, one should study whether the effect of the variables on house prices vary or interacts with the degree of centrality in the area. We have therefore interacted the commuting variables with a RUR-variable. This is a dummy variable taking the value of 1 if the zone is a rural zone, else 0. The results described above for the parameters related to the commuting variables were not altered as a result of this.

In Figure 4 we show the results when including IN-COM and OUT-COM in the smooth-function  $s(z)$ , one at a time, as described above. The graphs show that the way these variables affect house prices are quite complex. In the final model M4 we have therefore incorporated

flexible polynomial representations of these variables. We include logarithmic, squared and third-order terms of the two variables. In combination, the polynomial representation of the variables proves to be significant. A Wald test of their joint significance provides a  $p$ -value equal to 0.000. The  $p$ -value related to the Ramsey RESET test increases, and the amount of spatial error autocorrelation is reduced, so a more flexible representation of these variables is, hence advocated.

**Figure 4:** The variables IN-COM and OUT-COM are included in the semiparametric smooth function.



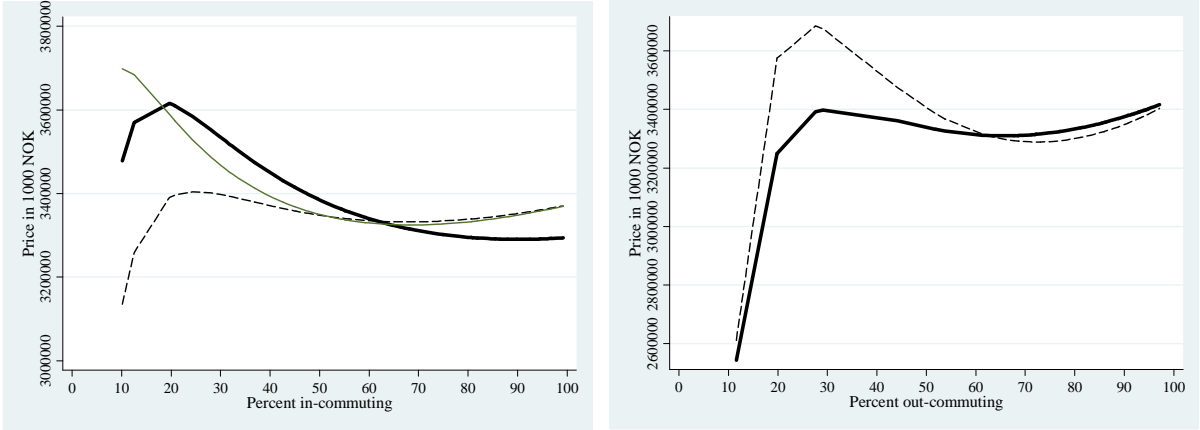
In Figures 5 and 6 we show how the predicted prices of a so-called standard house vary along with variation in the percentage of in-commuting, out-commuting and the gravity based accessibility variable. A standard house is defined as a house that is sold in 2007, it has a garage and has not been sold in a rural area. Except for this, all the continuous variables are set to its average values for the sample. We allow IN-COM, OUT-COM and the gravity based accessibility variable to vary in each graph in turn.

The dependent variable has been transformed from its logarithmic form to prices in accordance with the following transformation rule:

$$(8) \quad \hat{P} = \exp(\ln \hat{P}) \exp\left(\frac{\hat{\sigma}^2}{2}\right),$$

where  $\hat{\sigma}^2$  denotes an unbiased estimator of the residual variance. See also Wooldridge (2003).

**Figure 5:** Predicted house prices of a standard house.



The thick solid lines refers to M4 and the dotted line refers to M4 where the gravity based accessibility measure is not included. The thin solid line in the graph to the left refers to M4 where both out-commuting and the gravity based accessibility measure are excluded.

Figure 5 (to the left) indicates that for low values of in-commuting, predicted house prices from M4 will initially rise, thereafter they will fall quite sharply as the amount of in-commuting increases. When it comes to out-commuting, the solid line (M4) shows that house prices will initially rise when the amount of out-commuting is very low. Thereafter variation in the amount of out-commuting has approximately no effect on the predicted house prices. It should, however, be noticed that when the percentage of either in or out-commuting is lower than approximately 20% the houses are always located in the rural areas furthest south in the study-area. In these places there are also relatively few observations, which make these results less reliable.

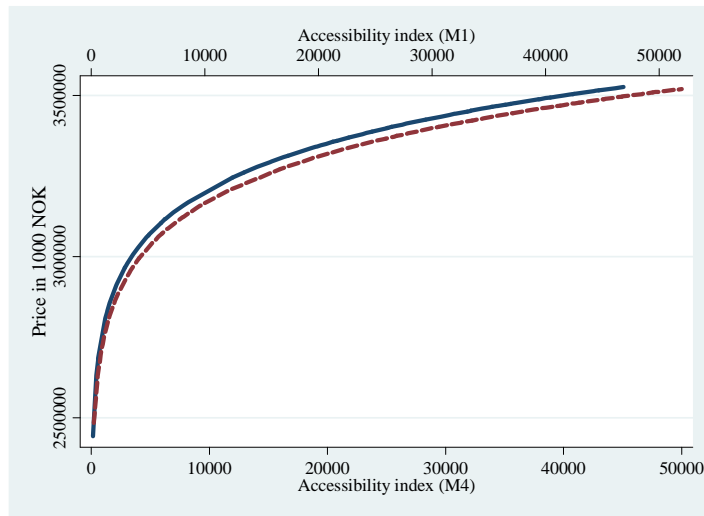
When it comes to the effect of out-commuting as estimated in M4 without the ACCESS-variable, the predicted house prices is relatively invariant to changes in in-commuting. The house price gradient related to the in-commuting variable is also very sensitive to whether the gravity based accessibility variable is included or not.

The shape of the OUT-COM gradient is less sensitive to whether the ACCESS-variable is included. The largest divergence in the gradient is found when the value of the out-commuting variable is between 20% and 40%. The variable takes these values only in 42 cases, and most of these cases are located in the southern most rural areas. These observations could to some extent be characterised as outliers. If IN-COM is excluded from this model, it has virtually no effect on the predicted house price-gradient, and is hence not included in this figure.

Figure 6 shows that the results related to the gravity based accessibility measure are not sensitive to whether we include the commuting variables or not. As the value of the accessibility indicator increases, so does the price of the standard house, albeit at a decreasing rate.



**Figure 6:** Predicted house prices of a standard house.



The solid line refers to M4 and the dotted line refers to M1 where the commuting variables are excluded.

What is then the effect on house prices by changes in accessibility? By way of example, assume a reduction in the number of jobs in a given zone. This will decrease the value of the ACCESS-variable, and the reduction will be largest in the zone where the number of jobs is reduced. In isolation, this will decrease the predicted value of housing prices. The reduction in the number of jobs will however also reduce the amount of commuting into this zone. This will mainly contribute to increase house prices. The overall result on predicted house prices from such a change is the number of jobs is, hence, not clear, and the effect of reduced in-commuting could partially offset the reduction in house prices in the relevant zone due to the reduction in the number of jobs.

## 5.2. Spatial Durbin Model

As a final step to verify the results regarding signs of parameters related to the commuting variables, we have estimated a so-called spatial Durbin model. According to LeSage and Pace (2009) this model-estimator is robust to omitted spatially related variables. Given that we have estimated very parsimonious model variants, and also given that most empirical hedonic house price models may be troubled with missing variables, the spatial Durbin model could reveal additional information in this respect. This spatial model variant is specified as follows:

$$(9) \quad P = \rho WP + X\beta_0 + \rho WX\beta_1 + \varepsilon$$

In the expression above,  $P$  is a vector of observations on prices,  $X$  is a matrix of observations on independent variables and  $W$  is the  $n \times n$  exogenous spatial weights. This model includes a spatial lagging of the dependent variable, in addition to a spatial lagging of all the independent variables, see Bivand (1984) and LeSage and Fischer, (2008). The inclusion of these variables will not bias any of the results presented in the BM. The spatial Durbin model has been estimated by using the same weight matrix as described above for the spatial error model, except that we use  $k=4$  in the weights.

According to LeSage and Fischer (2008) the estimated parameters related to this model has no straightforward interpretation. For this reason we only report the so-called spillover impacts. The computations of these impacts follow LeSage and Pace (2009, page 38). We have fitted the model using an exact dense matrix, and have carried out a Monte Carlo simulation to obtain  $z$ -values using traces of powers of the spatial weights matrix, which give results close to the exact computations but with greatly reduced running times.

The estimated spillover effects are due to the fact that in the spatial Durbin model (9), the price of a house  $i$  is a function of the neighboring house prices through the lagged dependent variable. Neighboring house prices are also a function of the values of its own attributes. Changing these attributes have an effect on own prices, and hence, also on the price of house  $i$ . In addition to this, the price of house  $i$  is dependent on the attribute values of its neighbours, as expressed through the spatially lagged independent variables. The dimension of the spillover effects depends upon the size of the estimated spatial autocorrelation parameters and the specification of the neighborhood matrix. See also LeSage and Fischer (2008), LeSage and Pace (2009) and Kirby and LeSage (2009). So in spite of the fact that the lagged independent variables are not significant, there may still be some significant spillover effects occurring through the spatially lagged dependent variable.

The estimated average impacts from the spatial Durbin model are found in Table 4. We have based the results on M3, excluding the polynomial variants of the commuting variables to ease the interpretation of the results. In our case the direct impacts are calculated as the average effect on a house price  $i$  of a change in each of the explanatory variables related to that house. By way of example, a 1% change in the size of house  $i$ , will on average increase the price of that house with 0.5%. The average total impact is the estimated effect on the price followed by a change in each of the variables, respectively, over all observations. Finally, the indirect impact is defined as the difference between total and direct impacts. This means that the indirect impact captures the average effects on a house price  $i$  of the change in each of the variables related to other houses.

What is important in this case is the results related to IN-COM, OUT-COM and the ACCESS-variable. The signs of the estimated parameters have not changed. The direct impacts yield results that are within the 95% confidence region of the ordinary least squares regression of M2. Only IN-COM have a significant indirect impact, and this indirect impact is also negative. This means that an increase in IN-COM of the neighbouring houses to a house  $i$ , will on average give a negative impact on the price of house  $i$ . There are, hence, negative spillover effects of having a house located in an area with high percentage of in-commuting. The average indirect impact related to the other two mentioned variables are positive, but not significant at the 5% level.

**Table 4:** Average direct, indirect and total impacts from the spatial Durbin formulation of M3

<b>Variable Name</b>	<b>Direct impact</b>	<b>Indirect Impact</b>	<b>Total Impact</b>
<b>Lotsize</b>	-0.2014 (-6.47)	0.1498 (2.21)	-0.0516 (-0.70)
<b>Lotsize<sup>2</sup></b>	0.0251 (9.69)	-0.0125 (-2.20)	0.0125 (2.01)
<b>RurLotsize</b>	-0.0277 (-8.89)	0.0066 (1.76)	-0.0211 (-8.10)
<b>Age</b>	-0.196 (-11.93)	0.0379 (1.05)	-0.1582 (-4.13)
<b>Age<sup>2</sup></b>	0.0159 (5.89)	-0.004 (0.71)	0.0118 (1.84)
<b>Garage</b>	0.0399 (6.48)	0.0263 (2.06)	0.0662 (4.70)
<b>Size of house</b>	0.5029 (52.91)	-0.0371 (-1.84)	0.4657 (21.11)
<b>YearDum04</b>	0.0991 (9.58)	-0.0293 (-1.24)	0.0698 (2.86)
<b>YearDum05</b>	0.2088 (19.93)	-0.0266 (-1.16)	0.1822 (7.48)
<b>YearDum06</b>	0.3725 (35.41)	-0.0137 (-0.57)	0.3588 (14.40)
<b>YearDum07</b>	0.5596 (56.92)	-0.0218 (-0.92)	0.5378 (21.51)
<b>Distance CBD</b>	-0.0805 (-3.45)	-0.0725 (-2.09)	-0.1530 (-4.86)
<b>Distance CBD<sup>2</sup></b>	-0.0237 (-4.20)	0.0082 (0.95)	-0.0155 (-1.94)
<b>ACCESS</b>	0.0844 (7.23)	0.0352 (1.87)	0.1195 (6.99)
<b>IN-COM</b>	-0.0726 (-4.67)	-0.0639 (-2.62)	-0.1364 (-6.18)
<b>OUT-COM</b>	0.0402 (2.36)	0.0327 (1.87)	0.0729 (2.72)

## 6. Conclusions

In relation to housing prices, gravity based accessibility measures have been suggested as a generalisation of modern polycentric labour market structures (Heikkila et al. 1989). This paper has investigated whether other intuitive and simpler measures could capture the relationship between housing prices and labour market accessibility. We use a range of different methods to obtain robust conclusions. Given that the percentage of in-commuting to a zone is found to be negatively related to house prices, this measure cannot by itself be used as an approximation to the access-space-trade off relationship. The introduced variables, however, add to the explanatory power of the model. In-commuting are probably related to some negative externalities. This result is in line with for instance Li and Brown (1980). In this paper it is claimed that there are two distinct factors connected with most micro location activities: First accessibility and second externalities which in most cases are negative. Together these two factors exert opposing effects on house prices. Out-commuting could be related to some excluded attractive neighbourhood characteristics, which are positively related to housing prices.

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## Appendix 1

**Table A1:** Estimated results for the three hedonic house price models based on the spatial error model formulation.

Variable Name	M0	M1	M2	M3	M4
<b>Constant</b>	13.0600 (120.88)	12.5057 (75.10)	13.031 (119.33)	12.2050 (68.73)	12.5208 (70.36)
<b>Lotsize</b>	-0.1871 (-6.11)	-0.2040 (-6.61)	-0.1831 (-5.94)	-0.2017 (-6.55)	-0.2033 (-6.49)
<b>Lotsize<sup>2</sup></b>	0.0243 (9.55)	0.0257 (9.98)	0.0241 (9.39)	0.0255 (9.974)	0.0257 (9.93)
<b>RurLotsize</b>	-0.0250 (-8.76)	-0.0213 (-7.26)	-0.0264 (-8.86)	-0.0230 (-7.83)	-0.0194 (-6.02)
<b>Age</b>	-0.1809 (-10.71)	-0.1776 (-10.51)	-0.1831 (-10.78)	-0.1821 (-10.81)	-0.1797 (-10.65)
<b>Age<sup>2</sup></b>	0.0130 (4.64)	0.0124 (4.43)	0.0134 (4.75)	0.0133 (4.76)	0.0127 (4.50)
<b>Garage</b>	0.0391 (6.71)	0.0397 (6.82)	0.0384 (6.59)	0.0390 (6.72)	0.0387 (4.50)
<b>Size of house</b>	0.4927 (52.31)	0.4911 (52.19)	0.493 (52.31)	0.4903 (52.19)	0.4904 (52.21)
<b>YearDum04</b>	0.0955 (9.87)	0.0960 (9.91)	0.0956 (9.87)	0.0959 (9.90)	0.0959 (9.91)
<b>YearDum05</b>	0.199 (20.41)	0.1994 (20.45)	0.1987 (20.39)	0.1990 (20.42)	0.1988 (20.40)
<b>YearDum06</b>	0.3702 (38.33)	0.3703 (38.34)	0.3702 (38.34)	0.3704 (38.36)	0.3702 (38.36)
<b>YearDum07</b>	0.5573 (58.91)	0.5570 (58.88)	0.5572 (58.92)	0.5567 (58.87)	0.5567 (58.87)
<b>Distance CBD</b>	-0.0574 (-2.58)	-0.1007 (-4.14)	-0.0402 (-1.58)	-0.1034 (-3.90)	-0.0751 (-2.66)
<b>Distance CBD<sup>2</sup></b>	-0.0468 (-11.06)	-0.0294 (-5.07)	-0.0529 (-9.17)	-0.0280 (-4.06)	-0.0367 (-4.97)
<b>ACCESS</b>		0.059 (4.36)		0.0861 (5.87)	0.0581 (3.98)
<b>IN-COM</b>			-0.0327 (-1.78)	-0.0817 (-4.41)	0.0127 (0.19)
<b>OUT-COM</b>			-0.0055 (-0.22)	0.0379 (1.84)	0.2079 (2.91)

<b>IN-COM<sup>2</sup></b>					0.1067 (1.20)
<b>IN-COM<sup>3</sup></b>					0.0392 (1.40)
<b>OUT-COM<sup>2</sup></b>					0.3304 (2.74)
<b>OUT-COM<sup>3</sup></b>					0.1342 (2.95)
<b><math>\lambda</math></b>	0.3735 (23.67)	0.3643 (22.85)	0.3730 (23.60)		0.3519 (21.74)
<b>Log-likelihood</b>	1420.26	1429.58	1422.56	1439.20	1445.73

z-values follow in parentheses.