Traffic Jamming House Prices

by

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Very Preliminary Version

Abstract

This study examines the effects of traffic congestions on local house price dynamics. Using a unique Dutch data set that covers 125,159 house transactions in 59 Dutch municipalities and nine years of detailed traffic information, we are able to examine the relationship between traffic jams and house prices during a period in which traffic jams have more than tripled. We use the monocentric city model to establish our theoretical framework and the Reilly's law of retail gravitation framework to select the housing markets to be investigated. We try to mimic each individual's travelling plan and aggregate the expected delay time due to traffic congestions. We add the variable *delay time* with various specifications to the hedonic pricing model and control for other dwelling as well as neighborhood characteristics. Our results show that the value of houses located nearby train station does not suffer from the heaviness of traffic congestions. The higher the level of traffic congestion in the corresponding routes to work, the more attractive to live close to train station and the more people value the convenient public transport. On the other hand, being too far away from public transportation leaves the owners no choice but travelling by car. Our empirical evidence also shows that conditional on the accessibility to public transportation, the value of remote houses suffers seriously from traffic congestions. Apart from the conventional travelling distance measurement, our study intends to introduce the traffic condition as a second dimension to describe the accessibility premium for residential properties.

Key words: Hedonic Model, House prices, Traffic Congestion

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1. Introduction

Traffic Congestion has become a worldwide phenomenon nowadays. Transportation planners often consider moderate rush hour traffic congestion as a sign of good planning, since it is a waste of money and space to build roads that seldom meet high traffic demand. However, for individual commuter traffic congestion brings extra cost due to higher fuel consumption and prolonged travelling time. Recent surveys reveal that the wasted time and fuel due to congestion is estimated to be over $90 billion in the US[1] and comparable amount in Europe (Dargay and Goodwin, 1999). Apart from the apparent monetary cost, traffic congestion has also changed households' residential preference. The ease of commuting from home to other places is inevitably influenced by traffic conditions.

Urban theory and practice tell us that accessibility is capitalized into the housing market and there is a trade-off between property value and commuting cost. Previous studies often take the Euclidean distance between a house and city center as a proxy for commuting cost. However, such distance measurement implicitly assumes constant speed and ignores the variation in travelling time due to traffic congestions. With the likelihood of facing traffic congestion as a priori, a rational home buyer would want to minimize his or her congestion cost (by choosing a less congested place to live) or at least be partially compensated for it (by asking for a price discount). Our study aims to examine the effects of traffic congestions on local house price dynamics. We combine a unique Dutch housing data set with a traffic congestion data set. The Dutch housing data set covers 125,159 house transactions with sound dwelling characteristics. The traffic congestion dataset contains nine years of detailed traffic information with characteristics and geographical coordinates of each event. By using this combined dataset we examine how expected delay time due to traffic congestion is capitalized into house prices during a period in which traffic jams have more than tripled. Our study contributes to the accessibility premium literature by showing that besides distance to destination, traffic condition is also a determining factor of house prices.

[1] American Road & Transportation Builders Association, the Costs of Traffic Congestion in America, August, 2006.

2. Accessibility and house prices

Urban economics has a long tradition to acknowledge accessibility as a crucial factor in determining location choices and home values. Accessibility refers to the ease of reaching destinations from homes and is often reflected in monetary term as commuting cost. The classic monocentric model (Alonso, 1964, Muth, 1969 and Mills, 1967) implies that commuting cost is a discount factor of property value assuming that rational households maximizing their utility function. Numerous studies have tested the relationship between accessibility and home values. There is widespread evidence that improvement in accessibility of homes often positively contribute to property values. Such improvement in accessibility is often associated with investment in transport infrastructures. For example, Smersh and Smith (2000) investigate the price impact of newly constructed bridge on the local housing market. The north of the city was expected to benefit the most from the new bridge since people from north can more easily travel to the south where most of jobs and services are clustered. The results show that houses in the north had 8% higher appreciation rate than the rest of the region. Mikelbank (2005) look into the impact of all kinds of transportation infrastructure investments (road, bridge, etc.) in Cuyahoga County, Ohio over the years 1995-2000. The evidence suggests that the price impact also depends on the location of the investment and the time when investment was made. Improvement in accessibility can also be done by providing alternative public transportation. Agostini and Palmucci (2008) find that a new metro line positively contributes to the value of neighborhood apartments.

Previous empirical evidence is in line with theoretical prediction that increases in accessibility should be a premium factor for house prices. However, the other side of the coin has not been paid much attention. The impact of decrease in accessibility on house prices has rarely been studied in the housing literature. Decrease in accessibility is often associated with increase in traffic congestions. Unlike transportation infrastructure improvement, traffic congestions are often temporary (i.e. rush hours) and stochastic (i.e. certain spot on the network). In addition, the traffic congestion data is rarely available on a smaller scale. The data limitation makes it very difficult to quantify the impact of traffic congestion on house prices. In our paper, we use a unique database to quantify the impact of traffic congestions. We intend to establish the link between traffic congestion and house values by constructing a delay time due to traffic congestion index for each home. For most of the previous studies about accessibility influencing property values, time has seldom been used as an explanatory variable. Most of the previous research use distance between home and employment center instead by assuming that speed is constant for each route. However, constant speed is no longer an appropriate assumption if traffic condition is introduced into the model. Therefore, we use this delay time index to proxy the extra commuting cost based on two reasons. Firstly, theorist often treat time as a synonym for travelling cost since there is a trade off between leisure time and travelling time in each household’s utility function. Secondly, if fuel consumption per kilometer is assumed to be constant, time will be a perfect proxy for fuel consumption cost, which explains most of the commuting cost. Our empirical work aims to show how delay time due to traffic congestions is capitalized into house prices.

3. Traffic congestion and house prices

We start with the hedonic framework proposed by Rosen (1974). Additionally, according to the classic monocentric city model, assuming that all households maximize their utility function, expected travelling cost should be capitalized into the value of houses,

$$P_i = x_i^{'}\beta + \gamma TC_i + \varepsilon_i \tag{1}$$

in which P_i represents the log transaction price, x_i is a vector of dwelling and neighborhood characteristics, TC_i represents the expected travelling cost. Assume travelling cost TC_i has a linear relationship with travelling time T_i :

$$TC_i = \varphi T_i + \eta_i \tag{2}$$

Due to different traffic conditions, households do not normally drive at constant speed for each trip, therefore total travelling time T_i can be split into two components, namely, an optimal time component OT_i and a residual time component $\sum \Delta T_i$, OT_i represents the time one spends on a trip with perfect traffic conditions (with no traffic jams), $\sum \Delta T_i$ represents the aggregate delay time due to traffic jams.

$$TC_i = \varphi(OT_i + \sum \Delta T_i) + \eta_i \tag{3}$$

OT_i can be written as travelling distance D_i divided by the optimal speed *OS*, optimal speed is related to the upper speed limit of highway, therefore we can treat it as constant,

$$TC_i = \varphi(\frac{D_i}{OS} + \sum \Delta T_i) + \eta_i \tag{4}$$

Since speeding up or making breaks will consume more petrol, more precisely, we assume two time components have different linear relationship towards TC_i. Then we reformulate equation (4) as,

$$TC_i = \varphi^{'} \frac{D_i}{OS} + \varphi^{''}(\sum \Delta T_i) + \eta_i \tag{5}$$

Combine equation (1) and (5), we have,

$$P_i = x_i^{'}\beta + \gamma_{OT} \frac{D_i}{OS} + \gamma_{\Delta T}(\sum \Delta T_i) + \omega_i \tag{6}$$

in which ω_i is a composite error term. Since optimal speed *OS* is treated as constant, the variation in distance D_i of each trip perfectly captures the variation in the optimal time component. Previous studies often use distance to employment center as a travelling cost proxy to explain variation in the value of houses. However, the aggregate delay time due to traffic jams $\sum \Delta T_i$ is often ignored in most of the empirical studies due to data limitation. Thanks to the new technology, Dutch home buyers can easily access to internet website[2] to gather historical traffic information on each neighborhood before buying houses. Not only the expectation of the optimal time component, but also the expectation of delay time due to traffic jams $\sum \Delta T_i$ could be capitalized.

[2] For example, see www.anwb.nl or www.viamichelin.com

4. Sample selection and descriptive statistics

4.1 Sample selection

We choose housing markets around the city Utrecht to conduct our empirical test. The city Utrecht is the capital of the Dutch province Utrecht. It is located in the center of the Netherlands, and is the fourth largest city with a population of more than 300,000 in 2007. According to the GDP volume reported by the Statistical Netherlands, Utrecht has always been the second largest employment center in the Netherlands. Therefore it attracts most of the inhabitants in the nearby neighborhoods to work there. Apparently, Utrecht is not equally attractive for all Dutch labors. According to the monocentric city model, it is not economically efficient to live too far away from the employment center, hence household live relatively far away from Utrecht might work in other employment centers. Figure 1 is the map of city Utrecht and its neighborhood housing markets. There are three competing employment centers relatively closer to Utrecht. Amsterdam, located in the northwest direction, is the largest employment center in the Netherlands. In the southwest, Rotterdam and Den Haag together generate comparable amount of GDP as Utrecht does. On the east side, Arnhem and Nijmegen together contribute approximately 75% of GDP as Utrecht does.

[Figure 1 about here.]

Theory does not tell us the maximum distance on average people would like to travel to work every day. Such preference may also vary by country or culture. We use the Reilly’s law of retail gravitation framework to create artificial employment boundaries around Utrecht. The Reilly's law of retail gravitation framework was developed by William J. Reilly in 1931. In urban economics, this framework indicates that larger cities have larger spheres of influence than smaller ones, meaning that people travel further to reach a larger city. Supposedly there are two adjacent cities, city A and B. The break points of two impact zones are determined by equation (7),

$$Breakpoint = \frac{Distance(AtoB)}{1 + \sqrt{\frac{GDP_A}{GDP_B}}} \tag{7}$$

in which, *Break point* represents the distance between breakpoint and B city center, *Distance(AtoB)* represents the Euclidean distance between two city centers and *GDP* represents gross domestic product of a city. From equation (7) we can see that the higher the GDP of city A relative to city B, the shorter the distance between B city center and break point, which implies that more people are willing to travel further to work in city A instead of city B. By using equation (7) and considering the three competing employment centers, we create artificial employment boundaries around Utrecht and assume that the majority of residence travel to Utrecht to work. For each house *i*, we calculate the Euclidean distances between itself and two nearby employment centers, say D_A and D_B. Then we compare D_B with *Breakpoint* calculated from equation (7), if D_B is bigger, then house *i* belongs to the impact zone of city A, and vice versa. After calculating all the houses in the Utrecht nearby housing markets, 59 housing markets/municipalities fall into the impact zone of Utrecht city. Table 1 provides the descriptive statistics of the highway distance between these 59 municipalities and the city Utrecht. The farthest away city is Rhenen, which is 58.5 km from Utrecht. The closet city is DeBilt, which is 1.2 km away from Utrecht.

[Table 1 about here.]

4.2 Construct delay time due to traffic congestion index

Utrecht is well connected to the main roads in the Netherlands. Four of the most important major freeways cross near Utrecht: A12 (west to east), A2 (NW to SE), A27 and A28 (SW to NE). Besides these freeways, many high speed national roads were also built around Utrecht. In the Netherlands, the maximum speed limit for freeways and national roads are 120km/h and 100km/h respectively.

We received the traffic congestion data from the Dutch Ministry of Transpiration. This data set contains all traffic congestion events in the Netherlands during 1998 to 2007. The entire Dutch highways, including freeways and national roads, are divided by approximately 6000 sections in the data set. Each section is called a *Ticvan* and represents a segment of a highway with no split. Each traffic jam event is associated at the *Ticvan* level. For each traffic jam event, the starting and ending time, length of the jam queue as well as the cause of congestion are recorded.

For each house we first find the nearest highway entrance. Then from the highway entrance we try to mimic each commuter's travel plan by identifying the shortest route to Utrecht city outskirt. As can be seen from Figure 1, the city Utrecht is surrounded by a ring-shaped highway. Individual travel route that we mimic from various directions is likely to end at different points of this highway ring. Our approach is slightly different from previous studies in which an employment center is often used as the destination for all trips. Instead we use various points at the city outskirt, or more precisely, the exits of the ring shaped highway as the destinations of mimicked trips. There are two reasons that we exclude within-city travelling from our analysis. Firstly, the true destination of each trip is unknown. Besides, as the fourth largest city in the Netherlands and second largest employment center, the city Utrecht has many office clusters. Assuming one of them as the destination of all trips would introduce too much noise in our empirical analysis. Secondly, the within-city traffic condition is not described in our data set. However, it is not entirely unreasonable to ignore within-city travelling in our analytical framework. As total travel time, within-city travel time can be divided into two components, namely optimal travel time and total delay time due to traffic congestions within the city. The within-city optimal travel time is relatively short compared to total travel time of the entire journey. Even if the cross sectional difference of within-city optimal travel time is large and observable, this difference wouldn't have any impact on the estimated relationship between house prices and traffic congestions. The within-city delay time is very hard to observe and estimate. It is much more random than it is on highways. However, the stochastic nature of within-city delay time allows us to make an assumption that all trips, at least at the aggregate level, suffer from the same level of within-city traffic congestions.

After we have identified each individual travel route, next we aggregate the annual total delay time during rush hours on weekdays for each route. The delay time is defined as the time difference between starting and ending time of each traffic congestion event. The rush hours are defined as three hours in the morning from 7:00 to 10:00 and three hours in the afternoon from 16:00 to 19:00. Since we assume travelers travel to work in the morning and return home in the afternoon, we only aggregate the delay time in the morning if the direction is towards Utrecht and in the afternoon if the direction is towards homes. Finally, we divide the aggregate hours by 250 working days and the quotient represents delay time per day index of each route.

The meaning of this time delay index needs further elaboration. Firstly, since individual's exact travel time is unknown, we do not know which traffic congestion event each individual has encountered. Thus the index we constructed is not a time delay index for each individual, but for each route. Secondly, the average highway distance of each route is 25.8 kilometers. The time that each traffic congestion event occurs on the same route can be overlapping. For example, two 3-kilometer jam queues exist for 30 minutes each might be found at both the head and tail of a route at the same time. When we aggregate the delay time, we sum up two 30 minutes to 1 hour instead of recording one 30 minutes. 1 hour delay time does not mean the entire route is occupied by traffic congestion by 1 hour, but cumulatively, traffic congestion causes 1 hour delay time on a route. Although the delay time index we constructed deviates from the variable we specified in equation (3) to (6), as long as our index can capture the variation of individual's total expected delay time, the above-mentioned two deviations do not hamper the ability of our index to fulfill its analytical purpose. The interpretation of our constructed delay time index is twofold. On one hand, by using historical data our index captures the variation of expected additional travel cost. Dutch home buyers can visit various Dutch website to acquire historical traffic congestion information before they make purchasing decisions. These websites use the same data as we do and the expected congestion time is also based on taking the shortest route to destinations. Therefore if home buyers would capitalize delay time into house prices, our index is the best proxy for such a priori information. On the other hand, our time delay index also captures the cross sectional difference of road conditions or highway usage rates. Therefore it makes more sense to accumulate delay time when occurring time of events is overlapping.

4.3 Descriptive statistics of traffic congestion

Figure 2 shows the delay time due to traffic congestion index per municipality during 2006. In order to make comparison, we scale the delay time index by the corresponded highway distance. The scaled delay time index represents how much time was lost due to traffic congestion per kilometer highway. During 2006, on average in 6 rush hours including morning and afternoon, roads were occupied by traffic jams by 2.6 hours per day. Around city Utrecht, we see a large variation of traffic condition among different municipalities. In general, traffic congestion problem is more severe in the east than in the south. Some roads were almost always busy with traffic, for example, the road from Bodegraven to Utrecht on average has 5.2 hours traffic jams per day. Some municipalities, on the opposite, hardly had any traffic during a year. Most of them are located nearby Utrecht and connected to Utrecht by special roads. These special roads are not used by other travelers from the same direction.

[Figure 2 about here.]

4.4 Descriptive statistics of housing market

The transaction prices and detailed dwelling characteristics used in this research are obtained from NVM (Dutch Association of Real Estate Agents), which currently has approximately 70 percent of the national market share. The NVM database contains 125,159 sales between year 1999 and 2007 in the selected municipalities, which represents more than 60 percent of the housing transactions in the same area.

In Table 2 we present the summary statistics for dwellings sold during 2007, which offers a snapshot of the housing markets around the city Utrecht. The median house in the selected area was sold for 255,000 euro in 2007. This median house offered on average 5 rooms and 120 square meter living space. The majority of the housing stocks are terraced houses (31.3 percent), and the rest are evenly spread across the various types. More than half of dwellings do not have parking or well kept gardens, which is not surprising since the Netherlands is the second most densely populated country in EU and only 6.2 percent of the surface is for housing. Less than 40 percent of the housing sold was built after 1980, which indicates that old houses were still popular and traded in the market. The mean population density is 1,087 persons per square kilometer, which is much higher than the Netherlands average (395p/km2) and EU average (114p/km2). This is because the selected 59 housing markets are located in the western part 'Randstad' area. The 'Randstad' is the most urbanized area and located in the western part of the country, covering about 20 percent of the country surface but has more than 40 percent of the Dutch population. Not surprisingly, more than half of the dwellings are not surrounded by green nature at all.

[Table 2 about here.]

5. Empirical Results

In this section we present the results of our empirical analysis. In order to facilitate the interpretation of our findings we offer these results in separate section. First, we present and discuss the results and performance of the hedonic model for the Dutch housing market. In the hedonic model specification, we use highway distance from home to the outskirt of city Utrecht as the conventional accessibility measurement. We then continue by adding 'traffic congestion' to the pooled hedonic regression. We discuss various issues of using the delay time index to study the influence of traffic congestion on local house prices. Next, we relax our assumption by allowing other travel alternative and introducing 'public transport' in the hedonic specification. We hypothesize that public transport leads to a different submarket, where traffic congestion might have different pricing impact. Finally, we test this hypothesis in various ways by taking into account the presence of train station and its accessibility from homes.

5.1 The hedonic model and conventional accessibility measurement

Table 3 presents a summary of OLS estimates of the hedonic model, in which we relate house transaction prices to a set of dwelling and neighborhood characteristics, location as well as transaction year dummies. Nearly all the coefficients of explanatory variables are both statistically significant and economically important and carry the signs that are expected. The two most expensive types of dwellings are detached and semi-detached house, which on average have 43.9 and 21.7 percent price premium compared to the terraced houses. In addition, the results show that every 10 square meters of additional living space or every extra room, for that matter, will on average increase the house value by 5.0 percent or 2.7 percent, respectively. Parking will increase the house value substantially with added value of 10.2 percent or 17.4 percent depending on the type of parking facility. A beautifully designed or well kept garden will on average add 5.3 percent to the value of the dwelling, when compared to homes without a garden. Furthermore, our results show that construction time is also an influential factor in determining Dutch house prices. Houses constructed during two periods are favorable in the market. Newly built dwellings, which are constructed after year 2000, on average receive 13% price premium compared to the reference period *Age1991to2000*. Dutch people also would like to pay more for houses built during 1930s. These houses are symbols of good quality and beautiful design and are on average 8% more expensive. On one hand, our estimated coefficients of construction time dummy variables of younger dwellings indicate a clear pattern of depreciation effect. On the other hand, we can also observe the so-called vintage effects, meaning popularity of ancient homes. The negative coefficient of population density variable suggests that people consider high urban density as a discount factor for housing value. On the contrary, the positive coefficient of *%Nature* indicates that people enjoy living in the ‘green’. We use time-on-the-market in the 5 digit postcode neighborhood as a proxy for demand side factors. In order to avoid endogeneity issue, we take one year lagged value. Negative estimated coefficient indicates that the shorter the time-on-the-market, the higher the demand for houses in the neighborhood, and the higher the house prices.

[Table 3 about here.]

Like most of pervious studies, we also use distance to employment center as the accessibility measurement in our hedonic model specification. However, instead of using Euclidean distance between two locations, we disaggregate the total distance into two components. One is the Euclidean distance between the nearest highway entrance and each house, and the other is the shortest highway distance between highway entrance and Utrecht city outskirt. The estimated negative coefficients for both accessibility measurement are consistent with previous studies, which support the theory that a trade off exists between house value and distance to employment center. Our estimated coefficients are not only statistically significant, but also economically significant. The median highway distance in our sample is 25.6 kilometer. This number multiplied by the estimated coefficient of highway distance indicates that an average distant house is expected to be 13.2% cheaper than the same house located at the outskirt of city Utrecht. The same logic can apply to the other distance component. A median distant house from highway entrance is expected to be sold 0.4% cheaper than the one close to highway entrance.

5.2 Adding 'traffic congestion' to the equation

The next step in our analysis is to incorporate the variable *delay time* into the hedonic model. Table 4 presents only the estimated coefficients of new variables. Instead of executing 9 cross sectional hedonic regressions[3], we pool the observations and create 9 interaction variables to capture, if any, the time varying influence of traffic congestion on house prices.

Before explaining the estimated coefficients of variable *delay time*, it is necessary to discuss the cause of traffic congestions and its implication in our empirical approach. Traffic congestion occurs in a particular part of networks when travelers would like to go to the same direction at the same time and the number of cars temporarily exceeds the road capacity. If people travel towards the same direction, they must come from the same direction and the majority of them might live in the same neighborhoods. Therefore one could argue that the estimated relationship between congestion and house prices might be explained by the variation of population in different housing markets. The evidence of relationship between regional population and house price is mixed in previous studies. On one hand, living in a densely inhabited area offers convenient access to service facilities such as supermarkets, shops or restaurants. On the other hand, high density also implies less space per capita which are not normally favorable. We believe the mediating effect of population is not a major concern in our empirical setting. Firstly, urban planners try to alleviate the traffic and increase the road capacity by adding more lanes in the crowded areas. Secondly, the correlation between congestion and population, if any, is very much determined by the population of several housing markets along a certain route. Therefore unless the size of housing markets is clustered, which is not the case in our sample, population of one housing market would not have prominent mediating effect on the aggregate relationship between congestion and house prices. Still, empirically, we control the influence of population by adding population density as a control variable. We control for the population density instead of the population in the hedonic regression since the size of the municipalities also needs to be taken into account. The estimated correlation coefficient of variable *population density* and *delay time* is only -0.042, which also supports our argument.

[3] We run 9 cross sectional hedonic regressions and compare the implicit prices of dwelling/neighborhood characteristics. The estimated coefficients show a clear tendency that the implicit prices of hedonic factors are time invariant. This justifies our choice of using pooling regression to present time varying effect of traffic congestion.

One may also argue that certain routes are often more congested since housing markets along these routes are more popular than others and attract more people to live. Therefore these housing markets must have some unobserved characteristics that boost the demand of houses. One of the building blocs of urban economics is that any temporary demand shock will deviate real house price from the equilibrium level, given that supply is inelastic in the short term. Perhaps one of the most difficult tasks in the housing literature is to measure the demand shock for housing. The observed transaction volume only indicates realized demand and does not tell much about latent or unrealized demand. We use yearly median[4] time-on-the-market at 5 digit postcode[5] to capture the variation in demand at neighborhood level. This variable has the advantage of capturing the information of both observed and unobserved demand. To avoid endogeneity issue, we use one year lagged time-on-the-market variable. The estimated correlation coefficient of variable *TOM(month)_t-1* and *delay time* is only 0.130, indicating that the estimated relationship is not intervened by demand side factors. As a matter of fact, as the initiator of traffic congestions, travelers live in different housing markets along a route, hence our congestion measurement is highly unlikely correlated with any particular housing market characteristics.

[Table 4 about here.]

Our estimated regression coefficients show that except for the coefficient of year 1999 interaction variable, all the other coefficients are significantly positive. The positive coefficient implies that on average house price is positively correlated with delay time on the highway due to congestions and people would pay more for houses in the congested area while highway distance is controlled. Although the results of positive estimated coefficient for congestion variables contradict our theoretical prediction, they are not entirely unreasonable. In our analytical framework, we assume that all the households,

[4] We use median instead of mean to avoid influence of extreme cases.
[5] In the Netherlands, a 6 digit postcode is equivalent to a street name, which often covers an area with a radius less 200 meter. Such small neighborhood cannot guarantee transactions every year. Therefore we use a larger neighborhood at 5 digit postcode level.

when travel to city Utrecht to work, must travel by car. However, in reality we cannot ignore the fact that a lot of people travel to work by public transport. In our 59 selected municipalities, 27 have a train station. If, in the extreme case, all the commuters choose to travel by train, we would not expect traffic condition has any impact on house prices. Hence the presence of public transport in our framework might indicate the existence of two ‘submarkets’ distinguished by two different commuting methods. If this is the case, it is not surprising to see positive coefficients of *delay time* for the ‘public transport submarket’ since living in the congested area with alternative commuting options might be considered a premium. On the other hand, we would expect negative coefficients of *delay time* for the ‘car submarket’ since time is valuable and delay time due to congestions is expected to have a discounting effect on house prices in our framework. Then it is reasonable to consider each estimated coefficient reported in Table 4 as a ‘weighted average’ of two estimated coefficients of two submarkets.

5.3 Adding ‘public transport’ to the equation

In order to test if the relationship between traffic congestion and house prices are different in two ‘submarkets’, we add two interaction variables *dummy_train*delaytime* and *dummy_notrain*delaytime* for each yearly cross sectional regression. *Dummy_train* equals 1 if located municipality has a train station, otherwise 0. We report 18 estimated coefficients in Figure 3, two coefficients for each yearly cross sectional regression. All the coefficients are significantly different from zero at 0.001 significance level except for coefficient of *dummy_notrain*delaytime* of year 2000. As we expected, the estimated coefficients for ‘public transport submarket’ are always positive after 2000, which implies that alternative travelling choice is favorable for the housing market. However, the curve for ‘car submarket’ is always above zero and higher than the public transport ‘submarket’ after year 2001.

[Figure 3 about here.]

The positive estimated coefficient of *dummy_train*delaytime* again contradicts to our theoretical prediction. By adding 'public transport' to the equation we automatically assume that the majority of households would use the train station in the municipality and therefore their preference is capitalized. Perhaps the assumption we made here is too strong. Firstly, although the Netherlands is known for its good public transport system, most of the travelers still prefer to travel by car. The car ownership has increased by 27% over the past 10 years, from 7 million in 1998 to 8.9 million in 2007. We have no information regarding travelers' preference and the usage rate of public transport. Therefore the dummy variable of train station might not well capture the influence of alternative commuting method. Secondly, the size of a municipality also influences the utilization rate of the public transport. In the Netherlands it is common to see that people ride bicycle from home to train station, park their bicycle outside train station and take train to work. However, considering the average speed of biking between 10 to 18 km/h, it would not be very convenient if someone lives at the outskirt of a big city and travels by public transport. On the other hand, small municipalities are often a few kilometers from each other and it is common that they share one train station. People may travel to adjacent municipalities to take train to work. Therefore using train station dummy variables might not be the best approach to identify these two 'submarkets' based on commuting preference. Accessibility of public transport from homes might be a more appropriate alternative.

5.4 Adding 'accessibility to public transport' to the equation

We hypothesize that the closer people live to a train station, the more likely they will regularly travel to work by train and therefore the less they suffer from traffic congestions. In order to test this hypothesis, we create an interaction variable by using *delay time* multiplied by distance to train station from home. We add this interaction variable to each yearly cross sectional regression. As it is shown in equation (8), the marginal influence of *delay time* on house price is not only determined by the beta estimates but also is conditional on distance to nearest train station from home.

$$\frac{\partial(\ln price)}{\partial(delaytime)} = \beta_{delay} + \beta_{interaction} * Distance\_train \qquad (8)$$

Table 5 reports 18 estimated coefficients of 9 cross sectional hedonic regressions. Control variables are the same as we present in Table 3. Except for the coefficient of *delay time* of year 1999, all the coefficients are significantly different from zero at 0.001 significance level. As we have shown in previous analysis, the coefficients of *delay time* are always positive after year 2000. The estimated coefficients of interaction variables are negative across 9 years, which implies that although *delay time* is positively correlated with house price, the strength of such relationship diminishes as the accessibility to public transportation decreases. As long as the distance between home and train station is large enough, the marginal influence of traffic congestion on house price will eventually vanish and become negative. We can easily calculate the breakeven point by taking the quotient of each pair of estimated coefficients as shown in equation (9),

$$Breakeven = \frac{\beta_{delaytime}}{\beta_{interaction}} \tag{9}$$

Then we draw a curve that summarizes all the breakeven points in Figure 4. The magnitude of the breakpoint represents estimated radius of a region from train station where value of houses do not suffer from traffic congestions. Beyond this distance, the marginal influence of *delay time* on house price is expected to be negative. The median distance to train station for the entire sample is 2.63 kilometers with maximum 13.53 kilometers and minimum 0.02 kilometers. This means half of the dwellings in our sample are built close to train station. If the majority of households travel by train, we would not expect the heaviness of traffic congestion to have any discounting effect on house prices.

[Table 5 about here.]

Figure 4 presents the estimated ‘artificial boundaries’ between two ‘submarkets’. It is apparently too early to conclude anything based on this curve since our specification is only one way to demonstrate the conditionality. We are in no position to argue that the interaction variable is the most appropriate way to fit our data unless we further analyze subsamples based on the conditional variable. Following this intuition, we form subgroups of houses by their distance to nearest train station and execute pooled hedonic regression for each group. The OLS estimates of *delay time* are reported in the Panel A of

Table 6. The first six regressions include houses only within certain distance from train stations. The distance varies from 1 to 6 kilometers. In contrast, the last six regressions include houses further from train stations by certain distance, which varies from 6 to 11 kilometers.

[Figure 4 about here.]

The estimated coefficients reported in Panel A of Table 6 formulate a more complex relationship than our initial expectation[6]. We segment the entire sample into four parts according to the homogeneity of our estimated coefficients. Firstly, for houses adjacent to train stations (within 2 kilometers), we hardly observe any significant relationship between *delay time* and house prices. Even for some years we observe significant relationships but economically they are more or less meaningless. This might be because residents who live very close to train stations are either younger first time buyers or senior citizens. They often do not travel by car and very much rely on public transport. If home owners have never experienced rush hour traffic jams or they no longer need to go to work anymore, it is not surprising to see that the variable *delay time* has no impact on house prices. Secondly, for houses located within the range of 2 to 6 kilometers[7] from train station, we observe significant positive relationship. We argue that the price premium comes from the alternative public transport. Still having access to public transport, people living in these houses do not sole rely on cars. Actually, the more serious the traffic congestion in the corresponding route to work, the more attractive the 'public transport submarket' and thus the more people value the convenient public transport. Thirdly, for houses within the range of 6 to 10 kilometers[8], in line with our theoretical expectation, the estimated coefficients are mostly significantly negative. People living in these areas cannot easily utilize public transport anymore and the value of houses is deteriorated by traffic congestions. Fourthly, for houses located beyond 10

[6] All our inference is based on results of all years except 1999. The results of year 1999 are a bit puzzled and we will discuss them later.
[7] The robustness check shows that beyond 2 kilometers from train station, estimated coefficients become significantly positive.
[8] The robustness check shows that for houses located within the range of 8 to 10 kilometers from train station, estimated coefficients are the most significantly negative.

kilometers from train stations, the estimated coefficients are much less negative. These remote homes often have unobserved characteristics, such as huge gardens or super space which are rarely available in the market and very attractive to wealthy people. Therefore the negative influence of their low accessibility is partially compensated by the limited supply.

[Table 6 about here.]

By presenting subsample results in Panel A of Table 6, we intend to show that as the distance to train station increases, the estimated coefficients of *delay time* change in a systematic pattern. We propose the presence of four housing segments, in which house prices have heterogeneous reaction towards traffic conditions. However, the magnitude of our estimated coefficients might be misleading. Each regression in Panel A of Table 6 assumes that homogenous estimates apply to all observations. In fact, the price dynamics of two segments might have joint influence on the price of houses located between these two segments. The joint influence of two dynamics might offset each other, resulting in strange coefficients of 'between segments' observations. In order to avoid the 'between segments' observations biasing the estimated coefficients of four housing segments, we exclude these observations from further analysis. In Panel B of Table 6, we conduct hedonic regressions on the four housing segments: less than 2 kilometers, 4 to 6 kilometers, 8 to 10 kilometers, and further than 11 kilometers from train stations[9]. To make easier comparison, we report results of the first and last segment again in Panel B. By excluding 'between segments' observations, the estimated relationships between *delay time* and house prices are enhanced for the middle two segments.

For houses located within the range of 4 to 6 kilometers from train station, *delay time* is significantly positively related to house prices. The positive relationship is also economically significant. An increase in *delay time* by one standard deviation (1.8 hour)

[9] We also conduct the same regression analysis for three 'between segments' groups: 2 to 4 kilometers, 6 to 8 kilometers and 10 to 11 kilometers from train station, the estimated coefficients are hardly significantly different from zero. Results are not reported in the paper. These results support our argument that the positive and negative effect offset each other in the 'between segments' observations.

will increase the expected house price by 3.8% to 17.6%, depending on the estimated year. In contrast, for houses located within the range of 8 to 10 kilometers from train station, *delay time* is significantly negatively related to house prices. An increase in *delay time* by one standard deviation will decrease the expected house price by 7.7% to 29.5% depending on the estimated year. For houses that are either very close to or very remote from train stations, clear relationship is hardly observable.

In our previous analysis, we can observe the time-varying preference towards traffic congestion. Firstly, the breakeven points we present in figure 4 show a clear inversed U-shaped pattern. At the aggregate level, traffic congestion is much more unfavorable in the early two years than the subsequent years. The indifferent attitude starts to change after 2002, when traffic congestion becomes more and more serious. In recent years, the preference stabilizes. This might be due to the fact that rush hour traffic congestion is everywhere and almost unavoidable. Therefore, people become indifferent to it. Secondly, subsample analysis in the Panel A and B of Table 6 shows that *delay time* almost always has very strong negative relationship with house price for year 1999. This might be because 10 years ago, when the traffic congestion was not as severe as nowadays, people had more location choices to avoid heavy traffic. Therefore a clear preference will result in more prominent statistical results. Thirdly, the fluctuations of estimates across years in Table 6 also reflect the aggregate trend of changing preference towards traffic congestion. In the middle two segments, in which the degree of traffic congestion is more relevant, the importance decreases over time.

6. Conclusion

In this paper, we apply a hedonic model in the monocentric city framework to investigate the relationship between traffic congestion and the Dutch regional housing markets. By using delaying time as a variable to quantify the heaviness of traffic congestion, we mimic each household's travel plan and link the historical traffic condition to the individual house price. We also take into account the possibility that people may travel by public transport. We find no relationship between traffic congestion and the price of houses located within 2 kilometers from train station. We argue that the availability of the public transport alleviates the discounting effect of congestion in households' utility function. For households that have alternative travelling choice, traffic congestion is mostly a "Not-In-My-Back-Yard" problem. We also find a positive relationship between traffic congestion and the price of houses located not too far from train station. However, the strength of such relationship diminishes as the accessibility to public transport decreases. We hypothesize that increases in the heaviness of traffic congestion make other travelling alternatives more valuable and therefore increase the attractiveness of living in neighborhoods that are easily accessible by public transport. On the other hand, people living in the neighborhoods which are not well connected to the public transport, have to travel by car. Travelers that suffer from inevitable delaying time due to traffic congestion would like to be compensated by lower house price. In addition, for extremely remote homes, prices are hardly influenced by traffic conditions. The low accessibility is compensated by the rarely available characteristics of these dwellings. We also observe the trend that the influence of traffic congestion on house prices decreases over the years in the Dutch housing market.

Our results are relevant for various stakeholders in the housing market. Homeowners are offered a very precise indication of how the value of their houses is related to the highway usage rate. Homeowners should realize the monetary benefit of living close to public transportation. Escaping from urban frenzy and living in remote places, as many homeowners wish, comes at a price. At the same time our results suggest that policymakers be cautious when develop employment centers. Job clustering often increases economic efficiency but its downside cannot be ignored. A continuously expanding metropolitan area is likely to be associated with deteriorating traffic condition, which would reduce its international competitiveness as a business center. Real estate developers that plan housing projects should realize that currently popular regions might not retain its attractiveness in the future due to the decrease in accessibility. The increase in traffic congestions is likely to depreciate housing values.

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Appendix.

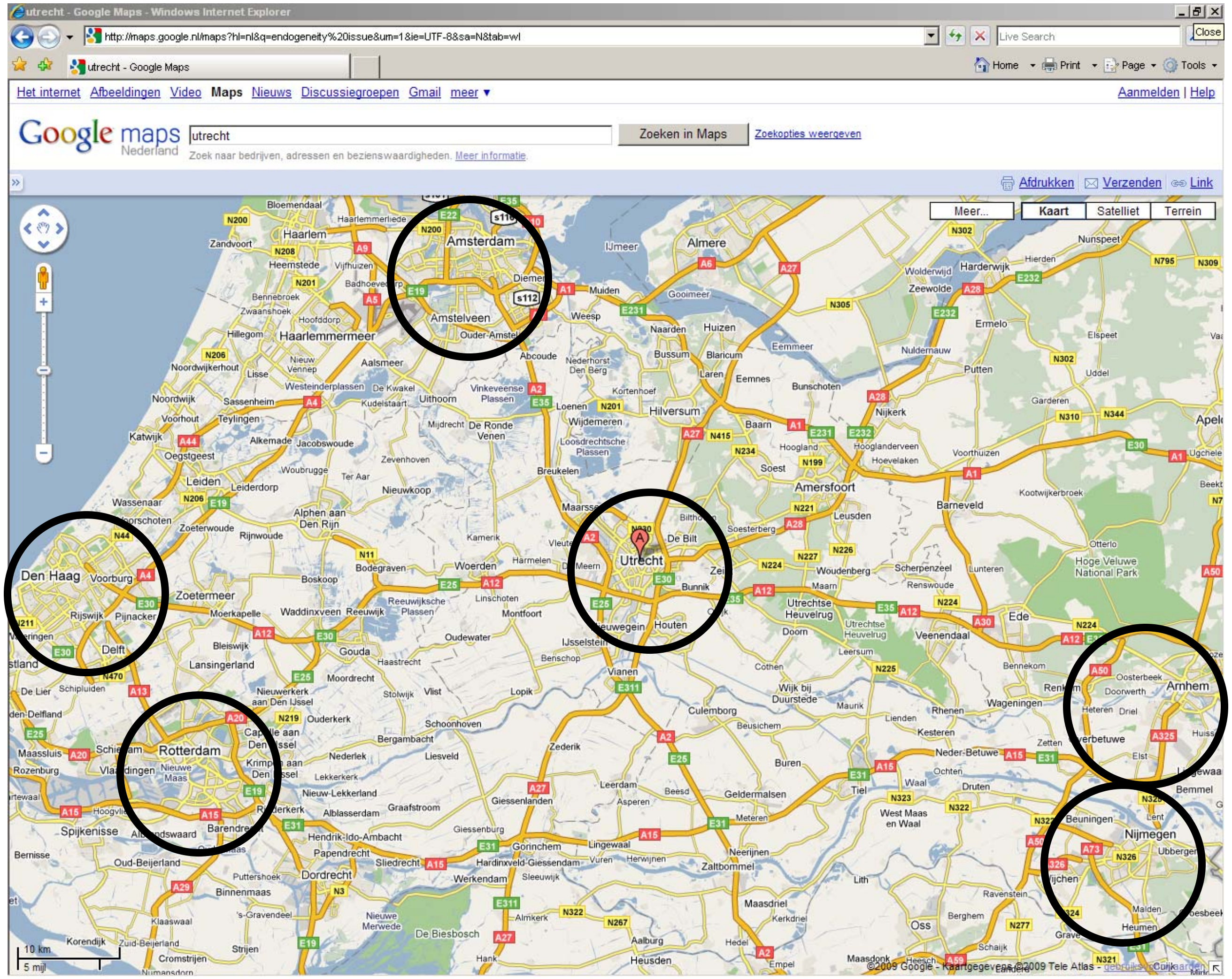


Figure 1. the Map of City Utrecht and its Neighborhood Housing Markets

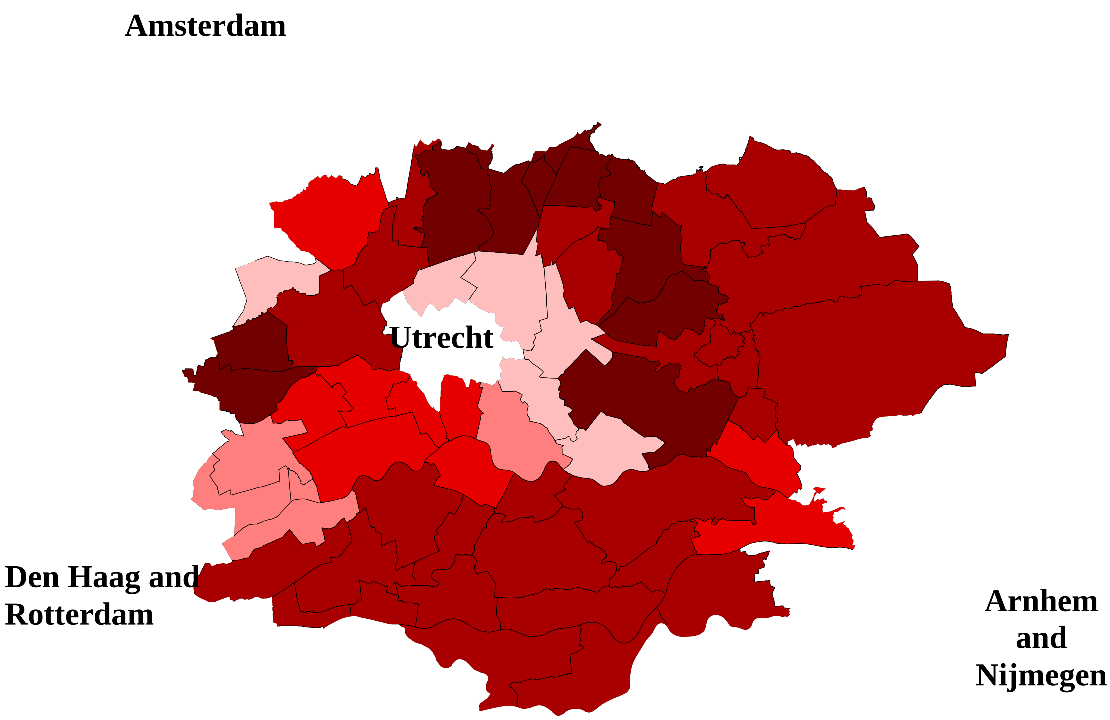
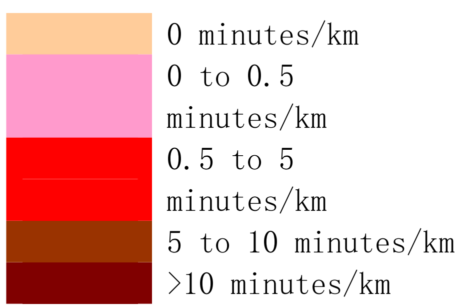


Figure 2. Delay time in traffic hours per day due to traffic congestions during 2006 (scaled by highway distance)



Note: For each house in the data set we find the nearest highway entrance. Then from the highway entrance we try to mimic each traveler's travelling plan by identifying the shortest route to Utrecht city outskirt. Next we aggregate the annual total time of lasted traffic congestions during rush hours on weekdays. The rush hours are defined as three hours in the morning from 7:00 to 10:00 and three hours in the afternoon from 16:00 to 19:00. We only aggregate the delay time in the morning if the direction is towards Utrecht and in the afternoon if the direction is towards homes. Finally, we divide the aggregate hours by 250 working days and the quotient represents delay time due to traffic congestion per day index. For illustration, we scale the lost time index by highway distance.

Table 1. Descriptive Statistics of Traffic Congestions during 2006

	Mean	Median	Max.	Min.	Std.
Highway Distance to Utrecht (km)	25.8	25.6	58.5	1.2	13.8
Total delay time per working day (hour)	2.6	3.0	5.2	0.0	1.8

Note: High way distance represents the highway distance between nearest highway entrance from home to the outskirt of city Utrecht. The total delay time per working day variable is constructed in the following way: firstly, for each house in the data set we find the nearest highway entrance. Secondly, Then from the highway entrance we try to mimic each traveler's travelling plan by identifying the shortest route to Utrecht city outskirt. Thirdly, we aggregate the annual total time of lasted traffic congestions during rush hours on weekdays. The rush hours are defined as three hours in the morning from 7:00 to 10:00 and three hours in the afternoon from 16:00 to 19:00. We only aggregate the delay time in the morning if the direction is towards Utrecht and in the afternoon if the direction is towards homes. Finally, we divide the aggregate hours by 250 working days and the quotient represents delay time due to traffic congestion per day index.

Table 2. Descriptive Statistics of Houses Sold in Selected 59 Municipalities During 2007

	Mean	Median	Max.	Min.	Std.
Transaction Price (Euro)	324,587	255,000	3,000,000	11,135	214,448
Living Space (M2)	128	120	525	30	49
No. rooms	4.6	5	15	1	1.4
%Nature	7.6%	0%	100%	0%	22.2%
Population density (person/km2)	1,087	749	3,148	146	820
Distance to Highway entrance (km)	2.9	2.3	12.5	0.03	2.1
Distance to Trainstation (km)	3.7	2.6	13.4	0.02	3.1

	Frequency
Dwelling type	
Apartment	19.7%
Terraced house	31.3%
Corner House	15.3%
Semidetached House	18.8%
Detached House	15.0%
Parking	
No parking	56.4%
Parking&Carpot	13.5%
Garage	30.0%
Garden	
No or poor Garden	65.8%
Well kept Garden	34.2%
Building year	
1500-1905	4.8%
1906-1930	10.3%
1931-1944	6.5%
1945-1959	6.6%
1960-1970	15.5%
1971-1980	19.7%
1981-1990	16.3%
1991-2000	17.3%
≥ 2001	3.0%
Train station in the municipality	
No	31.1%
Yes	68.9%

14,794 dwellings were sold in 59 selected municipalities during 2007

Table 3. OLS Estimates of Hedonic Regression

	Explantory variables	Coefficients	t-statistics
	Intercept	11.586	1355.459
	Transaction year dummies	*Not reported*	
Dwelling Type Dummies Terraced house as reference	**Corner**	0.053	24.621
	Semidetached	0.196	86.830
	Detached	0.364	130.109
	Benedewoning	0.036	6.226
	Bovenwoning	0.054	9.561
	Maisonette	-0.026	-5.447
	Portiekflat	0.033	10.842
	Galerijflat	-0.037	-10.719
	BenedenandBoven	0.068	2.382
Size	**Living Space (m2)**	0.005	220.652
	No. rooms	0.027	36.432
Age Dummies Age1991to2000years as reference	**Age1500to1905**	-0.026	-7.114
	Age1906to1930	-0.003	-0.909
	Age1931to1944	0.077	24.442
	Age1945to1959	-0.025	-8.033
	Age1960to1970	-0.116	-47.514
	Age1971to1980	-0.123	-54.447
	Age1981to1990	-0.056	-24.212
	Ageolder2000	0.123	20.809
Parking Dummies No parking as reference	**Parkingandcarpot**	0.097	42.481
	Garage	0.160	84.760
Garden Dummies No or Poor as reference	**Wellkeptgarden**	0.051	33.251
	LnPopulationdensity	-0.031	-31.565
	%Nature	0.027	7.756
	TOM (month)_t-1	-0.002	-6.190
	Highway Distance (km)	-0.005	-90.511
	Distance_highentrance (km)	-0.002	-4.799
	Adjusted R-square	0.762	
	No. Observation	125,159	

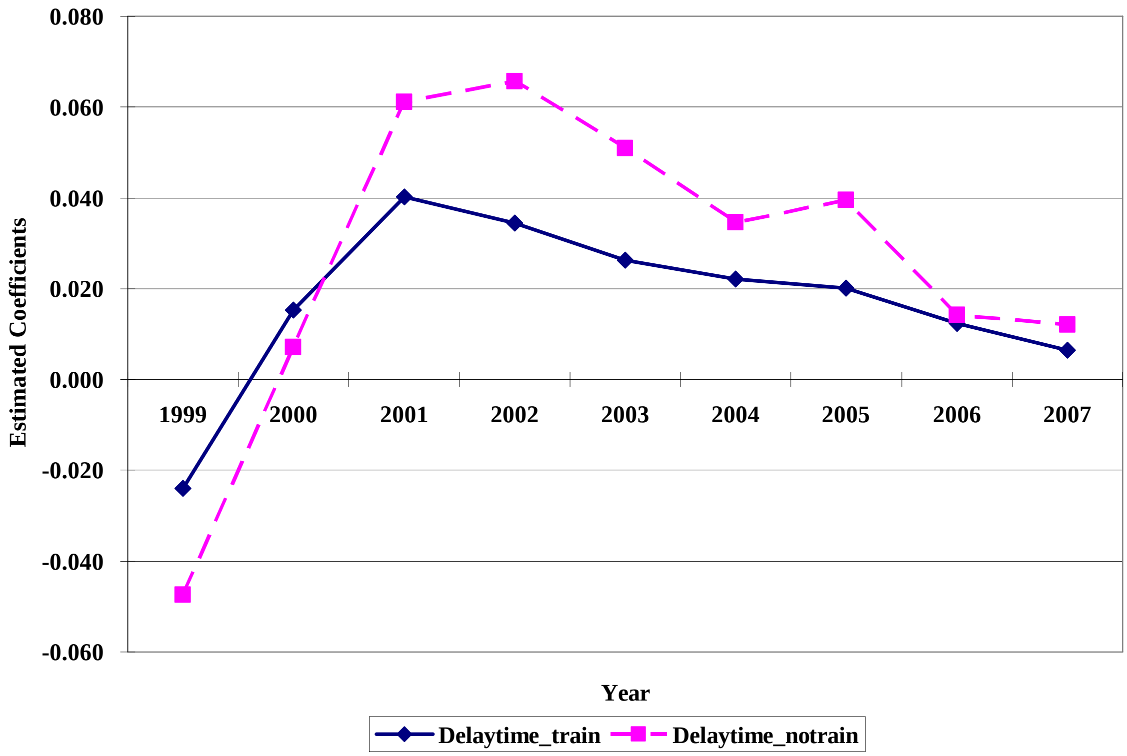
This table presents the results of the OLS estimation of hedonic model for the selected 59 housing markets around the city Utrecht for the period 1999-2007. Dependent variable is natural logarithm of transaction price. House prices are related to the dwelling characteristics, type of house, size of the house, construction time of the house, parking facilities, garden amenities, population density of located city, percentage of nature at 1 hectare around the house, previous year time on the market in the neighborhood, highway distance to the city Utrecht and distance to the highway entrance.

Table 4. OLS Estimates of Delay Time Due to Traffic Congestion

Explantory variables	Coefficients	t-statistics
Y1999*delaytime	-0.015	-4.990
Y2000*delaytime	0.018	7.430
Y2001*delaytime	0.039	17.491
Y2002*delaytime	0.041	19.105
Y2003*delaytime	0.030	13.551
Y2004*delaytime	0.024	11.104
Y2005*delaytime	0.024	13.251
Y2006*delaytime	0.014	9.911
Y2007*delaytime	0.010	8.383
Adjusted R-square	0.764	
No. Observation	125,159	

This table presents the results of the OLS estimation of delay time due to traffic congestion as a component of a complete hedonic model for the selected 59 housing markets around the city Utrecht for the period 1999-2007. Dependent variable is natural logarithm of transaction price. House prices are related to the dwelling characteristics, type of house, size of the house, construction time of the house, parking facilities, garden amenities, population density of located city, percentage of nature at 1 hectare around the house, previous year median time on the market in the neighborhood, highway distance to the city Utrecht and distance to the highway entrance. The estimation results for the total model is reported in Table 3. The additional 9 variables are delay time index interacted with transaction year.

Figure 3. OLS Estimates of Variable *Delay Time Due to Traffic Congestion*: Train Station vs. Non-Train Station in the Located Municipality



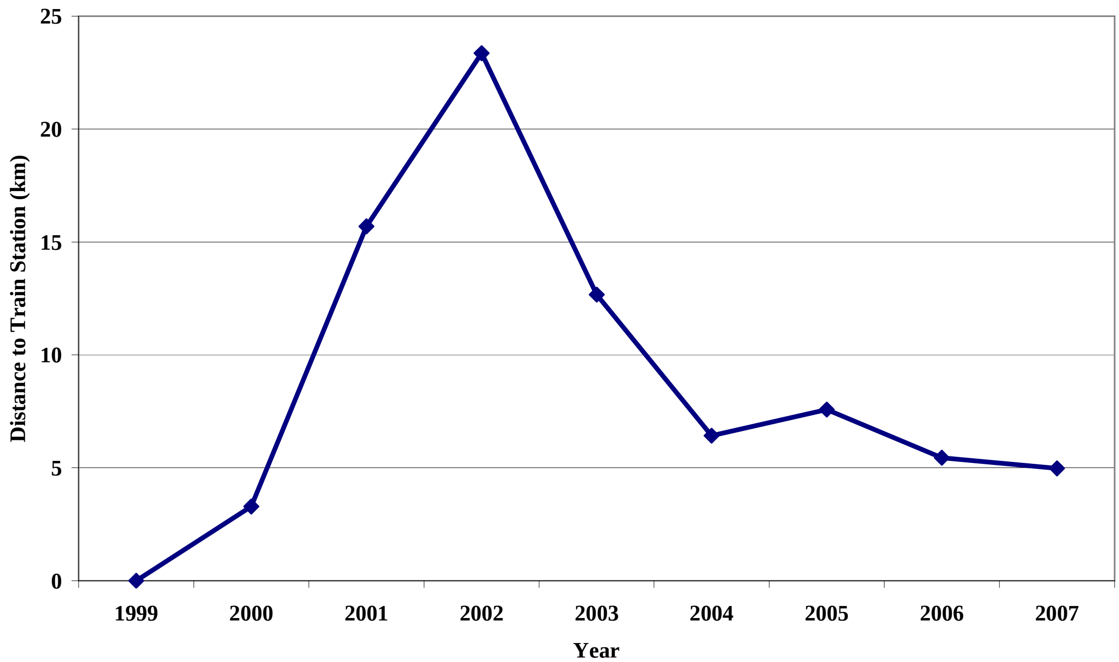
*This figure presents the 9 cross sectional OLS estimation results of delay time due to traffic congestion as a component of a complete hedonic model for the selected 59 housing markets around the city Utrecht during the period 1999-2007. Each year we conduct one cross sectional regression. Dependent variable is natural logarithm of transaction price. House prices are related to the dwelling characteristics, type of house, size of the house, construction time of the house, parking facilities, garden amenities, population density of located city, percentage of nature at 1 hectare around the house, previous year median time on the market in the neighborhood, highway distance to the city Utrecht and distance to the highway entrance. The estimation results for the total model are reported in Table 3. We add two interaction variables to the hedonic model we present in table 3. They are delay time due to traffic congestion index interacted with dummy variable train station and delay time due to traffic congestion index interacted with dummy variable non-train station. The train station dummy equals 1 if there is one train station in the located municipality and 0 if there is no train station in the located municipality. Except the coefficient of Delaytime*D_nontrainstation for year 2000 regression, all the coefficients are significantly different from zero at 0.001 significance level.*

Table 5. OLS Estimates of Delay Time Due to Traffic Congestion: Interaction with Distance to Train Station

	1999	2000	2001	2002	2003	2004	2005	2006	2007
Delaytime	-0.005	0.030	0.052	0.047	0.041	0.039	0.037	0.023	0.018
Delaytime*traindistance	-0.013	-0.009	-0.003	-0.002	-0.003	-0.006	-0.005	-0.004	-0.004
Adjusted R-square	0.743	0.748	0.760	0.761	0.765	0.758	0.755	0.759	0.759
No. Observation	12,445	12,932	13,964	13,668	13,263	13,666	15,260	15,167	14,794

This table presents the 9 cross sectional OLS estimation results of delay time due to traffic congestion and its interaction with distance to train station as two components of a complete hedonic model for the selected 59 housing markets around the city Utrecht during the period 1999-2007. Each year we conduct one cross sectional regression. Dependent variable is natural logarithm of transaction price. House prices are related to the dwelling characteristics, type of house, size of the house, construction time of the house, parking facilities, garden amenities, population density of located city, percentage of nature at 1 hectare around the house, previous year median time on the market in the neighborhood, highway distance to the city Utrecht and distance to the highway entrance. The estimation results for the total model are reported in Table 3. We add two variables to the hedonic model we present in Table 3. They are delay time due to traffic congestion index and its interaction with distance to train station. Except the coefficient of Delaytime for year 1999 regression, all the coefficients are significantly different from zero at 0.001 significance level.

Figure 4. Breakeven points of two 'submarkets'



The breakeven point indicates where marginal influence of traffic congestion on house prices from positive to negative as the distance to train station increases. Each year we estimated the breakeven point by taking the quotient of two betas estimated reported in Table 5.

Table 6. OLS Estimates of Delay Time Due to Traffic Congestions:

Conditional on Accessibility to Public Transport

Panel A

	<6Km		<5Km		<4Km		<3Km		<2Km		<1Km	
Explanatory variables	**Coefficients**	**t-statistics**	**Coefficients**	**t-statistics**	**Coefficients**	**t-statistics**	**Coefficients**	**t-statistics**	**Coefficients**	**t-statistics**	**Coefficients**	**t-statistics**
Y1999*delaytime	-0.007	-2.278	-0.009	-2.700	-0.012	-3.462	-0.017	-4.616	-0.030	-6.591	-0.040	-5.581
Y2000*delaytime	0.018	6.991	0.017	6.314	0.012	4.116	0.002	0.475	-0.015	-3.856	-0.024	-4.056
Y2001*delaytime	0.030	11.912	0.028	10.760	0.016	5.921	0.006	2.006	-0.003	-0.915	-0.009	-1.535
Y2002*delaytime	0.034	13.754	0.030	12.275	0.021	8.035	0.015	5.286	0.011	3.044	0.004	0.821
Y2003*delaytime	0.027	10.559	0.025	9.497	0.019	6.607	0.012	3.902	0.007	1.746	-0.005	-0.906
Y2004*delaytime	0.024	9.150	0.022	8.471	0.012	4.342	0.006	1.728	0.003	0.873	0.001	0.180
Y2005*delaytime	0.022	10.585	0.020	9.474	0.013	5.442	0.009	3.532	0.006	1.803	0.007	1.454
Y2006*delaytime	0.016	9.256	0.014	7.999	0.007	3.830	0.005	2.432	0.004	1.388	0.007	1.877
Y2007*delaytime	0.010	7.483	0.010	7.163	0.005	3.523	0.003	1.803	0.001	0.591	-0.004	-1.254
Adjusted R-square	0.777		0.783		0.788		0.797		0.803		0.797	
No. Observation	98,226		91,833		81,437		67,770		51,432		24,047	

	>6Km		>7Km		>8Km		>9Km		>10Km		>11Km	
Explanatory variables	**Coefficients**	**t-statistics**	**Coefficients**	**t-statistics**	**Coefficients**	**t-statistics**	**Coefficients**	**t-statistics**	**Coefficients**	**t-statistics**	**Coefficients**	**t-statistics**
Y1999*delaytime	-0.115	-14.966	-0.128	-15.394	-0.149	-15.453	-0.126	-10.739	-0.104	-6.692	-0.136	-4.862
Y2000*delaytime	-0.043	-6.805	-0.053	-7.820	-0.071	-8.955	-0.061	-6.307	-0.054	-4.264	-0.013	-0.580
Y2001*delaytime	0.027	3.848	0.004	0.552	-0.026	-2.594	0.004	0.358	0.027	1.684	0.029	0.847
Y2002*delaytime	0.018	2.828	0.008	1.073	-0.044	-3.790	-0.009	-0.623	0.033	1.659	0.078	1.714
Y2003*delaytime	-0.006	-0.874	-0.006	-0.783	-0.054	-5.485	0.002	0.177	0.017	1.029	0.040	1.227
Y2004*delaytime	-0.024	-4.357	-0.041	-6.730	-0.077	-10.657	-0.047	-5.657	-0.039	-3.615	-0.026	-1.274
Y2005*delaytime	-0.025	-4.670	-0.044	-7.218	-0.091	-11.565	-0.064	-6.833	-0.026	-2.107	-0.049	-2.001
Y2006*delaytime	-0.020	-6.158	-0.027	-7.437	-0.038	-9.330	-0.017	-3.593	-0.001	-0.200	-0.005	-0.438
Y2007*delaytime	-0.012	-4.533	-0.018	-6.401	-0.028	-8.590	-0.016	-4.277	-0.006	-1.344	-0.003	-0.401
Adjusted R-square	0.735		0.737		0.747		0.766		0.784		0.795	
No. Observation	26,933		21,733		16,313		11,769		7,212		2,950	

Panel B

	<2Km		4 to 6 Km		8 to 10 Km		>11Km	
Explanatory variables	**Coefficients**	**t-statistics**	**Coefficients**	**t-statistics**	**Coefficients**	**t-statistics**	**Coefficients**	**t-statistics**
Y1999*delaytime	-0.030	-6.591	0.021	2.315	-0.164	-13.311	-0.136	-4.862
Y2000*delaytime	-0.015	-3.856	0.061	8.003	-0.074	-7.170	-0.013	-0.580
Y2001*delaytime	-0.003	-0.915	0.098	13.672	-0.049	-3.865	0.029	0.847
Y2002*delaytime	0.011	3.044	0.095	13.882	-0.080	-5.508	0.078	1.714
Y2003*delaytime	0.007	1.746	0.073	9.832	-0.084	-6.753	0.040	1.227
Y2004*delaytime	0.003	0.873	0.075	10.544	-0.102	-10.294	-0.026	-1.274
Y2005*delaytime	0.006	1.803	0.073	12.540	-0.128	-12.396	-0.049	-2.001
Y2006*delaytime	0.004	1.388	0.058	12.712	-0.062	-11.263	-0.005	-0.438
Y2007*delaytime	0.001	0.591	0.037	9.703	-0.043	-9.390	-0.003	-0.401
Adjusted R-square	0.803		0.735		0.725		0.795	
No. Observation	51,432		16,789		9,101		2,950	

This table presents the results of the OLS estimation of delay time due to traffic congestion as a component of a complete hedonic model for the selected 59 housing markets around the city Utrecht for the period 1999-2007. Dependent variable is natural logarithm of transaction price. House prices are related to the dwelling characteristics, type of house, size of the house, construction time of the house, parking facilities, garden amenities, population density of located city, percentage of nature at 1 hectare around the house, previous year median time-on-the-market in the neighborhood, highway distance to the city Utrecht and distance to the highway entrance. The estimation results for the total model is reported in Table 3. The additional 9 variables are delay time index interacted with transaction year. Observations of each regression are selected based on distance to nearest train station.