Hedonic Pricing when Housing is Endogenous: The Value of Access to the Trans-Israel Highway

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Abstract

Standard hedonic house pricing assumes that house prices are independent of the intangible to be priced. A methodology is proposed in which the supply as well as the demand for housing depends on the intangible. The methodology is applied to value access to the Trans-Israel Highway (TIH), opened in 2002. Using spatial panel data during 2002 – 2008 we show that TIH had two effects on the housing market. It increased house prices in locations with greater access to TIH, and it affected housing construction. Standard hedonic pricing would have underestimated the value of access because it ignores the effects of housing construction on the intangible to be priced. A methodology is proposed to estimate both of these effects. We also show that the effects of TIH on the housing market diffuse slowly over time and they also diffuse over space. House prices began to increase three years before TIH was inaugurated, but housing construction did not anticipate the inauguration of TIH. In 2008 the willingness-to-pay for access to TIH is estimated at 1.25 percent of GDP per year.

1. Introduction

The Trans-Israel Highway (TIH) has transformed road transport since its inauguration in 2002. Running from north to south through the center of the country it currently is 150 kilometers long, and it is planned to extend it northwards to the Lebanese border at Rosh Hanikra and southwards to below Beer Sheva (see map). TIH was designed to cut travel times, increase vehicle efficiency and road safety, and reduce air pollution[1]. It was also expected to have dynamic benefits in terms of greater access and land use. To date there has been no evaluation of TIH[2] . Economic theory predicts that land values and house prices will be higher in locations providing greater access to employment and consumption opportunities. Theory also predicts that highway construction influences urban growth through land and house prices. Therefore the economic value of accessibility[3] due to TIH should be embodied in data for house prices and housing construction.

The use of hedonic house prices to estimate the economic value of intangibles has a long history. The methodology of hedonic pricing has implicitly assumed that the housing stock is independent of the intangibles to be priced. For example, Kiel and McClain (1995) use house price data to infer the environmental cost of a garbage incinerator. They take account of the fact that due to NIMBY effects the location of the incinerator might not be independent of house prices. However, they ignore the possibility that the location of housing might depend on the location of the incinerator. Building contractors might have built less in the incinerator's vicinity and built more elsewhere. If this happens, house prices will tend to increase in the vicinity of the incinerator relative to other locations, in which case the environmental cost of the incinerator is likely to be under-estimated. A methodological contribution in the present study is to take account of induced housing construction in the estimation of the costs and benefits of intangibles[4]through hedonic pricing, at the same time as allowing for NIMBY effects.

[1] These were the main benefits in the official cost benefit analysis carried out on TIH in 1994 (MATAT 1994)
[2] Frisch and Zur (2010) investigate the effect of TIH on commuting, but find only small effects.
[3] We distinguish between access and use. Since TIH is a toll road, the latter is expressed in tolls paid by users. Not all users live close to TIH, and no doubt not all with access use TIH.
[4] There are many other examples. McMillen and McDonald (2004) assume that the Midway Line did not affect housing construction. The same assumption seems to be present in Bao and Wan's (2004) study of a tunnel in Hong Kong and in the work of Chernobai , Reibel and Carney (2011) on an interstate highway extension. See also Bajic (1983) on a new railway and Gatzlaff and Smith (1993) on railway stations.

Like most of our predecessors we use a quasi-experimental design based on differences-in-differences (DID), comparing house prices and housing construction before and after TIH in treated and untreated locations. However, we break new ground by also taking account of threats to identification induced by the potential dependence of housing construction on TIH.

The evaluation of accessibility needs to deal with spatial and temporal aspects because the treatment effects of TIH are expected to vary directly with treatment dosage, as measured by travel time to the nearest TIH intersection, and they might vary directly with exposure time to the treatment. These spatial effects relate to three issues. First, do house prices fully internalize the amenities (or disamenities) related to greater accessibility? Second, what is the distance at which the treatment effect of TIH decreases or falls to zero, if at all? Third, is there any spatial spillover in the impact of highways on house prices and housing construction? On the temporal side, the issue relates to the stage in the process of highway construction at which the treatment effect is most felt. Does this effect vary with the stages of planning, construction and operation? How rapidly do treatment effects diffuse over time? Also, as TIH develops, untreated locations become treated. Furthermore, the treatment effect in treated locations increases because access varies directly with the length of TIH and the number of intersections. .

2. Methodology

2.1 Conceptual Framework

TIH is hypothesized to have two related treatment effects; on house prices and on housing construction, as illustrated in Figure 1 where house prices in a treated area are measured on the vertical axis and the housing stock is measured on the horizontal axis. The demand schedule for housing prior to TIH is represented by D_0, the housing stock is fixed at S_0, and the price of housing is P_0. Access to TIH increases the demand for housing in the treated area, and the demand schedule becomes D_1. If the housing stock is unchanged house prices

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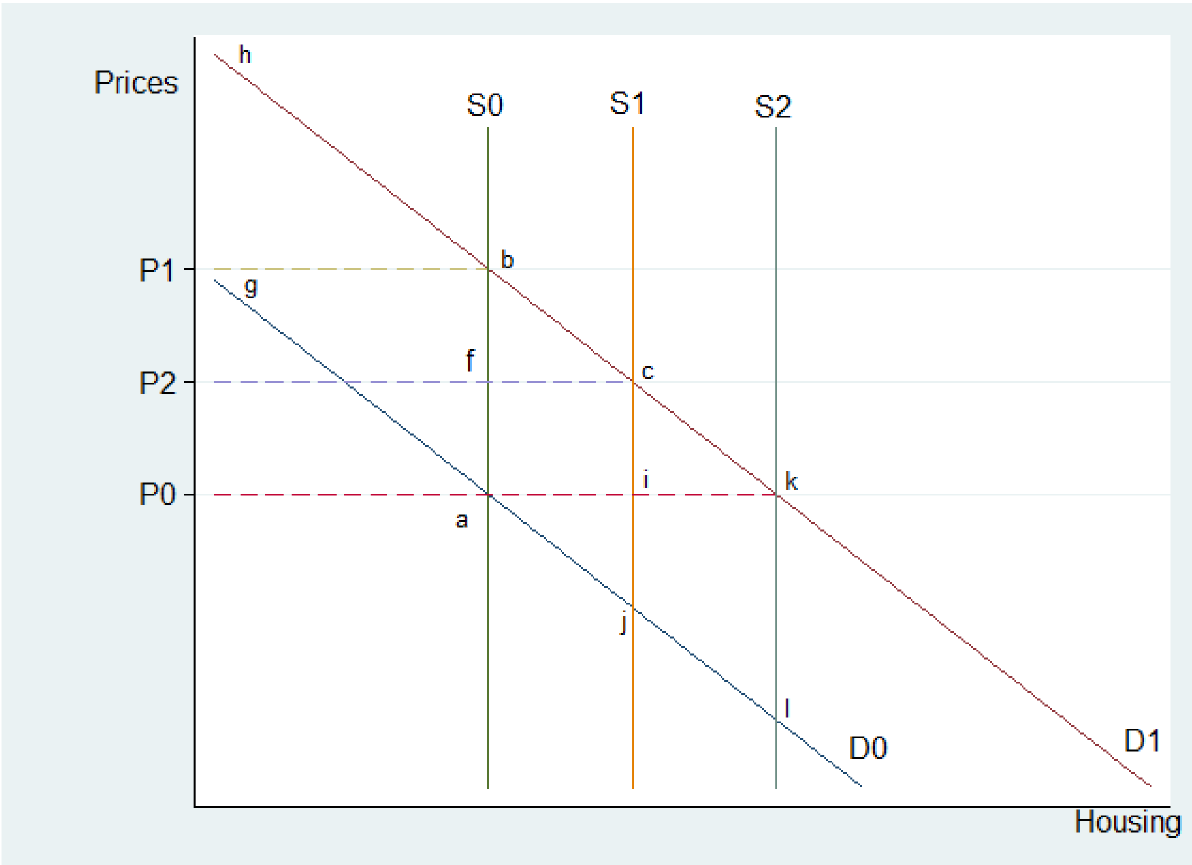
Boarnet and Chalermpong (2001) look at the effect of highways on house prices and induced travel but not induced construction. A related literature is concerned with the effects of access on economic outcomes e.g. Baum-Snow (2007), Michaels (2008) and Faber (2014) and on land use change (Funderburg, Nixon, Boarnet and Ferguson 2010) increase to P_1. The value of access to TIH is the rectangle $P_0P_1ba = S_0(P_1 - P_0)$ which, because demand is assumed to be linear, is equal to the increase in consumer surplus as measured by the trapezoid hbag. It may be shown that if the demand schedule is loglinear $S_0(P_1 - P_0)$, i.e. the change in the value of housing under-estimates the willingness-to-pay for access as measured by the change in consumer surplus.

Figure 1: The Effects of TIH on the Housing Market



TIH may also affect the supply of housing for two reasons. First, if house prices increase, building contractors will face a greater incentive to build in the treatment locations. Second, planners might rezone land in favor of housing in the treatment locations. If these effects induce the housing stock to increases from S_0 to S_1, house prices will increase to P_2 instead of P_1. In this case the increase in consumer surplus is the trapezoid hcjg which equals $(P_2 - P_0)S_0 + (P_1 - P_2)S_0 + (P_2 - P_0)\Delta S + (P_1 - P_2)\Delta S$. Note that the latter equals congruent triangles fbc + aij. Although $P_2 – P_0$ and ΔS are observed, P_1 is not observed. However, if the slope of the demand curve is β, $P_1 – P_2 = \Delta S/\beta$.in which case the increase in consumer surplus equals $(P_2 – P_0)(S_0 + \Delta S) +\Delta S(S_0 + \Delta S)/\beta$. Therefore, if the increase supply is ignored conventional hedonic pricing under-estimates the value of access by $\Delta S[(S_0 + \Delta S)/\beta + (P_2 – P_0)]$.

If the treatment effect of TIH on the housing stock is sufficiently large (S_2 in Figure 1) house prices would remain unchanged at P_0. In this case the value of access is represented by hklg. Conventional hedonic pricing would suggest mistakenly that because TIH made no difference to house prices, the value of access is zero instead of $\Delta S(S_0 + \Delta S)/\beta$.

House prices in Figure 1 are implicitly relative house prices. When housing demand in the treatment area increases, this is at the expense of housing demand elsewhere. Also, enhanced housing construction in the treatment area might be at the expense of reduced housing construction elsewhere. For expositional purposes in Figure 1 we have made the simplifying assumption that the treatment area is small relative to the rest of the country. House prices and housing construction are expected to decrease in untreated areas.

In Figure 1 it is assumed that the housing stock increases. However, in some locations it might decrease. Suppose, for example, that location A is closer to TIH than nearby location B and building contractors operate locally as suggested by Beenstock and Felsenstein (2015). Contractors might increase construction in A at the expense of construction in B. In this case housing supply in A would increase as in Figure 1, but it would decrease in B, P_2 would be higher than P_1 in B where willingness-to-pay by induced households would be negative.

2.2 Twin Treatment Effects Model

Suppose for expositional simplicity that treatment status T is dichotomous; T = 1 if the area has access to TIH and is zero otherwise. In period 0, T = 0 because TIH does not exist or is under construction, but in period 1, T = 1 in treated locations. The change between periods 0 and 1 in the demand for housing services (H^D) in location j is hypothesized to vary inversely with the change in house prices and directly with T_j. It is also likely to depend on other factors in location j denoted by X_j:

$$\Delta H_j^D = \alpha - \beta\Delta P_j + \gamma T_j + \delta X_j + u_j \qquad (1)$$

where u is a residual independent of X and T but not of ΔP.

The change in the supply of housing services (H^S) is hypothesized to vary directly with the change in house prices and T:

$$\Delta H_j^S = \mu + \phi\Delta P_j + \theta T_j + \pi Z_j + v_j \qquad (2)$$

where Z is a set of variables affecting housing construction, and v is a residual independent of T and Z but not of ΔP. The twin treatment effects are γ and θ, which are identified provided Z and X are mutually exclusive, and u and v are independent of T.

The latter assumption requires justification. The locations of the intersections were chosen in the 1970s whereas u and v were determined in the 2000s. Therefore T was determined decades ahead of u and v. We argue that time may dissolve dependence. Additionally, we distinguish between three types of intersections. The first type consists of intersections at existing local road network junctions that were subsequently incorporated into TIH. For example, two of the largest intersections (the Kesem and Ben Shemen intersections) were built in 1985 and 1981 to serve local routes #5 and #443 respectively but were already specified in NOP/3 (National Outline Plan for Highways) dating back to 1976. NOP/3 clearly demarcated eleven intersections for TIH, eight of which correspond to current intersections[5]. The second type, were designed ex nihilo for TIH. These also appear in NOP/3 and include the current intersections of Irron, Baka-Jat, Nitzanei Oz, Nachshonim, Nesharim and Sorek. A third, smaller group of intersections (Eyal, Horshim

[5]The highway envisaged in NOP/3 in 1976 was shorter than the current TIH (110k instead of 150k) and consequently had less intersections.

and Daniel) were added to the TIH through amendment #10 to NOP/3 that took effect in November 1991. No doubt the planners of TIH chose locations to maximize access potentially inducing correlation between anticipated house prices and housing stocks and T. Insofar as these anticipations were inaccurate this would reduce the correlation between actual house prices and housing stocks. In any case u and v refer to changes in house prices and housing stocks rather than levels. Therefore even if the anticipations of the planners happened to be correlated with P and H, this does not mean that they must be correlated with u and v. Consequently, we assume that T is weakly exogenous for γ and θ.

In a similar but different context Faber (2014) used instrumental variables to take account of potential endogeneity in the siting of Chinese highways. This was necessary because the outcomes occurred roughly at the same time as the development of the road network, and the outcomes were specified in levels rather than changes. By contrast, in our study the outcomes refer to differences rather than levels, and they occurred decades after the siting decisions of the intersections.

The reduced form for the DID of house prices is obtained by equating equations (1) and (2) and solving for ΔP:

$$\Delta P_j = a + bT_j + cX_j + dZ_j + \varepsilon_j \qquad (3)$$

$$a = \frac{\alpha - \mu}{\phi + \beta} \quad b = \frac{\gamma - \theta}{\phi + \beta} \quad c = \frac{\delta}{\phi + \beta} \quad d = -\frac{\pi}{\phi + \beta} \quad \varepsilon = \frac{u - v}{\phi + \beta}$$

The counterpart of equation (3) for the DID in housing construction is:

$$\Delta H_j = e + fT_j + gX_j + hZ_j + \eta_j \qquad (4)$$

$$e = \frac{\phi\alpha + \mu\beta}{\phi + \beta} \quad f = \frac{\phi\gamma + \theta\beta}{\phi + \beta} \quad g = \frac{\phi\delta}{\phi + \beta} \quad h = \frac{\pi\beta}{\phi + \beta} \quad \mu = \frac{\phi u + \beta v}{\phi + \beta}$$

The twin treatment effects in the reduced forms are b and f. Notice that b = 0 when $\gamma = \delta$ but f = θ. The reduced form residuals are independent of T, X and Z. Identification of the structural parameters requires that exclusion restrictions apply to X and Z. Equation (1) may be estimated by IV using equation (3) as its instrument to obtain estimates of γ, and equation (2) may be estimated by IV using equation (4) as its instrument to obtain estimates of θ. Note that β = -d/h is identified by Z regardless of X. As noted in section 2.1 the value of access requires treatment effects for house prices changes and changes in housing supply by area, and it requires β, which are generated by estimates of equations (3) and (4)

In models involving rational expectations agents on both sides of the market form expectations of the exogenous variables. Therefore, the demand for housing depends on expectations of the supply shifters (Z) and the supply of housing depends on expectations of the demand shifters (X). Our identification strategy would break down if there was perfect foresight, in which case demand and supply would depend on X and Z. When foresight is imperfect the parameters continue to be identified because expectations of X and Z are not identical to actual X and Z (Pesaran 1987, chapter 6.5.2).

2.3 Treatment Effect Diffusion

In equations (1) and (2) the treatment effects are assumed to be instantaneous. Dynamics are introduced by allowing long-term treatment effects to differ from their short-term counterparts. If the treatment occurs at time 1, the instantaneous treatment effects b_1 and f_1, are estimated by using differences between times 0 and 1 in equations (3) and (4). The treatment effect during periods 1 and 2, b_2 and f_2, may be estimated using differences between periods 1 and 2 in equations (3) and (4). The cumulative treatment effects up to period 2 are $B_2 = b_1 + b_2$ and $F_2 = f_1 + f_2$. B_2 and F_2 may also be estimated by using the differences between periods 0 and 2 in equations (3) and (4). The long-term treatment effects are obtained when B and F cease to change with further differencing.

Since equations (3) and (4) are estimated for consecutive years, the estimates of a_t and e_t are temporal fixed effects which express national developments in the housing market regarding house price changes and housing construction respectively.

But not all the treatment occurs in period 1 since TIH is an ongoing project. Suppose that in period 2 a new intersection is opened. Some locations untreated in period 1 become treated in period 2. Also, in period 2 the value of treatment to those already treated in period 1 increases because they benefit from the intersection opened in period 2. Strictly speaking the treated should be disaggregated into cohorts according to when they were first treated. However, we resolve this difficulty in a different way as explained in the next subsection. The temporal diffusion of treatment effects has typically been ignored in previous research in hedonic pricing.

So far the treatment effect refers to its "on-line" definition; i.e. when TIH was inaugurated. Or it implicitly assumes that in period 0 the highway was constructed without the public's knowledge. Suppose that TIH was planned in period -1. The change in house prices and housing construction between periods -1 and 0 might embody an anticipatory treatment effect. To estimate it, equations (3) and (4) may be applied using DID's between periods -1 and 0. If anticipatory effects are weaker than on-line effects, we expect estimates of b and f of the latter to be greater than their counterparts in the former.

2.4 Specifying the Treatment

In the case of TIH treatment status is not dichotomous since access depends on distance to the nearest intersection with TIH, i.e. the treatment dosage varies. We define T in terms of travel time to the nearest intersection with TIH. This means that all locations are treated in period 1, however, the effect of the treatment varies inversely with distance from the nearest intersection. The treatment effect might be expected to be zero for locations that are far away from TIH. When a new intersection is opened, travel time to the nearest intersection does not change in areas close to existing intersections, but it decreases in areas further away.

Since the spatial diffusion of the treatment effect is not known a priori, we use a polynomial in travel time to the nearest intersection with TIH as our measure of T. For example, a 2nd order polynomial allows the treatment effect to be larger at intermediate distances from intersections than short distances because there may be adverse effects to intersections due to traffic concentrations in their immediate vicinity. This flexible functional form permits a broad spectrum of spatial diffusions. In the absence of a priori restrictions, the order of the polynomial is chosen according to goodness-of-fit. Moreover, the diffusion process is allowed to vary over time since there is no a priori reason why the spatial diffusion in one year should be the same in subsequent years. The alternative of forcing a common spatial diffusion function is strongly rejected on empirical grounds.

2.5 Spatial Econometrics

In equation (3) it is assumed that house price changes are spatially independent. This assumption may be incorrect for two reasons. First, the residuals may be spatially autocorrelated (SAC). In this case ε_j is correlated with residuals in the neighborhood of j. The first order SAC model is:

$$\varepsilon_j = \rho\varepsilon_{nj} + \omega_j \qquad (5)$$

where ρ is the SAC coefficient, ε_{nj} is the average residual among j's neighbors, and ω is an iid idiosyncratic residual. Ignoring SAC does not bias the parameter estimates, but it biases their standard errors.

Secondly, there may be spatial spillovers in house prices. House price changes among j's neighbors might spillover onto house prices in j. In this case equation (3) should include a spatial lag:

$$\Delta P_j = a + bT_j + cX_j + dZ_j + \lambda \Delta P_{nj} + \varepsilon_j \quad (6)$$

where P_nj denotes house prices in the neighborhood of location j and λ denotes the spatial lag coefficient. Unlike SAC, ignoring λ biases the parameter estimates. The spatial lag model implies that the global treatment effect of TIH is greater than its local counterpart since the spatial lag coefficient is between zero and one.

Similar considerations apply to equation (4). The residuals might be spatially autocorrelated and equation (4) might be spatially dynamic. Furthermore, ε and η might be correlated within locations as well as between locations as in the spatial SUR model.

2.6 Bootstrapping Treatment Effects

As reported below, the residuals η and ε turn out to have non-standard distributions despite the fact that the sample sizes are not small, and the residuals are expected to be asymptotically normally distributed. For these purposes we use the Jarque-Bera statistic which tests for skewness and fat-tails under the assumption that the residuals might be spatially dependent. Consequently hypothesis tests based on the assumption that these residuals are asymptotically normally distributed are unreliable. Robust standard errors may be a palliative for heteroskedasticity, serial correlation and SAC, but they are not valid if the residuals are not normally distributed. Hence t-tests, chi-squared tests and F tests may mislead. We suggest that hypothesis tests about the parameter estimates in equations (3) and (4), and especially the treatment effect parameters b and f, be carried out using their bootstrapped distributions.

The literature on bootstrapped IV and GMM estimators (Moreira et al 2009) has been motivated by problems of weak instruments and heteroskedasticity. If the instruments are in fact strong, standard tests for weak instruments (Staiger and Stock 1997) might lead to erroneous conclusions because the F statistic is only valid if the residuals are normally distributed. The same applies if the instruments are in fact weak; they might be incorrectly deemed to be strong. The bootstrapped distributions of the parameter estimates may be used to test hypotheses about the parameter estimates when they do not have standard distributions, and they are also informative if the instruments are weak and the residuals are heteroskedastic (Zhan 2010).

3. The Data

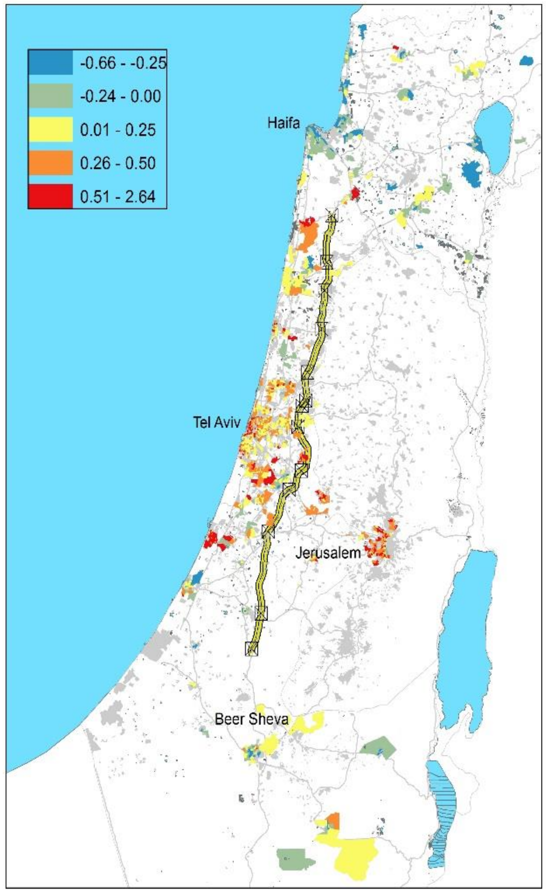
3.1 Outcomes

Since 2010 the Israel Tax Authority has operated a website containing prices on individual housing transactions[6]. These transactions date back to 1988 and are updated continuously. The data record location, the size of the house or apartment, as well as other parameters. At our request, the Central Bureau of Statistics (CBS) provided annual average house prices in about 1800 statistical areas during 1998-2010. The number of statistical areas varies from year to year because in statistical areas with small populations there might have been insufficient housing transactions. In the nature of things, the geographical size of statistical areas varies inversely with population size. The statistical areas may be seen in Figure 2 which maps changes in house price per square meter, by statistical area during 2000 – 2008.

We requested average house prices regardless of size and other hedonic parameters to maximize the number of transactions per statistical area. CBS also supplied data on the average size of housing transacted by statistical area. We used these data to calculate the average house price per meter. We assume, *force majeure*, that other aspects of housing quality are either correlated with size, or average out to be similar across statistical areas. In any case, the DID design differences away potential specific effects of statistical areas, induced by differences in unobserved housing quality. These spatial panel data are used to represent ΔP_{jt} in equation (3).

Figure 2: Percent Change in House Prices per Square Meter, by Statistical Area 2000 – 2008

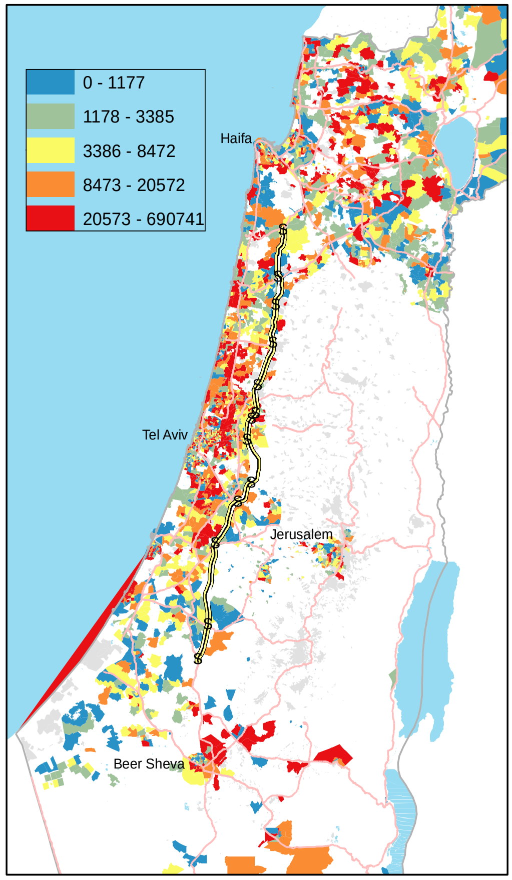
[6] Purchasers of apartments must pay stamp duty. For these purposes they must present certified evidence of the transactions price. These price data are published on the website.



Unfortunately, data on housing stocks are not readily available. However, CBS publishes data on housing completions by statistical area. We use these data to calculate the gross change in housing stocks (measured in thousands of square meters) since 1995. In the absence of data on housing stocks by statistical area, we express the change in housing construction as a proportion of the population in 1995 (from the 1995 census), which is the nearest year to 2001 for which population data by statistical area are available. These data, which are used to represent ΔH_{jt} in equation (4), are mapped in Figure 3.

The anticipatory period of TIH (period -1 in section 2.2) was long and protracted. TIH was first mooted in 1976, but it was only after 1995 that construction work began. Subsequently, construction was delayed because of numerous legal claims by environmentalists and claims for compensation arising out of compulsory land purchases. The first sections of TIH were opened in 2002 (see map). In the absence of house price data prior to 1998 we are only able to investigate anticipatory effects during 1998 – 2002. However, in the case of housing construction we are able to investigate anticipatory effects from 1995.

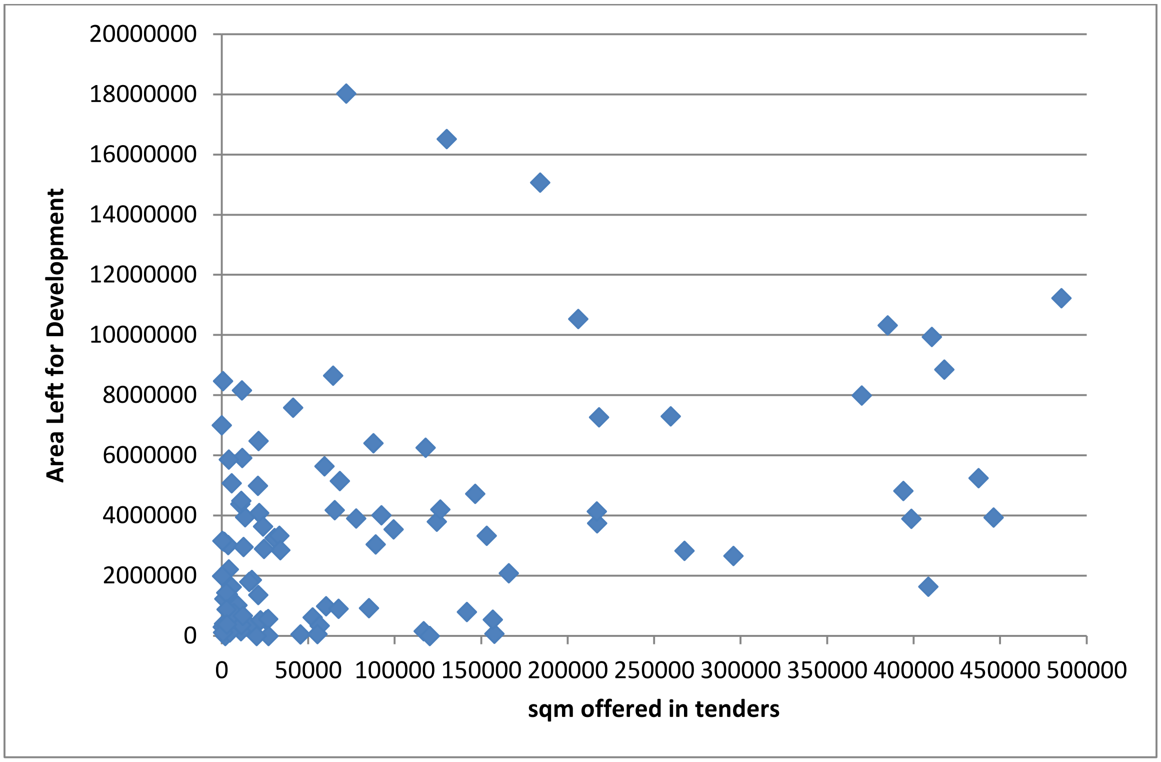
Figure 3: Cumulative Housing Construction Per 1995 Population 2000-2008



3.2 Instrumental Variables

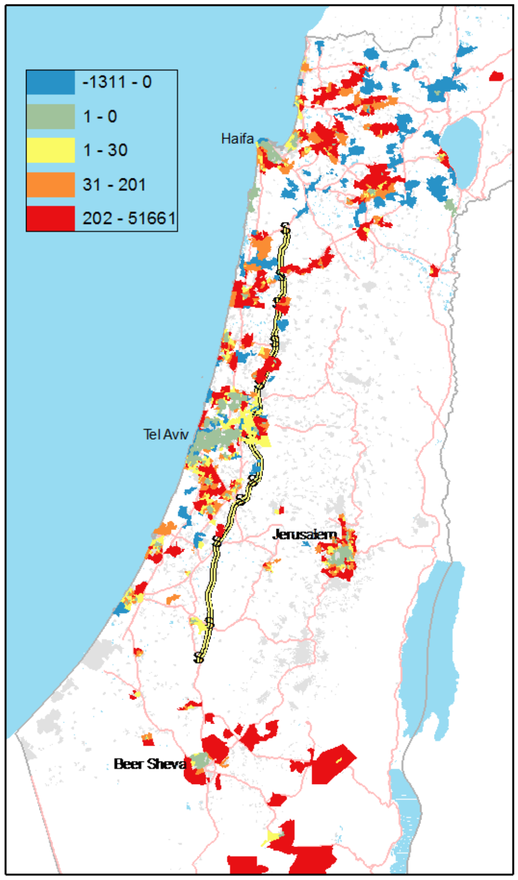
As an instrumental variable (Z) for housing completions we use land reserves for housing, constructed by us from administrative data which happen to be available for 1998. These reserves are vested in the Israel Land Authority (ILA) which conducts land auctions for new housing construction. Figure 4 plots the positive correlation between land reserves and land auctions (r=0.561). However, we use land reserves rather than auction data because the latter are not available by statistical area. Given everything else, housing construction should vary directly with these reserves. However, there is no reason why the change in house prices should be directly affected by this variable. These data are mapped in Figure 5.

Fig 4: The relationship between land reserves and land offered for tenders, by local authority 1998-2013



Potential instrumental variables for the demand for housing (X) include amenities such as crime rates and school matriculation rates. These data are not available by statistical area but for 130 local authorities (LA's) i.e. on average there are about 14 statistical areas per LA. We therefore assume that statistical areas in the same LA have the same crime and matriculation rates. The only amenity by statistical area is the distance from the nearest large city (Tel Aviv, Haifa, Jerusalem and Beer Sheva), which is hypothesized to increase the demand for housing.

Figure 5: Land Reserves per population 1995



3.3 Treatments

Access to TIH is measured by the estimated travel time in minutes (solved by Arc GIS) from the centroid or each polygon (statistical area) to the nearest intersection with TIH. This serves as the main treatment variable, “time”, which is continuous. The treatment effect varies inversely with ”time” because the treatment is expected to vary inversely with distance.

Notice that geographical proximity to TIH is not important unless there happens to be an intersection. The value of access to TIH is expected to vary directly with its length, since the addition of sections as well as intersections increases access services provided by TIH. Therefore, the treatment effect should increase over time as TIH gets longer. We handle this by allowing the treatment effect to vary over time.

3.4 Sample Selectivity

There are currently almost 3000 statistical areas in Israel. However, many of them are uninhabited and are not relevant to the present study. The house price data refer to 1844 statistical areas of which 1282 statistical areas have continuous data for 2002 - 2008. In some statistical areas with thin housing markets there were insufficient housing transactions in particular years[7]. To maximize the sample, we use data for all (1844) statistical areas by estimating equation (3) using first differences from one year to the next year during 2002 – 2008. The alternative was to limit the study to the 1282 statistical areas for which the data are available for all years. This means that the sample size varies from year to year and different statistical areas are represented in the data in different years. Although the vast majority (1282) of statistical areas is always represented in the data, questions naturally arise regarding sample selectivity.

The main question is whether sample selectivity is related to treatment status. A Poisson regression shows that although the 1844 observation counts (reported in footnote 7) vary inversely with land reserves and distance to nearest big city they do not depend significantly on treatment status[8] (z statistics in parentheses). If the treatment effect is assumed to be linear the z statistic for D is -3.94, i.e. closer statistical areas to intersections are more likely to be observed. However, since the treatment effect is nonlinear (see section 4), we ignore this in what follows.

Equation (4) is estimated using cumulative housing construction since 2000 relative to the population in 1995. Sample selectivity in the case of housing construction depends on several criteria. First, the statistical area had to be inhabited in 1995 because housing construction is normalized by the population in 1995. Secondly, housing construction did not occur in some statistical areas. The question of sample selectivity also arises in the case of housing construction. Are the statistical areas used to estimate equation (4) more or less likely to be observed in the data the closer they are to TIH? To answer this question seven separate logit models were estimated for each year during 2002 – 2008 using the same covariates as in the Poisson model. In all of these models except for 2007 and 2008 the chi

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[7] Counts for years of observations: 1 year 121, 2 years 81, 3 years 74, 4 years 54, 5 years 66, 6 years 64, 7 years 102, 8 years 1282.

[8] $$\underset{}{\text{Count}(1\text{-}7)} = \underset{(0.48)}{0.034\text{time}} - \underset{(-0.64)}{0.00017\text{time}^2} + \underset{(0.54)}{0.000002\text{time}^3} \underset{(-2.54)}{-0.067\text{DIS}} \underset{(-2.59)}{-0.00003\text{LR}}$$

square statistic for the treatment effect polynomial is not significant[9]. In summary, the sample of statistical areas used in the estimation does not seem to be related to the treatment.

4. Results

As mentioned, there are two ways to estimate the temporal diffusion of treatment effects; by using a sequence of rolling first differences in house prices and housing construction, or by using cumulative differences. Because of practical considerations of data availability and in order to maximize the sample size, we use rolling first differences in the case of equation (3) and cumulative differences in the case of equation (4).

We began by estimating equations (3) and (4) using OLS, and most of the specification search was undertaken using OLS. However, according to Jarque – Bera tests (Jarque and Bera 1987) the OLS residuals turned out to be not normally distributed despite the relatively large sample sizes. The estimated residuals are fat-tailed in equations (3) and (4), right-skewness in equation (3), left-skewness in equation (4), and the p-values of their Jarque-Bera statistics for normality were close to zero. Since statistical tests based on the normal distribution may mislead under these circumstances, we resorted to nonparametric bootstrapping (10,000 replications) to estimate equation (3) and (4). Indeed, parameter estimates that seemed to be not statistically significant by t – tests, chi square tests and F tests, turned out to be statistically significant using their bootstrapped distributions. As expected by asymptotic theory the bootstrapped parameter estimates turned out to be almost identical to their OLS counterparts but not their p-values.

Spatial dynamic models, such as equation (6), are estimated by maximum likelihood. Since ML is based on the assumption that the residuals are normally distributed, the problem of hypothesis testing raised in the previous paragraph also applies to equation (6). Since bootstrapping theory for spatially dependent data is much less developed than for spatially independent data, we do not resort to bootstrapping estimates of equation (6). However, since asymptotic theory suggests that first moments are more immune to non-

[9] Chi squared p-values are: 2002 0.074, 2003 0.211, 2004 0.445, 2005 0.405, 2006 0.111, 2007 0.0178, 2008 0.0001.

normality than second moments, we think that the ML parameter estimates are consistent as are their OLS counterparts.

4.1 House Prices: 2002 – 2008

Table 1 summarizes results from bootstrapped estimation of equation (3) for various years. The order of the polynomial (n) for travel time to the nearest TIH intersection varies from year to year according to goodness-of-fit criteria. At first n = 1 but after 2003 n varies between 2 and 4. The largest p-value on these treatment effect polynomials is 0.0804, so these effects are clearly statistically significant. The number of observations (N) increases over time, as does the explanatory power of the models, which is generally low but statistically significant.

Table 1: Bootstrapped Estimates of Equation (3): House Prices

Variable	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Time	-0.0008	0.0053	0.01250	-0.0023	0.0011	0.0153	0.0047
	0.0009	0.025	0.0002	0.0034	0.0021	0	0.1066
Time2		-0.0002	-0.0005	0.00001	-6.71E-06	-0.0007	-0.0003
		0.0338	0.0009	0.0509	0.0085	0	0.0167
Time3		1.89E-06	6.22E-06			8.05E-06	5.11E-06
		0.0558	0.0024			0	0.0151
Time4		-5.61E-09	-2.04E-08			-2.57E-08	-1.83E-08
		0.0779	0.0039			0	0.0172
DIS-ln distance to city	-0.0077	-0.01054	-0.0027	-0.0279	0.0054	-0.0158	-0.0039
	0.114	0.0132	0.0359	0	0.0573	0.0011	0.0143
DIS-ln distance to city^2	0.0007	0.0012		0.0025	-0.0005	0.0008	
	0.1238	0.0064		0	0.0698	0.046	
Crime rate				-0.5077		-0.3553	-0.8736
				0.0009		0.0345	0.0005
Education					0.0004		0.00068
					0.0236		0.0371
Constant	0.1252	-0.0612	-0.0394	0.1560	-0.04570	0.0507	0.1576
	0	0.0038	0.0474	0	0.0013	0.0481	0
N	1353	1390	1392	1400	1348	1524	1377
Adj R^2	0.0059	0.0072	0.0279	0.0313	0.0104	0.1432	0.04275156
χ^2	10.55	6.29	28.24	30.79	10.14	163.14	32.83
p-value	0.0012	0.1786	0	0	0.0063	0	0

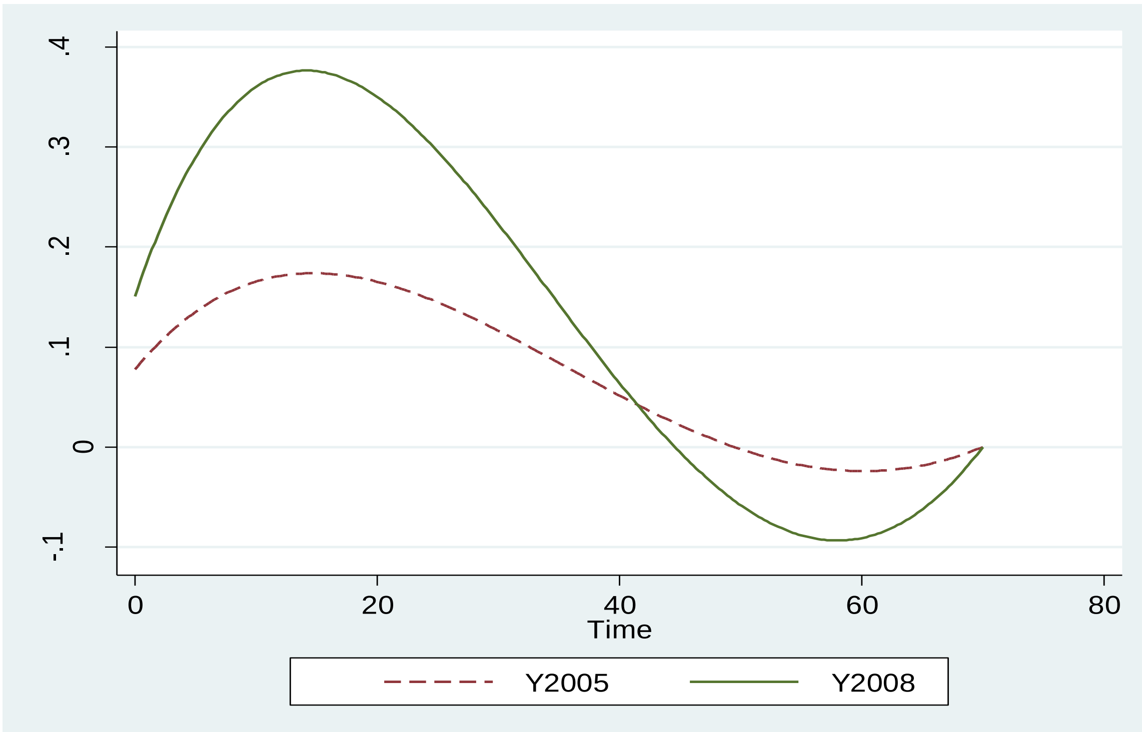
Legend: Dependent variable: Annual percentage change in house prices per sq.m.
N: number of observations (statistical areas). Bootstrapped p-values (10,000 nonparametric replications) reported below parameter estimates. ”time”: travel time in minutes to nearest TIH intersection. χ^2: value for n=0.

There is only one demand effect in Table 1, distance to nearest large city, which is specified as a quadratic, and implies in all years with the exception of 2006, that demand varies inversely with this distance but the marginal effect decreases. Other potential amenity effects such as crime and matriculation rates are statistically significant in some years. Recall, however, that data for these variables are only available from 2005, and that they refer to local authorities rather than statistical areas. The χ^2 value all models is significant, rejecting the hypothesis that the polynomial for travel time is zero

Figure 6 plots the cumulative treatment effects generated from the bootstrapped estimates of the treatment effect polynomials in Table 1. The diffusion schedule for 2002 (not shown) is obtained directly from the estimate of the model for 2002 since the dependent variable refers to the percentage change in house prices between 2001 and 2002. The diffusion schedule for 2003 (not shown) is obtained by adding to its counterpart for 2002 the change in house prices between 2002 and 2003 estimated from the model for 2003. In this way diffusion schedules may be constructed for each year. Figure 5 reports the diffusion schedules for 2005 and 2008.

The treatment effect schedules plot the estimated effect of TIH on the change in house prices since 2000 in terms of travel time to the nearest intersection. Each schedule expresses the spatial diffusion of treatment effects up to the relevant year. The different schedules express the temporal diffusion of treatment effects, which is measured by the vertical difference between the chronological difference between them.

Figure 6: Spatio-temporal Diffusion of Treatment Effects on House Prices



Note: 2005= cumulative effect of treatment time on house prices 2002-2005 and 2008= cumulative effect of treatment time on house prices 2002-2008

The diffusion schedules have been normalized so that the treatment effect is zero when the travel time is 70 minutes. Alternatively, the treatment effects are expresed relative to their counterparts where travel time is 70 minutes. The upper schedule refers to the cumulative treatment effect in 2008 since 2002. For example, house prices 15 minutes away from the nearest intersection with TIH rose by 4 percent more than they did at 70 minutes. The treatment effect is just over 2 percent in the immediate proximity of TIH, and it is in fact largest at a distance of 12 minutes from TIH. At 45 minutes' distance the treatment effect tends to zero.

The second schedule in Figure 6 refers to the spatial diffusion of the treatment effect by 2005. Not surprisingly, it lies below its counterpart for 2008 because the temporal diffusion of the treatment effect is naturally smaller in 2005, but it too peaks at about 12 minutes. If travel time to TIH is 20 minutes, the vertical difference between 2005 – 2008 is slightly more than 2 percent but at 48 minutes it is zero. Notice, however, that because the diffusion schedules in Figure 6 are not homothetic; the temporal diffusion is not constant and depends on travel time.

4.2 Housing Construction: 2002 – 2008

Table 2 summarizes bootstrapped estimates of equation (4) for various years. In this case a 4th order polynomial in travel time to nearest TIH intersection is estimated for each year according to goodness-of-fit criteria. The largest p-value on the coefficients of the treatment effect polynomial is 0.104, so these coefficients are jointly and severally statistically significant. The inverse chi-squared meta statistic[10], which tests for the joint significance of the treatment effects polynomial, is 40.32 which easily exceeds its critical chi squared value (p = 0.95) of 15.05. Table 2 also shows that housing construction varies directly with land reserves zoned for housing and attractiveness of the location as measured by educational level. Construction varies inversely with the disamenities associated with a place (crime level) and with distance to nearest large city. This effect is positive until 2004 and negative subsequently. In Table 2 the number of observations is larger than in Table 1 because housing was completed in statistical areas in which housing transactions did not occur. Also the explanatory power for housing construction is much greater than for house prices.

[10] $-2\ln\sum_{t=1}^{T} PV_t \sim \chi_T^2$

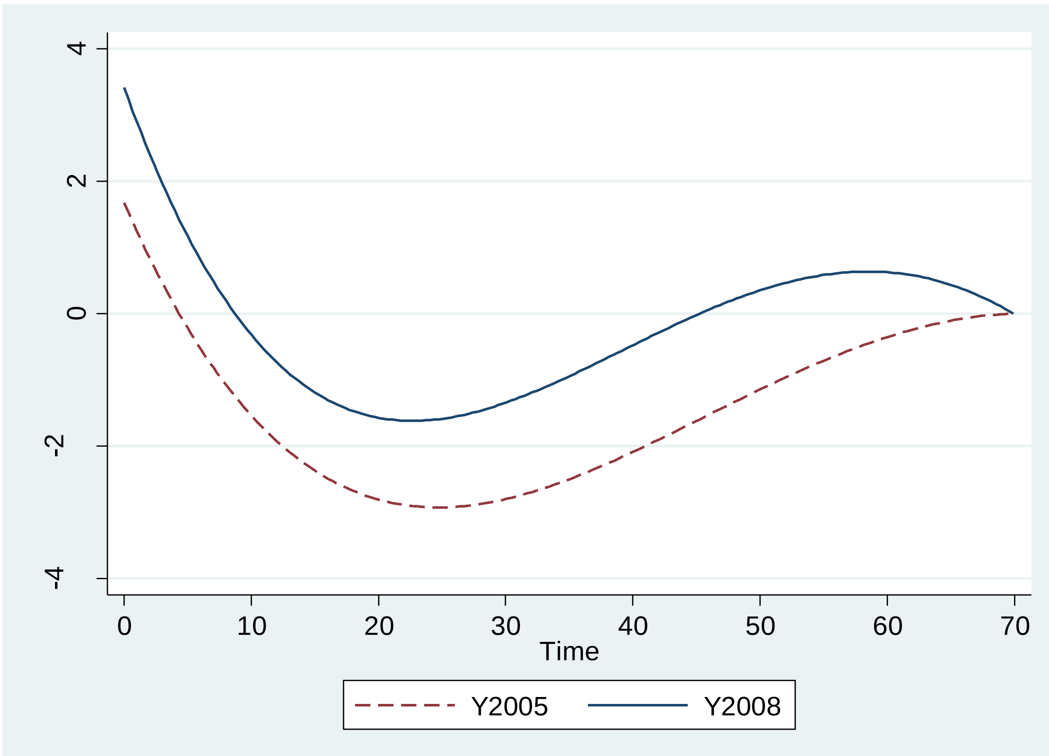
Table 2: Bootstrapped Estimates of Equation (4): Housing Construction

	2002	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Time	-0.0214	-0.0325	-0.0391	-0.3755	-0.4380	-0.5271	-0.4682
	0.0019	0.0016	0.001	0.0075	0.0077	0.0056	0.0511
$Time^2$	0.0006	0.0010	0.0012	0.0116	0.01295	0.01566	0.01644
	0.0006	0.0011	0.001	0.0059	0.0091	0.0063	0.0795
$Time^3$	-6.08E-05	-1.10E-04	-1.23E-04	-0.00012	-0.00013	-0.00016	-0.0002
	0.0003	0.0011	0.0016	0.0078	0.0104	0.0059	0.0976
$Time^4$	1.67E-07	3.31E-07	3.65E-07	3.54E-07	3.90E-07	4.78E-07	6.66E-07
	0.0005	0.0015	0.0024	0.009	0.0107	0.0062	0.1046
DIS-ln Distance to city	0.0095	0.0078	0.0085	-0.1691	-0.1358	-0.1372	-0.0815
	0.0029	0.05	0.06	0.0061	0.0351	0.0457	0.1417
Crime rate				-51.9218	-55.0836	-71.622	-80.84
				0	0.003	0	0.0001
Education				0.0852	0.0817	0.0833	0.1049
				0.001	0.0052	0.0132	0.0102
Land Reserves	0.0002	0.0003	0.0003	0.0032	0.0039	0.0043	0.0046
	0	0	0	0	0	0	0
Constant	3.2600	4.6500	5.9300	6.8798	8.4370	10.6370	9.1380
	0	0	0	0.0027	0.0013	0.0006	0.0012
N	1541	1536	1539	1,467	1,469	1,473	1,470
Adj, R^2	0.1690	0.1711	0.1962	0.1839	0.1973	0.1871	0.1649
χ^2				7.17	6.89	8.32	5.84
p-value				0.127	0.1418	0.0806	0.2112

Dependent variable: Cumulative Change in Housing Construction by SA 2000-2008, as a proportion of population in 1995.
See Notes to Table 1.

Figure 7 plots the diffusion schedules for treatment effects on cumulative housing construction in 2005 and 2008. These schedules show building contractors increased housing construction within 12 minutes travel time from the nearest intersection, at the expense of housing construction at intermediate distances. This substitution effect is strongest at about 25 minutes distance from the nearest intersection. Contractors seem to have engaged in spatial substitution within the treatment zone of TIH rather than between the treatment zone and the rest of the country. The latter would have implied that the diffusion schedules were always positive regardless of distance. The diffusion schedule for 2008 naturally lies above its counterpart for 2005 and the spatial substitution effect is weaker in 2008 than in 2005.

Figure 7: Spatio-temporal Diffusion of Treatment Effects on Housing Construction



4.3 Anticipatory Effects

In this section we investigate whether house prices and construction responded ahead of the inauguration of TIH in 2001. To investigate the former, equation (3) is estimated as in Table 1 using house price data that are available from 1998. Unfortunately, it is not possible to begin this investigation at an earlier date. Nevertheless, three years of data should be sufficient to indicate the presence of anticipatory treatment effects. In the case of housing construction the investigation begins in 1995. The anticipation effect is tested with respect to treatment status in 2004 since in 2002 TIH had only 3 intersections, but by 2004 it had 7 intersections.

In the case of house prices the polynomial order is 3 for 1999, 2nd order for 2001 and first order for 2000. The p-value for 1998 is much higher than its critical value. However, matters are different subsequently, suggesting that there is an anticipation effect that started in 1999. However, the p-values in Table 3 are larger than their counterparts in Table 1, suggesting that the anticipation effect is less statistically significant than its on-line counterpart.

Table 3: Bootstrap Estimates of Equation (3): Anticipated Price Response

	1999	**2000**	**2001**
Time	-0.0056	0.0008	-0.0007
	0.008	0.0014	0.0051
Time^2	0.0001		7.63E-06
	0.0241		0.0010
Time^3	-4.19E-07		
	0.0542		
ln distance to city	-0.0033	0.0003	0.0034
	0.008	0.3713	0.0034
Constant	0.1466	-0.05124	-0.0146
	-	-	0.2240
N	1255	1267	1288
Adj.R^2	0.01048	0.0074	0.0083
χ^2	10.33	7.98	0.94
p-value	0.016	0.0047	0.6255

See Notes to Table 1.

In the case of housing construction a 4th order polynomial is used throughout. The p-values consistently exceed their critical values. Therefore, in contrast to house prices, there is no anticipated effect in the case of housing construction. Figure 7 therefore includes the anticipated spatial diffusion schedule for house prices cumulated from 1999. It has been normalized at zero at 70 minutes travel time, and indicates that the anticipatory effect is largest but small (1 percent) in the immediate vicinity of TIH. Indeed, the treatment effect approaches zero when travel time exceeds about 20 minutes. By contrast, Figure 7 does not include any anticipatory response for housing construction.

4.4 Spatial Spillover

Thus far it has been assumed that although treatment effects diffuse spatially, the treatment effects are spatially independent, i.e. the treatment effect in a statistical area is independent of the treatment effects in neighboring statistical areas. Spatial weights are based on contiguity between statistical areas, and are row-summed to one. Table 4 reports the spatial autocorrelation coefficient (SAC) statistic (ρ in equation 5) which tests for spatial autocorrelation in the residuals of the models reported in Tables 1 and 2. The SAC coefficients for house prices have p-values less than 0.1 for about half of the years. According to the inverse chi-squared metastatistic the SAC coefficients are jointly statistically significant; the residuals are positively spatially autocorrelated, although the SAC coefficients are not large.

Spatial autocorrelation often implies that the spatial dynamics of the model are misspecified. This happens when there is a spatial common factor (Anselin 1988). Table 4 indicates that this is true for house prices but not for housing construction. In the case of house prices the SAR coefficients (λ in equation 6) are statistically significant in years in which the SAC coefficients are statistically significant. By contrast, in the case of housing construction none of the SAR coefficients is statistically significant (with the exception of 2008) regardless of the statistical significance of the SAC coefficients.

Table 4: Spatial Spillover

	Housing Construction		House Prices	
	SAR (λ)	SAC (ρ)	SAR (λ)	SAC (ρ)
1999			0.036 (0.343)	0.036 (0.345)
2000			0.132 (0.000)	0.128 (0.000)
2001			0.102 (0.100)	0.102 (0.012)
2002	0.027 (0.426)	0.065 (0.078)	0.042 (0.260)	0.033 (0.374)
2003	0.028 (0.408)	0.068 (0.067)	0.003 (0.004)	0.004 (0.036)
2004	0.028 (0.411)	0.068 (0.063)	0.070 (0.005)	0.007 (5.50E-04)
2005	0.029 (0.412)	0.063 (0.085)	0.003 (0.375)	0.043 (0.249)
2006	0.041 (0.225)	0.079 (0.031)	0.003 (0.449)	0.002 (0.510)
2007	0.054 (0.107)	0.091 (0.013)	0.026 (6.66E-16)	0.025 (9.92E-13)
2008	0.068 (0.045)	0.101 (0.005)	0.002 (0.065)	0.001 (0.072)

Estimated by maximum likelihood. P-values in parentheses.

The SAR coefficients for house prices, when significant, are small. They imply that there are modest spatial spillovers in treatment effects through which enhanced access in one statistical area enhances access in neighboring statistical areas. In short, access has its own epidemiology so that the whole is more than the sum of its parts. Alternatively, the social value of access is greater than its private counterpart. Since solving these spatial dynamics is complex, their strength and significance are small and limited, and do not apply to construction, in the next section we do not use these spatial estimates to calculate the value of access.

4.5 The Value of Access

We use the estimated treatment effects of TIH on house prices and housing construction embodied in the diffusion schedules in Figures 6 and 7 for 2008 to calculate the value of access in that year. According to Figure 1 the value of access in statistical area j has two components. The first is the increase in value of the incumbent housing stock (H_0) at the time TIH was inaugurated. This component equals $H_{0j}(P_{Tj} – P_{0j}) = Y_{Pj}$ where P_0 denotes the price before the inauguration (2001) and P_T denotes the treated price in 2008. The treated price equals the initial price plus the treatment effect for prices (at constant 2001 prices) or $P_{Tj} = P_{0j} (1 + TEp_{Tj})$. In the absence of data on initial housing stocks in 2001 (H_0) we impute it by using the census for 1995 to determine the number of households by statistical area in 1995, which is inflated according to the rate of growth in the number of households between 1995 and 2008 according to the census of 2008.

The second component is induced by the increase in housing supply resulting from TIH. Since the treatment effect for housing construction (TEh_j) in statistical area j is expressed in terms of square meters relative to the 1995 population, whereas the house price data refers to the average housing unit, we divide TEh_j by the average size of housing (s_j). The change in the housing stock attributed to TIH is therefore $\Delta H_{Tj} = TE_{hj}POP_j/s_j$. Finally, the second component of the value of access is $(P_{Tj} – P_{0j})[H_{0j}+\Delta H_{Tj} + \Delta H_{Tj} (H_{0j} + \Delta H_{Tj})/\beta] = Y_{Hj}$. According to most studies the price elasticity of demand for housing space is small. Bar Nathan, Beenstock and Haitovsky (1998) estimate the price elasticity of demand for housing in Israel at -0.2, which implies $\beta = 0.2H_0/P_0$. We use this estimate but we also use other assumptions. Note that because according to Figure 6 TEh_j is negative for statistical areas beyond 11 minutes travel time from TIH, Y_{Hj} may be negative.

The sum of the two components is $Y_j = Y_{Pj} + Y_{Hj}$, which is the willingness-to-pay for access to TIH in statistical area j. WTP varies because some statistical areas are more populated than others, and also because they vary in terms of their access to TIH. The total value of access is $Y = \Sigma_j Y_j$. The aggregate estimate of Y_P does not depend on β and is 256b shekels (2001 prices). The aggregate estimate of Y_H, assuming the price elasticity of demand for housing, is -0.2 is -15.9b shekels. It is negative because the positive treatment effects for housing construction up to 11 minutes travel time from TIH are outweighed by the negative treatment effects beyond 11 minutes. Y_H varies inversely with the price elasticity of demand for housing. If the elasticity is -0.5 Y_H = -6.3b shekels and it falls to -3.2b shekels if the elasticity is -1.

The total value of access is 240b shekels (2001 prices), or a quarter of GDP in 2008. This represents the present value of access to TIH. Using a discount rate of 5 percent this is equivalent to an annual WTP for access to TIH of about 1¼ percent of GDP in 2008.

5. Conclusions

The main methodological contribution in this paper is the extension of hedonic house pricing to the case where the housing stock depends on the intangible to be valued. Typically, hedonic estimates of benign and malign intangibles are under-estimated if their potential effects on housing construction are ignored. Specifically, access to TIH might affect housing construction as well as house prices. We find that housing construction increases in the immediate vicinity of TIH at the expense of housing construction at intermediate distances. As a result, the effect of housing construction on the value of access to TIH turns out to be relatively unimportant. This result could not, of course, have been known in advance, although it is consistent with the claim that contractors operate locally rather than nationally (Beenstock and Felsenstein 2015). It certainly cannot be taken for granted in other contexts where hedonic house pricing is applied.

A second methodological contribution concerns the use of bootstrapping in cases where the model residuals are not normally distributed. We note that most investigators rely on asymptotic theory and assume that the residuals are normally distributed without checking. Had we adopted standard practice we would have rejected good models simply because their residuals do not happen to be normally distributed. The need to check for normality and the use of bootstrapping is general and is not specific to the estimation of treatment effects, or hedonic pricing.

Third, because housing markets are likely to be spatially dependent, the estimation of spatial treatment effects should take account of potential spatial dependence between the treatment areas. Our results show that this is more important for house prices, where there is positive spatial spillover, than for housing construction. Positive spatial spillover implies that standard (non-spatial) estimates of treatment effects are biased downwards because positive treatment effects diffuse spatially.

There are asymmetries between the effects of TIH on house prices and housing construction. As already mentioned, the former are always positive whereas the latter may be both positive and negative due to spatial substitution. Second, there is evidence of spatial dynamics in house prices, but not in housing construction. Third, house prices began to increase three years before TIH was opened, but no anticipatory evidence exists for housing construction.

Finally, the willingness-to-pay for access to TIH is large. In 2008 it stood at 25 percent of GDP, which is equivalent to an annualized value of about 1¼ percent of GDP. The economic benefit of TIH is larger than this because apart from the value of access, it includes the value of using TIH. However, the latter may be estimated by road user charges since TIH is a toll road.

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