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Urban Complexity & Parameter Instability: Assessing Amenity Capitalization in the Presence of External Heterogeneity

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January 16, 2007

Abstract

In principle, spatial and temporal variations in the price of real estate within an urban area offer an excellent source of data with which any number of economic or policy questions might be addressed. Be it the value of proximity to public goods – schools, parks, pollution, etc. – or proximity to private goods – retail and consumption activities, for example – these locational amenities should be capitalized into property prices. It is on this premise that much of the empirical literature on access or proximity rests. Unfortunately, in a complex urban setting, common empirical approaches to measuring the value of proximity can be highly sensitive to choice of subsample and to the parameterizations of proximity itself. This is a direct result of an urban context in which distinct housing submarkets can exist even within small areas, variations across which swamp the relatively simple controls employed in traditional hedonic analysis. This paper demonstrates that external heterogeneity significant complicates traditional hedonic analysis and may preclude its use in complex urban land markets. In this setting, appeals to the Law of Large Numbers may be inappropriate. This paper reports the extent to which commonly-used empirical approaches produce widely inconsistent estimates using the example of a valuation exercise of proximity to mass transit. The paper proposes a more robust approach that offers a greater degree of confidence in parameter estimates. In contrast to the instability of parameter estimates under traditional models, the more robust, nonparametric approach yields a consistent finding of no significant capitalization of light rail into single-family home values.

†This paper has benefited from the comments and support of Genevieve Giuliano. Thanks to John Wilson, Jennifer Swift and USC's GIS Laboratory for help with problematic geocoding. I am grateful also to METRANS for providing financial support, and to Raphael Bostic and Jennifer Gold for their comments.

1. Introduction

Rarely do cities conform precisely to the specifications commonly used in the empirics of urban issues. Where concentric rings and monotonicity have venerable places in urban economic theory, their use in micro-level empirics can problematic. For example, urban theory predicts a decline of land prices and the density of land use with distance from the city center (Alonso 1964, Mills 1967, Muth 1969). However, the smoothness and symmetry found in the theoretical models of cities may be a poor guide to local land prices as they are influenced by secondary and tertiary employment centers, by irregularly scattered spatial amenities, and, more generally, by neighborhood idiosyncrasies. Indeed, the nature of neighborhoods – characterized by unique development and maintenance histories, complex coordination problems, externalities, and expensive adjustment costs – can lead to proximal neighborhoods that deviate substantially from one another and from general spatial trends. In this setting, common applications of hedonic analysis can lead to significant bias among parameter estimates.

Traditional hedonic analysis has focused on the heterogeneity among dwellings' structural characteristics, with a far more ad hoc approach to sources of variation that exist beyond a property's boundaries. But this *external heterogeneity* is comprised of omitted variables that may be spatially correlated with included variables and spatial variation in implicit prices that invalidate appeals to the Law of Large Numbers. This paper demonstrates that this external heterogeneity is a significant and regular feature of urban and suburban neighborhoods throughout the Los Angeles metropolitan area and – using the case study of capitalization of access to mass transit – that its presence significantly complicates traditional hedonic analysis. The paper reports pronounced instability in parameter estimates resulting from fairly innocuous decisions about model specifications and sampling frames. This distinct lack of robustness should serve as a red flag to policy makers. In the case of capitalization of light rail access into surrounding dwellings, for example, the choice of specification and sample is in effect an implicit choice of the estimated value of light rail. More problematic, however, is that this phenomenon – that of parameter instability in a complex urban setting

– is likely to be manifest in the empirics of myriad urban policy issues.

In exploring external heterogeneity and its influence on estimated parameters, it is necessary to examine standard applications of hedonic models (and more generally, "constant quality" methods) and the assumptions they require in order to recover unbiased parameter estimates. It is also necessary to further define and quantify the extent of external heterogeneity. At issue is whether the variation in a complex urban context swamps the relatively simplistic controls employed in the standard models. To be clear, complexity in this sense is not simply larger variance. Rather, it is systematic variation across neighborhoods, along major roads, around idiosyncratic historic locales, etc. – a patchwork of real estate submarkets resulting from decades of individual maintenance and investment decisions leaving a spatial arrangement of land uses and prices that follow only broad spatial trends, but defy simple parameterization locally. Note that this systematic variation is not the clustering of physical characteristics in the housing stock from neighborhood to neighborhood – which alone would not necessarily be problematic for traditional hedonic analysis. Rather, it is asymmetric exposure to omitted spatial amenities and the marked spatial correlation in the implicit prices paid for the physical attributes of dwellings.

Of course, these forms of misspecification are common concerns to empiricists, the relevant issue is whether or not the imposition of misspecified models in an urban context leads to significant bias in the parameters of interest. It may be that traditional hedonic analyses are sufficiently good approximations of the underlying relationships. This is a particularly important question for models used to measure the capitalization of local amenities into property prices because of the possibility that the proximity measures are measuring omitted sources of price variation. Estimating capitalization is commonly employed to assess how markets price proximity to locational amenities and disamenities alike (Bollinger and Ihlanfeldt 1997, Kahn 2001, Bowes and Ihlanfeldt 2001, Gayer, Hamilton, and Viscusi 2000, McMillen and Thorsnes 2003, Schwartz, Susin, and Voicu 2003, Linden and Rockoff 2006). In these types of studies, it is the capitalized value of the service flow (or cost) into dwelling or land prices that is used to estimate market valuation of proximity to a local amenity (or disamenity). Based on these estimates, assessments are made as to the net aggregate benefit (or cost) enjoyed (or borne) by local property owners. When the data afford a clean estimate of capitalization, this approach allows for a market-based assessment of the value of proximity which is generally preferred to contingent-valuation methods.

The central empirical challenge in measuring capitalization is the control for other factors correlated with proximity – occurring both among the housing attributes as well to other locational amenities and disamenities. Traditional hedonic approaches to this class of empirical problems have, however, typically employed parsimonious models with simple parameterizations of surrounding economic topography, and have pooled scarce sales data over relatively large areas in order to make feasible a variety of statistical techniques. Tractability, however, may have come at the cost of interpretability.

Bowes and Ihlanfeldt (2001) make clear that the measured effect of proximity to light rail is some combination of access to transit, access to associated retail and commercial activities, noise and pollution from increased congestion, and the increased exposure to crime. Moreover, they show that the effect of distance varies by station and by the income of the surrounding neighborhoods. A single coefficient on a single distance variable in a traditional hedonic cannot be reliably interpreted, nor can it be generalized. This is a specific example of external heterogeneity – variation in the set of spatial amenities and variation in how local markets price them. The assumption that there should be a spatially or temporally uniform price for any housing attribute seems to be associated with the notion that there are independent markets for them. In fact, the sellers of pools in Beverly Hills aren't competing in any direct sense with sellers of pools in Compton. Rather, they are competing with other sellers of bundled goods in Beverly Hills and other luxury submarkets. Prices for attributes are determined within submarkets and may vary widely based on the bundles of goods and the households that occupy them. In this context, appeals to the Law of Large Numbers may not hold – pooling observations across submarkets may lead to bias rather than convergence.

This paper documents the sensitivity of estimated parameters to model specification and choice of sample in a complex urban area using an exercise in the valuation of proximity to light rail in Los Angeles County, California. The results indicate that the implicit price of proximity to light rail stations varies markedly across commonly-used empirical models and sampling regimes. The range of parameter estimates is stunningly large, suggesting an equally wide range of prescriptions regarding the wisdom of light rail as a net social cost or benefit. The degree to which this case is representative of capitalization of other local amenities and related empirical research remains an open question. However, the primary conclusion of the paper is that parameters may be exceedingly difficult to interpret – whether they are statistically significant or not – because the measures of proximity in misspecified models pick up the substantial external heterogeneity that is common to urban areas.

Following Baum-Snow and Kahn (2000) and Gibbons and Machin (2005), this paper argues that parameter identification generally requires the use of time-series data. In addition, however, flexible statistical models are needed in order to control for *external* as well as *internal* heterogeneity. Identification is cleanest when neighborhood variation can be controlled for using observed sales that bracket the introduction of the amenity of interest – to make clean "treatment" and "control" comparisons that help hold neighborhood effects as constant as possible. Flexibility can come in many forms, but locally-weighted regression is employed in this paper to contrast results with more rigid specifications. Given temporal variation in the presence of a local amenity and flexible estimation, there appears to be – in contrast to the sensitivity of the traditional models – a relatively robust finding of no significant net capitalization of proximity into residential properties for either the Red or Gold Lines of the Los Angeles light rail system. This result speaks directly to the assessment of "value-capture" programs in which capitalization is taxed in order to fund investment in public goods. They appear to have little to offer in this setting and it may be necessary to revisit benefit-cost calculations that include capitalization estimates based on traditional analyses.

The paper is organized as follows. Section 2 examines a set of common empirical models to make clear the maintained hypotheses required to recover the implicit price of proximity to locational amenities – and the implications if they do not hold. The benefits of time-series data are also addressed. Section 3 introduces the data and illustrates the nature of the complexity that empiricists face in an urban area. Section 4 presents regression results using a variety of common empirical approaches as well as a more robust locally-weighted regression.

The paper closes with Section 5, a discussion of how the results may be interpreted and of their generalizability to the empirics of other locational amenities.

2 Modeling the Capitalization of Local Amenities

The central empirical challenge for assessing the capitalization of local amenities into property prices is the control of numerous sources of heterogeneity across properties. The literature most focused on this issue is the housing price index literature. There, a great deal of attention has been directed to the construction of so-called constant-quality price indexes. Common hedonic specifications focus on controlling for *internal* heterogeneity – that which is derived from variation in the physical characteristics of the structure and parcel. In fact, the most widely used of the "constant-quality" indexes, the repeat sales index, omits external variation by construction.[1] This section focuses on *external heterogeneity* and its influence on the performance of hedonic regressions in its presence.

The list of relevant external factors may usefully be grouped into three broad categories: club, environmental, and proximal factors. Club factors are those in which properties are either members of a distinct geographic club or not. These include school districts, municipalities, tax assessment districts, etc. Environmental factors are continuous variables with spatial tendencies but no point source per se, such as weather, crime, air quality, etc. For example, the air quality in the Los Angeles Basin generally declines from west to east, but there is no single point at which the air turns from "good" to "bad." Proximal variables are the variables of interest in this paper and include distances to local amenities like employment, retail and entertainment activities, open space, etc.[2] Of course, proximity to disamenities can be categorized analogously.

[1] As typically executed, the data used by this method are paired sales of homes that remain "identical" between two sales. These paired sales are defined as identical if they remain unchanged across internal (to the parcel) characteristics. Changes to external characteristic are implicitly attributed to aggregate price changes.

[2] Distance can be measured a number of ways: "as-the-crow-flies", travel distance, travel time, etc. The problems examined in this paper exist for all of them.

2.1 Cross-Sectional Hedonic Models

Using the notation of Gibbons and Machin (2005), a standard version of a cross-sectional hedonic regression is given in Equation (1).

$$(1) \quad \ln p_i = \alpha + \mathbf{x}_i'\gamma + f_i + \varepsilon_i$$

p_i is the observed sale price of dwelling i, $\mathbf{x}$ is a vector of dwelling and parcel attributes, and f_i is a neighborhood fixed effect. In principle, the neighborhood fixed effect will capture the "club"-type external variables, and, if the geography of the neighborhood is small enough, the "environmental" variables as well.[3] $\mathbf{x}_i'\gamma$ should capture priced variation in both the structure and parcel attributes of the property. In the presence of a single known local amenity, the standard hedonic is amended to incorporate the amenity and control for its systematic influence on dwelling prices. Using the example of a light rail station, Equation (1) becomes

$$(2) \quad \ln p_i = \alpha + \mathbf{x}_i'\gamma + d_i^s\beta^s + f_i + \varepsilon_i$$

The distance to the local amenity is d^s, with s in reference to a light rail $s$tation, which is used as an example in the empirical section.

Under what assumptions is the estimated parameter on distance to the light rail station, $\widehat{\beta^s}$, a consistent estimate of the true parameter, β^s? The three causes of concern outlined in the introduction were a) the presence of omitted variables correlated with distance to the local amenity, b) misspecified functional form of the relationship between distance to the station and the observed sales price, and c) inappropriate pooling from areas around the stations. First, consider the presence of a relevant external variable omitted from Equation (2). Assume for now that the omitted variable is the distance to nearest freeway ramp and is captured by d_i^r. Its omission in the regression implies that the residual contains both random noise, μ_i, as well as the omitted variable.

$$(3) \quad \varepsilon_i = d_i^r\beta^r + \mu_i$$

[3] This needs consideration on a variable-by-variable basis. For example, both ZIP Code- and Census tract-level dummies would capture variation in weather; but ZIP Codes may contain significant internal variation in crime, where census tracts may not.

If the distance to light rail station is correlated with the distance to the highway on/off ramp, the estimate of β^s will be biased when Equation (1) is estimated using least squares.

(4) $\rho(d^s, d^r) \neq 0 \quad \Rightarrow \quad \rho(d^s, \varepsilon_{it}) \neq 0 \quad \Rightarrow \quad \widehat{\beta^s} \neq \beta^s$

Is this a relevant problem? Are locational amenities spatially correlated? In the case of light rail, Bowes and Ihlanfeldt (2001) provide evidence that other locational amenities and disamenities are spatially correlated with rail stations. While they find that the direct effect of access dominates, both improved proximity to retail and heightened exposure to crime are associated with rail stations and are significant influences on surrounding dwelling values. More generally, mass transit is organized to provide service to high-demand locales – demand often created by dense retail and commercial activity which may also be capitalized into surrounding real estate prices. Disentangling the independent effects of proximity to mass transit would require measures of each. Without such data, cross-sectional regressions are not likely to produce robust estimates of the individual components of these bundled locational amenities.

The effect of misspecifying the relationship between distance to the station and its capitalization into dwelling prices can also been seen using the same framework. Assume that the true relationship is quadratic, but that the specification in Equation (2) is estimated. (Assume also that there is no second spatially correlated locational amenity – that there is no highway ramp to complicate this example.) As such, the quadratic term of the true specification of distance to the station is analogous to the omitted variable problem.

(5) $f(d^s) = d_i^s \beta_1^s + d_i^{s2} \beta_2^s$

(6) $\varepsilon_{it} = d_i^{s2} \beta_2^s + \mu_{it}$

And, as with the case of the omitted distance-to-ramp variable, the estimate of β^s will be biased. Furthermore, if other covariates are correlated with distance from the station, their parameter estimates may be biased as well.

2.2 Longitudinal Models

If certain locational amenities and disamenities are likely to co-locate, cross-sectional models that lack independent spatial variation among all priced amenities and disamenities will produce biased results – measuring a net effect rather than the value of proximity to any one amenity. Baum-Snow and Kahn (2000) recognize this and look for temporal variation in the distance to mass transit to identify its effect on a number of outcomes. They exploit the arrival of new stations that effectively change the distance from some dwellings to mass transit. If the arrival of stations is independent from the arrival of the other local amenities that are spatially correlated with distance to stations, then the independent effect of proximity can be measured.

Gibbons and Machin (2005) take this a step further and examine the difference-in-differences between changes in dwelling prices in a "treatment" group – which has experienced a change in the distance to the nearest station – and a "control" group – which has not. The general formulation for the differenced equations is as follows:

$$(7) \quad \ln p_{it} - \ln p_{i\tau} = \alpha_{it} - \alpha_{i\tau} + d^s_{it}\beta^s_t - d^s_{i\tau}\beta^s_\tau + \mathbf{x}'_{it}\gamma_t - \mathbf{x}'_{i\tau}\gamma_\tau + f_{it} - f_{i\tau} + \varepsilon_{it} - \varepsilon_{i\tau}$$

Gibbons and Machin (2005) apply this framework to two different groups: a treatment set of dwellings in post-codes which have experienced a change in distance to the nearest station (via the opening of a new station) and a control group of dwellings in post-codes that have not. Their difference-in-differences equation is

$$(8) \quad (\ln p_{it} - \ln p_{i\tau})^T - (\ln p_{it} - \ln p_{i\tau})^C = (d_{it} - d_{i\tau})\beta^s + (\varepsilon_{it} - \varepsilon_{i\tau})$$

where T and C index "treatment" and "control" groups, respectively.[4] Note the assumptions required to move from Equation (7) to Equation (8). First, in order for the attribute heterogeneity to drop out, both attributes and their implicit prices have to remain constant. Both of these assumptions prove inappropriate in numerous settings. Second, differences in the fixed effects have to remain constant. This is an empirical question, but numerous studies have

[4] To be precise, Gibbons and Machin (2005) estimate a linear spline function of distance to the stations. So, their version of Equation (8) includes an interaction term allowing for a different coefficient on the distance variable inside of and outside of a 2km concentric ring around the stations.

shown that submarkets have idiosyncratic price movements around the metropolitan price level (Mayer 1993, Case and Mayer 1996, Smith and Ho 1996, Ortalo-Magné and Rady 1999). This assumption is especially strong if the location choice of stations is endogenous and tied to expected changes in surrounding land and dwelling prices. If a station is a net negative for local property owners, it is likely to be fought most successfully where land prices are high and property owners are most able to fight the site choice. If, on the other hand, station location is a net benefit due to the redevelopment of blighted areas, the expected price path of the treatment group is higher than that of the control simply due to the removal of the blight – not necessarily due to the improved access to mass transit.

This scenario is analogous to the problem of omitted variables in cross-sectional models. Correlation between the amenity of interest and other local amenities and/or disamenities presents problems with interpretation even using time-series data. The contribution of both Baum-Snow and Kahn (2000) and Gibbons and Machin (2005) is to make use of "natural experiments" to improve identification of the value of proximity relative to cross-sectional models. Even here, however, the time-series data do not afford a test of competing hypotheses regarding the sources of improvement in relative house prices. For example, in addition to the alternative hypothesis that the removal of blight could be the cause of higher price appreciation nearer the station, so too could relatively larger investments in improvements and maintenance in areas nearer the station; newer stations may be designed explicitly with strong retail components from which surrounding dwellings benefit; also, it may be that with the redevelopment of the station comes the probability of having parcels rezoned to higher and better uses may rise – again, leading to a rise (in expected terms) of the rent flow from proximal parcels.

2.3 Sampling

The last of the three problems discussed in the introduction is inappropriate sampling – sampling across submarkets with different implicit prices on attributes. The case of inappropriately pooled data may or may not be considered similarly to the omitted variable examples, depending on the nature of the sampling errors. First, in a situation that is not analogous, consider the simple problem of the inclusion of properties outside the area in which proximity to the rail station is capitalized. Here the estimated effect would be understated (biased towards zero) as the contribution of proximity is averaged over the distance to all sampled dwellings, not just those for which it may, in fact, be relevant.[5]

In a more complex spatial setting, samples drawn from greater distances include observations from distinct property submarkets as well as those exposed to other locational amenities. Exposure to other local amenities that are not included among the regression covariates implies another version of the omitted variable problem – with the omitted variables correlated with distance by construction. The problem of distinct submarkets may be manifest in spatial correlation of dwelling attribute prices with distance from the station. It is easy to see how this may arise. Suppose there is a tendency for dwellings to have higher prices for their attributes as the distance from the station increases. By forcing the hedonic prices on these attributes to be constant across submarkets, bias is introduced to the distance measure meant to capture the market value of proximity to the station. A change in the specification of the functional form of the distance variable to log or quadratic may result in the impact of the rail line disappearing or becoming highly significant as the various functional forms pick up different influences from among any number of external sources of variation.

The neighborhood around the Allen Street station along the Gold Line in Los Angeles, for example, is comprised of a segmented housing market that complicates the analysis and interpretation of the regression estimates. A concentric ring of 1.5 miles from the Allen Street station includes neighborhoods of starter homes, older apartment buildings, gentrified historic bungalows and their less-well attended siblings, as well as luxury homes. In 2003 – the year the Gold Line began operation – this concentric ring around this station contained census tracts with median detached home sale prices from $187,000 to $550,000.[6] Note that these are tract-level medians and not measures of population dispersion. In the next section, it is shown that these price level differences are due, in no small part, to different

[5]This would be an appropriate situation for a spline of some sort, as in Gibbons and Machin (2005).

[6]These figures are calculated using tracts with at least 10 sales during 2003. If a minimum of five is used, the range widens from $187,000 to $1.11 million.

implicit prices on parcel and structure attributes. An appeal to the Law of Large Numbers is not appropriate when increasing the diameter of the sample area draws observations from different submarkets – with different hedonic price vectors. In this example, an additional observation may be from any number of submarkets and lead to bias, not convergence. It is an empirical question as to the appropriateness of pooling data – one that is examined below.

2.4 Flexible Estimation

Traditional hedonic specifications used to estimate capitalization rely on several assumptions that appear to be inappropriate in this data. First, implicit prices are not constant; they are neither uniform nor concentric across space or time. Rather, they are irregularly distributed in clusters – in what might be thought of submarkets. In this setting, the assumption that larger samples leads to better parameter estimates is also inappropriate. In this section, an estimation procedure is developed that relaxes this fixed-implicit price assumption.

The procedure is based on locally-weighted regression (or *loess*). Locally-weighted regression involves the estimation of a vector of slope parameters at each observation using a subsample of observations that are "close." Here "close" can refer to spatial proximity, temporal proximity, or to some other metric of similarity that might include spatial and temporal proximity as well as attribute proximity. As such, observations in any one local regression are what could be considered a set of close substitutes at the time of sale. The motivation for this is that implicit prices among close substitutes should be similar.

The specific set of observations used is determined by a similarity measure that is the Euclidean distance between observations across a number of dimensions:

$$(9) \quad d_{ij} = ((lon_i - lon_j)^2 + (lat_i - lat_j)^2 + (int_i - int_j)^2 + (det_i - det_j) + (d_i^t - d_j^t))^{\frac{1}{2}}$$

The "distance" between observations i and j is a function of spatial proximity (lon and lat, are longitude and latitude, respectively), structural similarly, and time of sale. int_i is the interior area of dwelling i, det_i indicates whether or not dwelling i is a detach single-family home. d_i^t is the date of sale; observations are included in the calculation if their sale falls in either the preceding or following quarter. Each of the variables in the distance equation is normalized so that all have standard deviations of 1 – ensuring that the similarity measure is not dominated by any one component due to its scale. The nearest 100 observations are included in each regression.[7]

The general specification of the regression at each point is given by

$$(10)\quad \ln p_i = \alpha_i + \mathbf{x}_i'\gamma_i + d^t + \varepsilon_i$$

where p_{it} is the observed sale price of dwelling i at time t, $\mathbf{x}_i'\gamma_i$ includes parcel and structural characteristics, and ε_i the residual. Because observations are drawn from a quarter before and a quarter after the observation's quarter of sale, d_t is a set of three quarterly time dummies, included to control for temporal variation within the sample period. Spatial variables are omitted; as within the smaller, local sample, they should be approximately constant. The effect of dissimilar observations – even from within the closest 100 – is minimized by estimating Equation 10 using weighted least squares, with weights given by Equation 11. Within the local sample, observations are weighted by a *kernel* function, with closer observations receiving more weight. The specific kernel used in this research is the commonly-used tri-cubic function, given by:

$$(11)\quad w_j = \left(1 - \left(\frac{dist_{ij}}{dist_i^{max}}\right)^3\right)^3 \quad ,$$

where w_j is the weight on observation j, $dist_{ij}$ is the distance from the point of the local regressions to the other observations within the window. $dist_i^{max}$ is the largest distance from the point of interest to any point within the window. In this way, observations receive decreasing weight – at an accelerating rate – as distance from the regression point increases; the furthest point receives no weight.[8]

The central tradeoff made when implementing the loess approach is between local accuracy and smoothness. The larger the sample size used in the local regressions, the smoother

[7] This is conditional on having no sales further than 0.75 miles away. Where there are less than 100 sales in the three-quarter/0.75 mile window, all sales are included. If this number is less than 50, the observation is excluded and no vector of implicit prices is estimated at that point. Generally this problem is encountered at the edge of the data. For this reason, the raw data is geographically more extensive than the data used in the capitalization exercise below. This is done to move the "edge" of the locally weighted regression area beyond the boundaries of the capitalization exercise.

[8] To be specific, the nearest 101 observations are included so that there are 100 observations receiving non-zero weights. For more on loess see (Cleveland and Devlin 1988). Urban applications include (Fu and Somerville 2001, McMillen and McDonald 1997, McMillen 1996, Meese and Wallace 1991).

the resulting prices will be: as more observations are used in local regressions, the resulting prices will be less reflective of local structure because the additional observations will be less and less comparable. In this research, the local sample size of 100 amounts to approximately 1.5 to 2.2 percent of the observed sales in each quarter.[9]

By estimating a vector of implicit prices at each observation it is possible to control for internal heterogeneity while leaving external heterogeneity intact. That is, by pricing a hypothetical dwelling with a typical set of attributes, structural and parcel variation are held constant explicitly, leaving spatial variation in dwelling prices solely a function of implicit prices and external factors. By looking to systematic differences in these "internally standardized" prices as a function of distance to light rail stations before and after a station's introduction, it may be possible to infer capitalization due to access to light rail. The locally weighted regressions also afford the opportunity for explicit tests of the assumptions required of traditional hedonic analysis in order to recover the parameters of interest.

3. Quantifying External Heterogeneity

Two parts of Los Angeles County form the basis for this research. The first are the approximately 100,000 parcels that produced sales of attached or detached single-family dwellings along the Red Line of Los Angeles' Metro from downtown's Union Station to the San Fernando Valley's North Hollywood station. The second is a similarly-sized set of observations from around stations along the Gold Line, which runs, again, from Union Station to the Sierra Madre Villa station in the San Gabriel Valley. Figures 1 and 2 map the parcels, as well as the location of the Red and Gold Line stations and the local highways and on/off ramp locations. The differences between the two maps are striking with regard to the relative proximity to stations and ramps. Along the Gold Line route, no station is more than a half a mile from a major freeway – in many cases, using the same rights of way as the freeways. In the first example of external heterogeneity, it is clear in this sample that distance

[9] Many different specifications of the similarity measure and different local sample sizes were tried. There appears to be little qualitative difference across choices. In general, a sample size was considered to be too small when the influence of individual vectors of implicit prices were visible in price surfaces. On the other had, the local sample size had to be quite large for the multi-nodal quality of the price surfaces to be smoothed into a single-peaked surface.

Figure 1: Red Line Parcel, Station, and Ramp Data

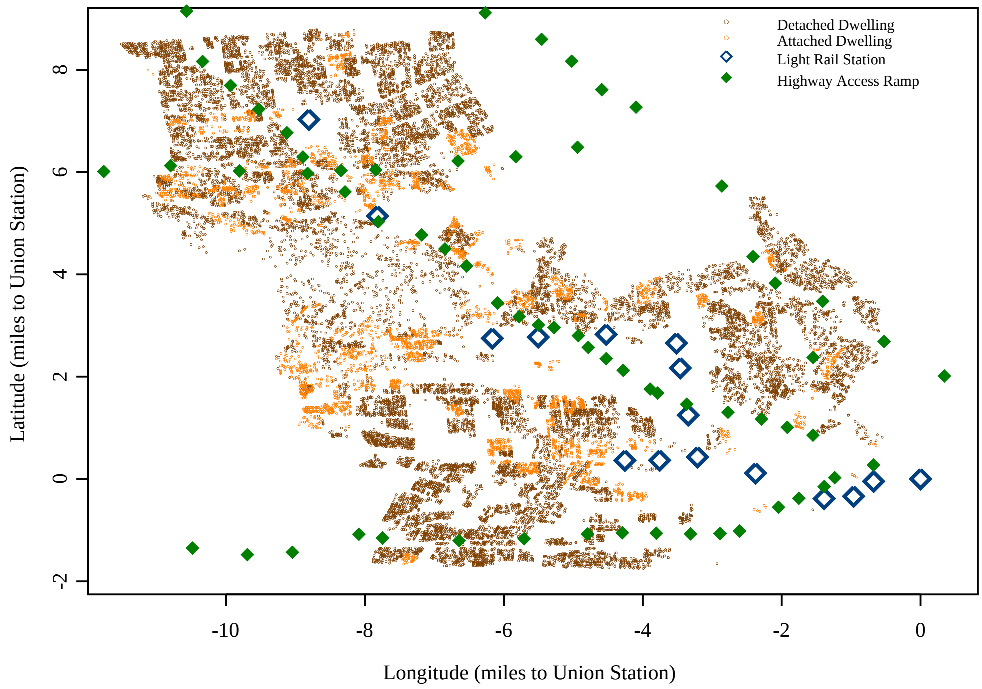
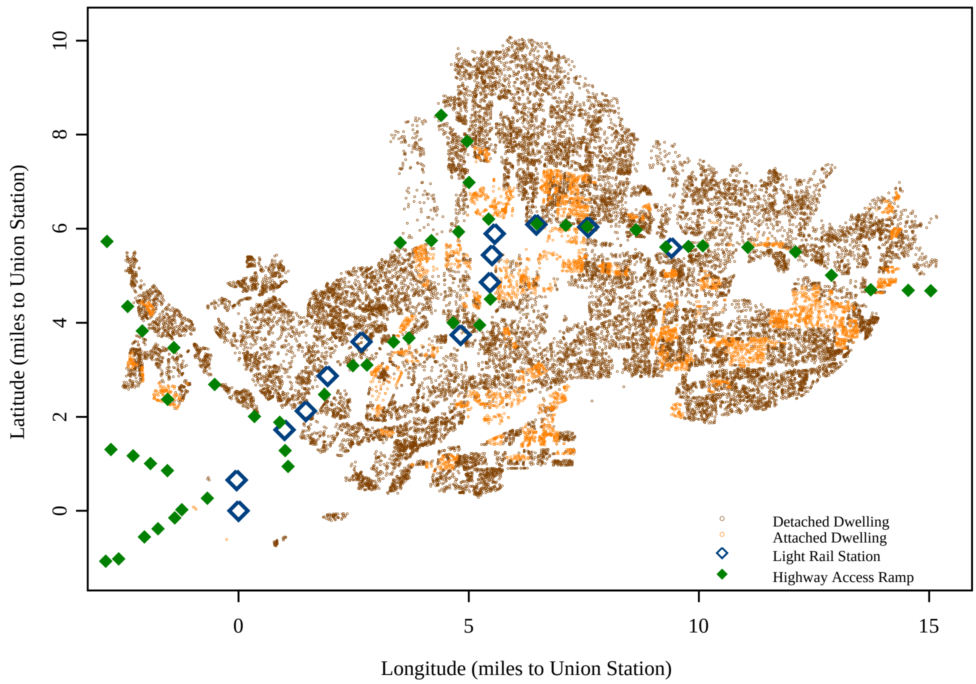


Figure 2: Gold Line Parcel, Station, and Ramp Data



from station can't be used alone to identify the independent value of proximity to mass transit, because a regression coefficient on a variable measuring distance to a rail station would capture the net effect of access/exposure to both the rail line and the freeway. Along the Red Line, the stations are located underground, incurring huge costs but obviating the dependence on freeway rights of way and offering independent variation between access to the two means of transit.

The data are constructed from two sources. The first is the Los Angeles County Assessor's Office, which records data on parcel and structure characteristics as well as transaction information, including sale price and date of sale. The second data source is the Los Angeles County Planning Department, which provides the GIS shape files from which the location of the parcels could be extracted.[10] The combination of these data allow for an inventory of parcel characteristics by neighborhood, as well as a variety of statistical methods aimed at identifying the independent influence of proximity to light rail stations on dwelling prices.

Tables 1 and 2 report standard summary statistics for several different samples from the Red and Gold Line observations. These are typical slices of the data, partitioned into attached and detached subsamples – in columns two and three – and into observations within and beyond a mile and a half from the nearest light rail station – in columns four and five.[11] The columns reveal an apparent similarity between the observations across the two lines and across the distance-based subsamples. There are several broad differences between the samples, but the differences in means are not significant given the large variances. For example, on average, detached dwellings are larger and on larger lots than attached dwellings.[12] However, the variances for both indicate that a wide variety of large and small dwellings comprise both samples. The trends in amenities is similarly vague: amenity sets are generally richer among detached dwellings than attached and dwellings further from light rail stations than those closer. Despite these differences, there is little evidence from these

[10] DataQuick accumulated and provided the parcel level and sales data. USC's GIS Laboratory extracted the longitude and latitude of each parcel.

[11] This is an arbitrary division of dwellings as "close" and "far" from light rail stations. It is common in this literature to use a reasonable walking distance to a station as an appropriate catchment area for stations. A mile and a half from the station represents the upper end of this distance.

[12] Attached dwellings are 2- to 4- unit single-family residences, and do not include condominiums.

Table 1: Red Line Means
(Standard Deviation in Parentheses)

Variable	All Obs.	Detached	Attached	< 1.5 mi	≥ 1.5mi
Observations	90398	66381	24017	57829	31649
closest.station.dist	1.33	1.40	1.14	0.93	2.07
	(0.67)	(0.67)	(0.64)	(0.36)	(0.43)
price	314245	317931	304153	322262	299597
	(270180)	(261594)	(292169)	(288062)	(233296)
int.area	1672	1690	1623	1695	1629
	(924)	(901)	(982)	(951)	(871)
lot.area	6560	7083	5126	6334	6973
	(11398)	(10920)	(12501)	(12507)	(9010)
bathrooms	2.05	2.03	2.10	2.08	2.00
	(1.06)	(1.05)	(1.09)	(1.09)	(1.00)
bedrooms	2.63	2.69	2.48	2.61	2.68
	(1.09)	(1.05)	(1.17)	(1.14)	(0.98)
garage	0.61	0.67	0.45	0.57	0.69
	(0.49)	(0.47)	(0.50)	(0.50)	(0.46)
pool	0.14	0.16	0.11	0.13	0.16
	(0.35)	(0.36)	(0.31)	(0.34)	(0.37)
view	0.10	0.11	0.07	0.11	0.08
	(0.29)	(0.31)	(0.25)	(0.31)	(0.27)
fireplace	0.48	0.52	0.39	0.48	0.49
	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)
owner.occ	0.86	0.86	0.84	0.85	0.88
	(0.35)	(0.34)	(0.37)	(0.36)	(0.33)

two tables that would support the notion that pooling observations might be inappropriate.

The level of aggregation of the samples in Tables 1 and 2 is shown to be too high in Figures 3 through 5, which suggests the relevance of external heterogeneity and the risks associated with ignoring it. Figure 3 shows the median age of sales by Census tract in the area around the Gold Line's Lake Street station. Clearly, this is an area of older housing stock with regions of substantially older dwellings immediately surrounding and to the south of the station. If implicit prices are, in fact, constant, this spatial heterogeneity is not problematic for traditional hedonic analyses. But, Figures 4 suggests that there may, in fact, be a problem with assuming of fixed implicit prices. It displays the mean residual by Census tract of the

Table 2: Gold Line Means
(Standard Deviation in Parentheses)

Variable	All Obs.	Detached	Attached	< 1.5 mi	≥ 1.5mi
Observations					
closest.station.dist	1.76	1.84	1.49	0.84	2.99
	(1.33)	(1.35)	(1.26)	(0.34)	(1.16)
price	277991	279165	274241	264468	296100
	(224604)	(220643)	(236783)	(230117)	(215681)
int.area	1629	1640	1594	1509	1788
	(933)	(920)	(971)	(830)	(1033)
lot.area	7461	7996	5748	6570	8654
	(8323)	(8684)	(6769)	(8231)	(8297)
bathrooms	2.07	2.03	2.21	1.94	2.25
	(1.05)	(1.05)	(1.04)	(0.95)	(1.15)
bedrooms	2.76	2.81	2.60	2.60	2.96
	(1.04)	(1.02)	(1.09)	(1.03)	(1.01)
garage	0.62	0.69	0.39	0.57	0.68
	(0.49)	(0.46)	(0.49)	(0.49)	(0.47)
pool	0.12	0.13	0.10	0.09	0.17
	(0.33)	(0.33)	(0.31)	(0.28)	(0.38)
view	0.07	0.08	0.01	0.07	0.06
	(0.25)	(0.28)	(0.11)	(0.25)	(0.24)
fireplace	0.46	0.51	0.32	0.44	0.49
	(0.50)	(0.50)	(0.47)	(0.50)	(0.50)
owner.occ	0.89	0.90	0.86	0.88	0.90
	(0.31)	(0.30)	(0.35)	(0.32)	(0.30)

following regression:

(12) $\ln p_{it} = \alpha + \mathbf{x}_{it}'\gamma + d^t + \varepsilon_{it}$

where all variables are as previously defined, with $\mathbf{x}$ including the log of interior size, the log of parcel size, the number of bathrooms, the number of bedrooms, the presence of a garage, pool, or view, the log of dwelling age, whether the dwelling is attached, and whether or not the dwelling is the owner's primary residence.

Figure 4 suggests that the pooled, constant-implicit price regression residuals are also clustered – in this case, north and east of the station as well as to the south. While a variety of factors could explain this, Figure 5 suggests one likely contributor. It shows the median implicit price on the log of age from the locally weighted regressions aggregated by Census

Figure 3: Median Dwelling Age by Tract: Lake St. Station Neighborhood

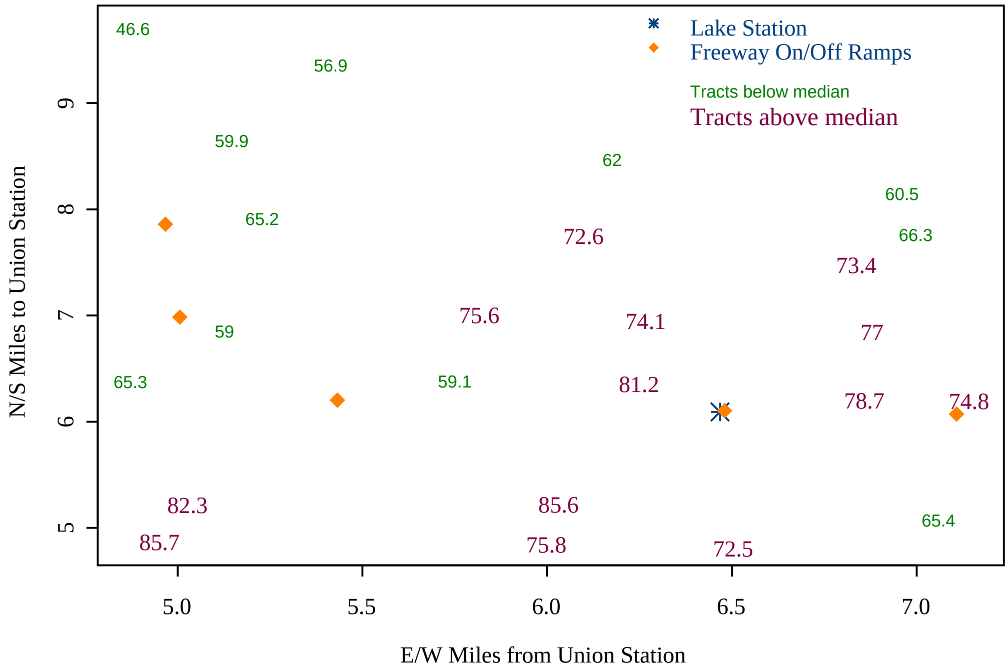


Figure 4: Mean Residuals by Tract: Lake St. Station Neighborhood

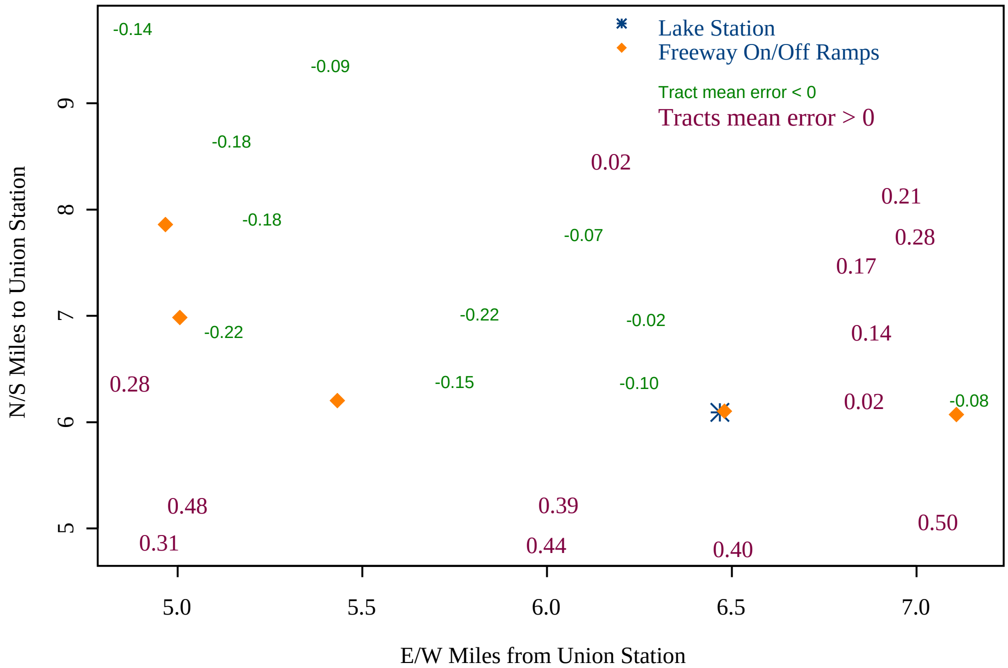
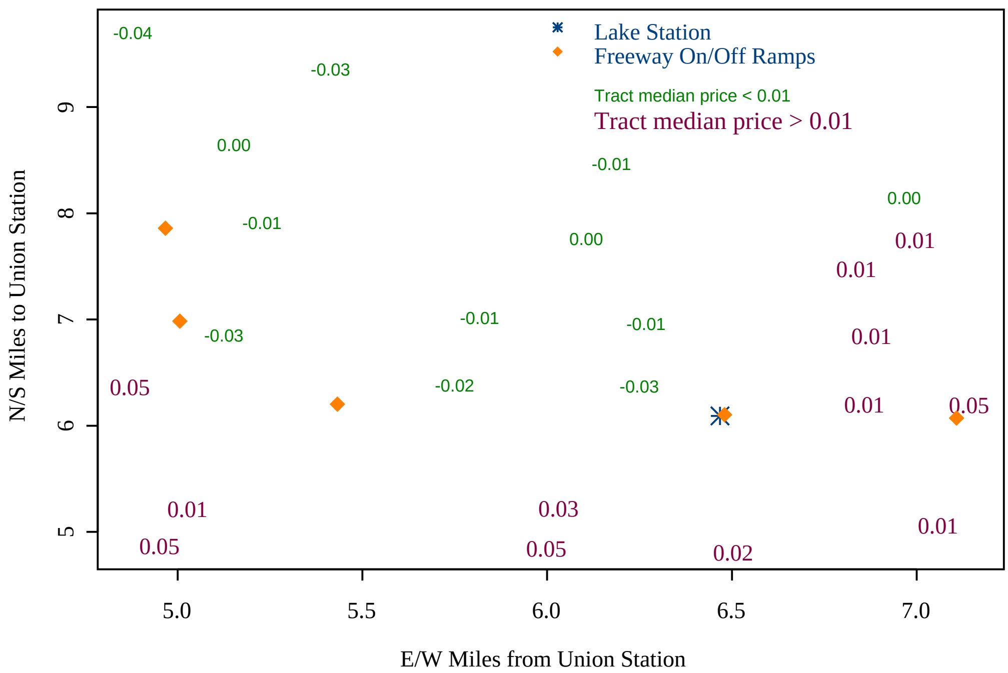


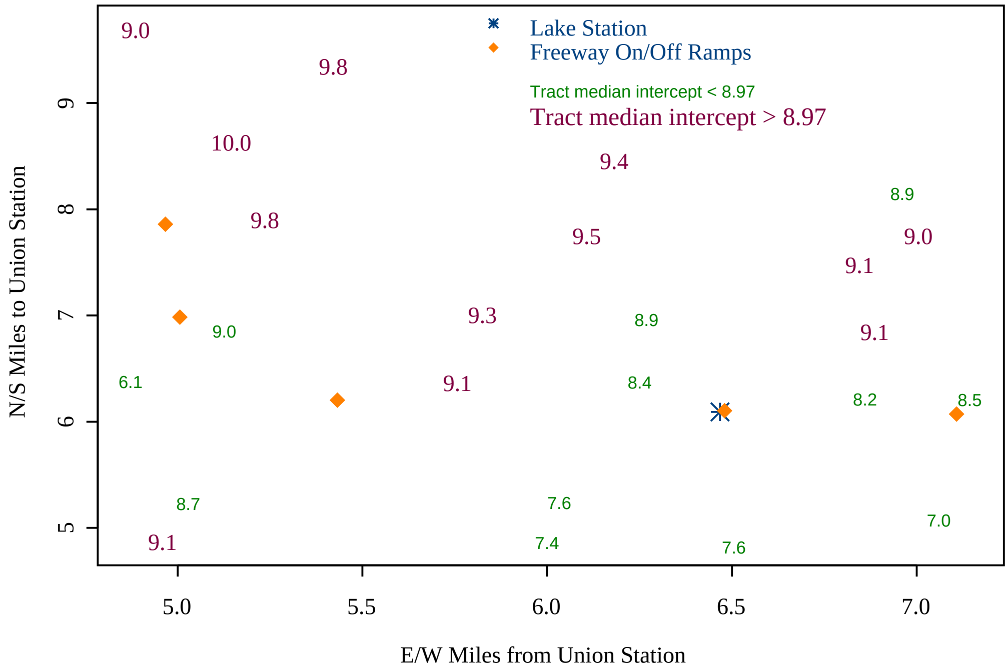
Figure 5: Median Implicit Price on log(Age) by Tract: Lake St. Station Neighborhood



tract. The patterns apparent in it are quite similar to that of the tract residuals shown in the previous figure. The implicit prices are generally higher where homes are oldest – in historic neighborhoods in which older homes are desirable. The post-WWII homes found in the other tracts appears to be less valuable as they age, reflecting depreciation of structures generally thought to be less valuable than their older, pre-WWII counterparts. The difference in implicit prices makes sense: among historic homes older dwellings may be more valued, while among a newer vintage of homes, they may not be. Moreover, the difference in local prices of age appear to contribute heavily to the clustered residuals shown in Figure 3, as the correlation between the tracts' median implicit prices on the log of age and the tract mean residual is 0.66.

It should be noted that the implicit price on the log of age from the traditional hedonic regression – using the pooled observations from the Lake Street station neighborhood and constant implicit prices – is 0.064, which is higher than *any* of the tract median prices. This is due to the fact that more of the price variation in the pooled sample is forced to be explained via variation in the structural characteristics; there are no other sources of variation to explain the variation in dwelling prices. The intercept captures the average land value of the entire sample, when it is not likely that this is constant across such varied submarkets. Figure 6 shows exactly this, demonstrating that no tract median intercept is

Figure 6: Median Intercept by Tract: Lake St. Station Neighborhood

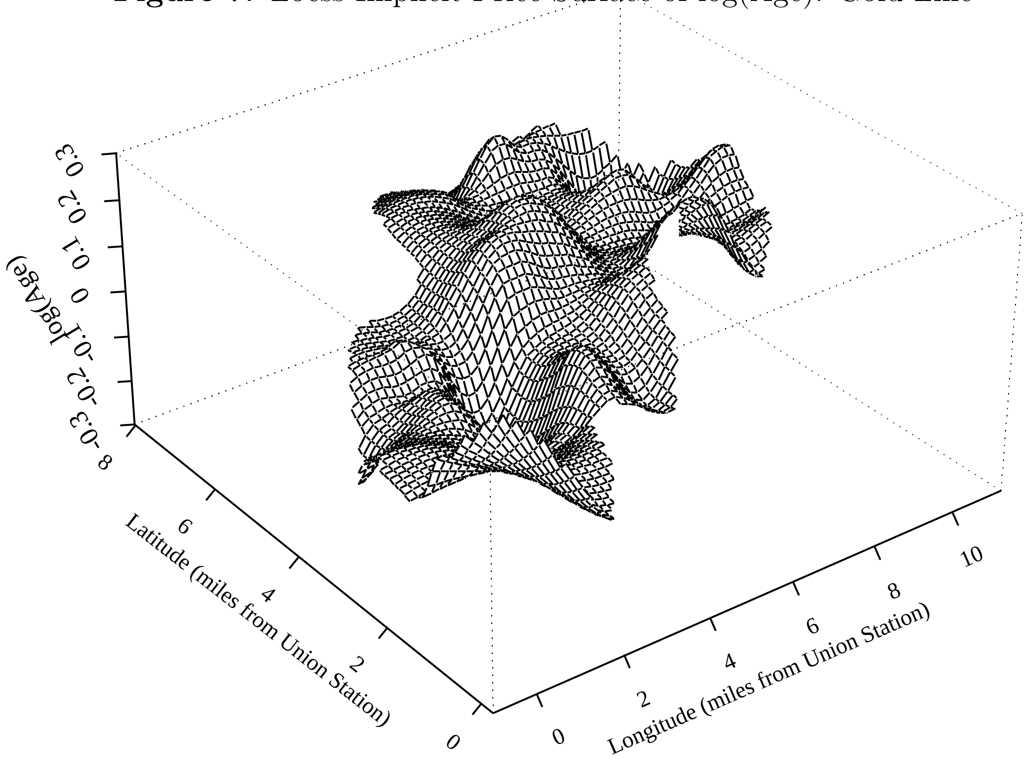


less than the pooled regression intercept of 5.763. Again, this is intuitively appealing in that within a neighborhood, implicit prices should be smaller than in a pooled sample across neighborhoods: move a house to various locations on the same street and it's unlikely that the house's value would change – but, move it to various locations across town and dramatic shifts in its value are likely.

Note, too, that within the flexibility of the local regressions is nested the possibility of both constant implicit prices as well as constant implicit prices with intercept shifts by neighborhood. One common approach when neighborhood heterogeneity is a concern is to append to a standard hedonic regression a set of dummies to capture neighborhood fixed effects. This approach is difficult in practice, because neighborhoods are hard to define *a priori* (and because hard boundaries with discrete price changes seem inappropriate for all but the obvious cases of jurisdictional differences). In fact, the results of the locally weighted regressions provide evidence to reject this specification. By estimating regression locally, it was possible for the intercepts to vary while allowing the implicit prices on the structural and parcel characteristics to be constant. This appears not to hold in Figure 5, and is more formally tested below.

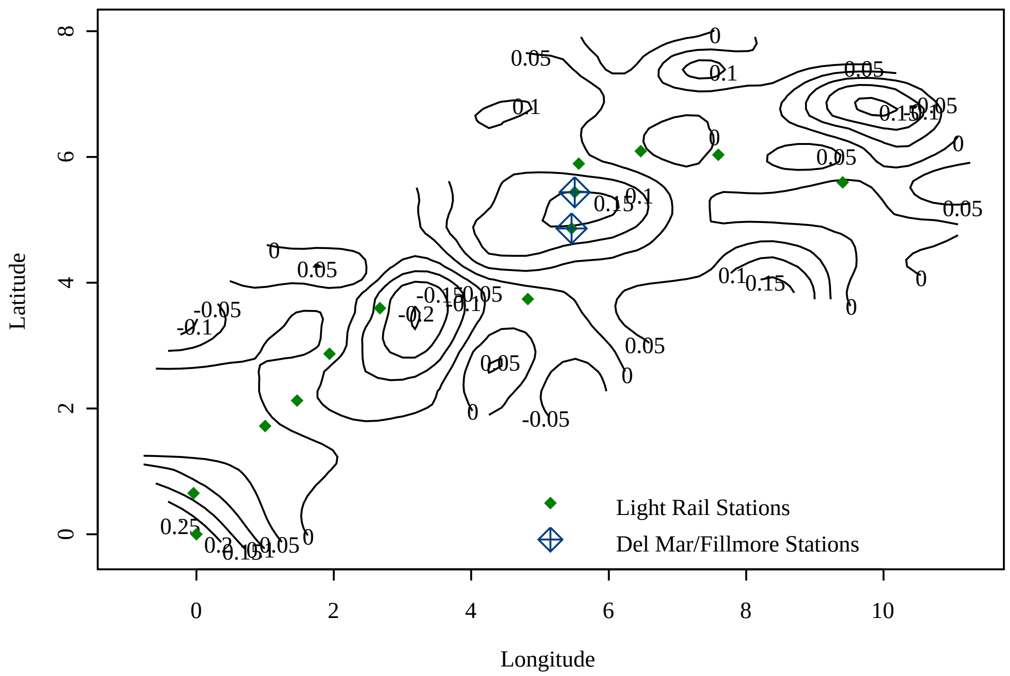
Figure 7 shows the price surface for the coefficients from the locally weighted regressions

Figure 7: Loess Implicit Price Surface of log(Age): Gold Line



for the 1997 cross section of the Gold Line sample. It generalizes the results shown in Figure 5. Like the more localized figure, the price surface shows pronounced fluctuations in the implicit price of age over the sample area. While the median coefficient is close to zero (-0.006), both the min/max (-0.427/0.355) and interquartile (-0.071/0.058) ranges are quite large. Figure 8 displays the same surface on a contour map, with station locations superimposed on top. Again, the relevance of external heterogeneity for studies of capitalization can be readily seen in the neighborhood around the Del Mar and Fillmore stations. Here, the implicit price of age falls quickly to approximately zero within about two miles of the stations. In a constant implicit price regression using data from around these two stations, this spatial variation in implicit prices would be attributed to a variable capturing distance to the light rail stations.

Figure 8: Loess Implicit Price Contour of log(Age): Gold Line



In this case, it is easy to see one source of bias in the capitalization exercise. Over the rest of the sample area – around other stations – there are other regularities that may contribute to other sorts of bias in the traditional hedonic analyses. The spatial organization of the implicit prices of the remaining structural and parcel characteristics are equally resistant to simple explanation or parameterization, meaning that the size and direction of the bias will be unknown. Furthermore, they appear to evolve idiosyncratically over time – the time series of surfaces for each implicit price are significantly correlated from period to period, but the correlation coefficient is less than one.

Collectively, these figures raise two issues. The first is the extent to which the variances reported in Tables 1 and 2 are the relevant distributions to consult when considering pooling observations. If there are analogous implicit price distributions that are not aspatial, and if dwellings' implicit price vectors are drawn from a large number of distributions by neighborhood, then the Law of Large Numbers may not hold in the traditional – pooled – empirics of urban issues. The systematic irregularity in the implicit price surfaces in Figures 5, 7, and 8 suggest that the overall variation in dwelling value results in no small part from variation in implicit prices that is greater across neighborhoods than within them.[13]

This conjecture can be tested by partitioning the sum of squares into that from the variation from across-tract differences and that from within-tract differences. By treating the observations from each tract as a sample, it is possible to test the hypothesis that the samples share a common mean. Equation 13 gives the test statistic

$$(13)\quad U^2 = \frac{S^2_{across}/(c-1)}{S^2_{within}/(n-c)}$$

U^2 is distributed F with $c-1$ and $n-c$ degrees of freedom. S^2_{across} is the sum of squares:

$$(14)\quad S^2_{across} = \sum_{i=1}^{c} n_i(\widehat{X}_i - \widehat{\widehat{X}}_i)^2$$

c is the number of Census tracts, $\widehat{X}_i$ is the mean of variable X in tract i. $\widehat{\widehat{X}}_i$ is the population mean. This represents the variation arising from difference across tracts. The second sum of squares on the right-hand-side of Equation 13 is the variation that results from deviations of dwelling attributes around the mean attribute level in their tract and is calculated by

$$(15)\quad S^2_{within} = \sum_{i=1}^{c}\sum_{j=1}^{n_i}(X_{ij} - \widehat{X}_i)^2$$

where n_i is the number of observations in tract i.

Tables 3 and 4 report a set of statistics regarding the appropriateness of constant implicit prices within a pooled regression model. The first column of each table reports the estimated coefficients on the independent variables for both the Red and Gold Line samples. (The set of coefficients on the quarterly time dummies have been excluded.) All of the reported coefficients from the pooled regressions are significant at the one-percent level. Interpretations of these coefficients is familiar, with interior area, lot size, the number of bathrooms, and the other amenities being significant contributors to overall home values. The negative coefficient on bedrooms is indicative of smaller rooms, as total living area is held constant. The age variable – which has been the source of some discussion (Coulson and Lahr 2005) as either a measure of depreciation or measure of historic content – is positive, suggesting that on average the variable captures the perceived value of the older dwellings in the sample.

[13] This is not the first observation that the common assumption of fixed implicit prices is rejected in practice and may be problematic for the recovery of population parameters. See, for example, Meese and Wallace (1997).

Table 3: Tests for Equivalent Distributions: Red Line

	Pooled OLS	Locally Weighted Regression			
Variable	Coefficient	Coefficient	% > 0	F-Statistic	P-Level
Intercept	6.04	9.67	1.00	19.06	0.00
log(Int. Area)	0.70	0.29	0.90	15.36	0.00
log(Lot Area)	0.13	0.10	0.74	18.31	0.00
Bathrooms	0.09	0.00	0.51	7.01	0.00
Bedrooms	−0.10	−0.01	0.44	5.12	0.00
Garage	0.15	0.05	0.61	7.11	0.00
Pool	0.20	0.07	0.74	5.87	0.00
View	0.27	0.04	0.65	14.87	0.00
log(Age)	0.06	−0.04	0.49	25.25	0.00
Attached	−0.13	0.00	0.49	6.57	0.00
r2	0.55	0.43	1.00	23.36	0.00

Table 4: Tests for Equivalent Distributions: Gold Line

	Pooled OLS	Locally Weighted Regression			
Variable	Coefficient	Coefficient	% > 0	F-Statistic	P-Level
Intercept	4.83	8.98	1.00	41.42	0.00
log(Int. Area)	0.76	0.34	0.93	40.94	0.00
log(Lot Area)	0.20	0.11	0.80	29.16	0.00
Bathrooms	0.06	0.00	0.49	8.21	0.00
Bedrooms	−0.07	−0.01	0.43	7.93	0.00
Garage	0.13	0.04	0.62	12.54	0.00
Pool	0.16	0.05	0.70	7.04	0.00
View	0.00	0.04	0.61	12.73	0.00
log(Age)	0.05	−0.01	0.47	21.85	0.00
Attached	−0.05	0.00	0.47	12.07	0.00
r2	0.61	0.47	1.00	51.73	0.00

The second column in both tables reports the average coefficient on the same set of variables from the locally weighted regressions. The signs are generally consistent with the pooled regression coefficients, with two exceptions: the coefficients on dwelling age and the indicator or whether the dwelling is a unit in a duplex, triplex, or four-unit structure. These exceptions are potentially informative as to the role of an estimated parameter in a fixed-coefficient hedonic regression in the presence of external heterogeneity. In the case of age, the average locally weighted regression coefficient is negative, perhaps because it actually captures depreciation where the pooled coefficient picks up neighborhood differences across older and newer parts of the sample areas. In the locally weighted regressions, these neighborhood differences are found in the intercept – as all observations used in each local regression should be (approximately) from the same neighborhood. Here, within neighborhoods, differences in age are more likely to reflect depreciation. A similar story can be told for the coefficient on the attached variable: more expensive neighborhoods are those where there are fewer attached units. In either case, variation in a structural characteristic picks up variation due to external heterogeneity and may significantly bias the resulting coefficients.

With regard to the spatial distribution of implicit prices, both tables report that the null hypothesis that the set of Census tracts simply represent different draws from the same distributions can be flatly rejected. The p-level for the test statistic for each of the housing characteristics is zero.[14] It is clear that sampling across neighborhoods – as proxied by Census tracts – implies drawing from distinct distributions of implicit prices for these attributes.[15]

One further comparison makes clear the last step in the locally weighted regression approach to constructing a constant quality price surface. Once the locally weighted regressions have been estimated, the vectors of local hedonic coefficients allow the same dwelling to be priced at each location and time period. In this case, the "standard" Red Line dwelling contains 1605 square feet of interior area, on a lot size of 6650 square feet. It has two bathrooms, three bedrooms, and a garage, but no pool or view. It is detached, with an owner-occupier, and is 62 years old. These attributes are the mean of the Red Line sales' continuous variables and the median of the dichotomous variables. This standard dwelling is then interacted with the local implicit prices to arrive at Figure 10, the smoothed surface of standard prices over the Red Line sample area. This surface should be compared with Figure 9, which is the analog using actual sales prices. Both figures use 1997 data.

On both of the figures two local maxima and two local minima are indicated for illustrative purposes. The maxima are the neighborhood around the Wilshire Country Club (to the south) and the neighborhood around Laurel Canyon (to the north). The ratio of their

[14] Note that this is not simply a function of the choice of Census tracts as the unit of geography. The same results hold testing within- and across-variation using ZIP codes. Furthermore, similar results hold for both the aggregate samples as well as for station-by-station tests. There are a handful of exceptions in the station-by-station tests, but these are generally from stations with fewer owner-occupied dwellings around them.

[15] While the tests reported in the tables are for 2000, the same holds in each of the annual cross-sections of prices from 1988:I through 2004:II. Moreover, the distributions of prices appear to evolve somewhat independently over time, so that even the relationships among implicit prices are not constant over time.

Figure 9: Contour of Observed Dwelling Prices: Red Line

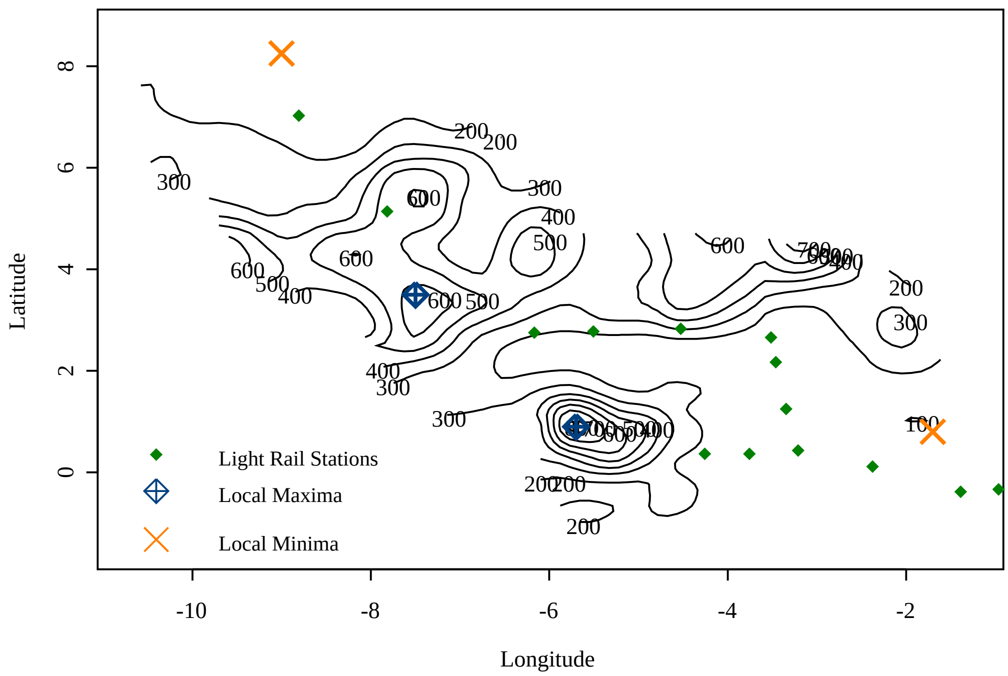
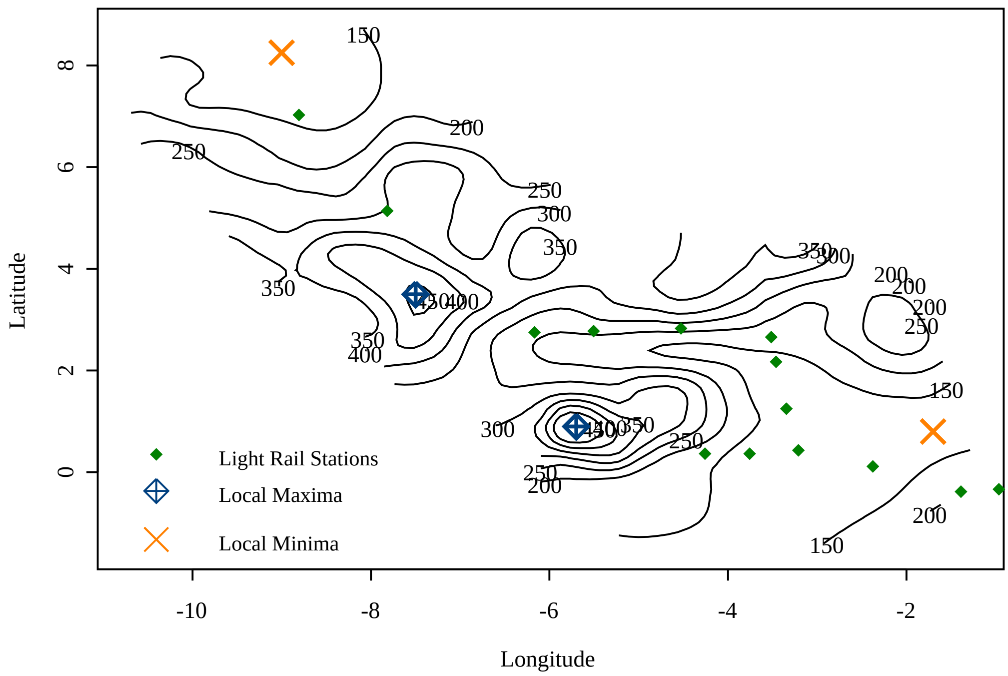


Figure 10: Contour of Standardized Dwelling Prices: Red Line



prices varies between the two figures, indicating that the dwellings around the Country Club are more expensive due to greater size and structural amenities, while the underlying locational amenities are approximately equal in value. The relative low regions indicated in the northwest and southeast of the figure are more expansive using the raw prices. Using the standardized dwelling characteristics suggests that the relatively large flat areas of low prices are not due to constantly low quality and low locational amenity value. Rather, it appears that the balance of value shifts – with the external amenities rising more rapidly away from the indicated local minima than overall prices. One feature of the surfaces is particularly noteworthy. As expected, the surface of standardized dwelling prices is smoother than the observed price surface in terms both of range and number of peaks and troughs. While there remains a great deal of implicit price variation, the parcel and structural variation has been removed by using a "standardized" dwelling.

4. Estimating the Value of Access to Light Rail

Having employed the flexible loess procedure to develop a constant quality price surface, it is now possible to explore how locally weighted regression can be used to estimate the value of access to a local amenity. Earlier, it was argued that a single cross section of data would be unlikely to provide clean identification of the capitalization of access because of the many confounding spatial factors that exist in urban areas. Rather, following Baum-Snow and Kahn (2000) and Gibbons and Machin (2005), differences in price appreciation of dwellings will be looked for in areas around the new light rail stations. Fortunately, numerous stations opened along the Red and Gold Lines during the sample period. The Red Line extension from the Wilshire and Vermont station to the North Hollywood station was opened over the 1999/2000 period, so appreciation is calculated from 1997 to 2002. This allows for anticipation effects (McMillen and McDonald 2004) as well as a period of market learning after the opening. For the Gold Line, which opened in July of 2003, the before and after periods are 2002 and 2004.[16]

[16] The Gold Line window is smaller because the data end in 2004, precluding a longer period of examination. The earlier opening of the Red Line extension offered numerous combinations of control and treatment years – none produced qualitatively different results.

The estimation of capitalization proceeds in two ways. The first is to examine aggregate (internally standardized) price changes by Census tracts before and after station openings.[17] The standard dwelling attributes are priced at each observation using the local regression estimates of implicit prices. The median of dwelling prices within each Census tract will be calculated for a control year – two years prior to a station opening – and a treatment year – two years after. Appreciation in standardized prices will be regressed on distance to the light rail stations.

The second approach is to look for potential omitted spatial amenities that might better explain the pattern of local appreciation. One problem with the first approach is that while prices may have appreciated faster near the station than further, this average relationship may mask other dynamics. That is, suppose the source of higher appreciation is the growth of local retail options, at the end of which the new station is located. On average, appreciation will decline with distance from the station. However, this could be due to declining access to the retail strip, and using the center of the retail strip may better explain the pattern of local appreciation. This is an attempt to ascertain the weakness of statistical tests based solely on the station location without regard to other local amenities that may be the source of asymmetric price capitalization.

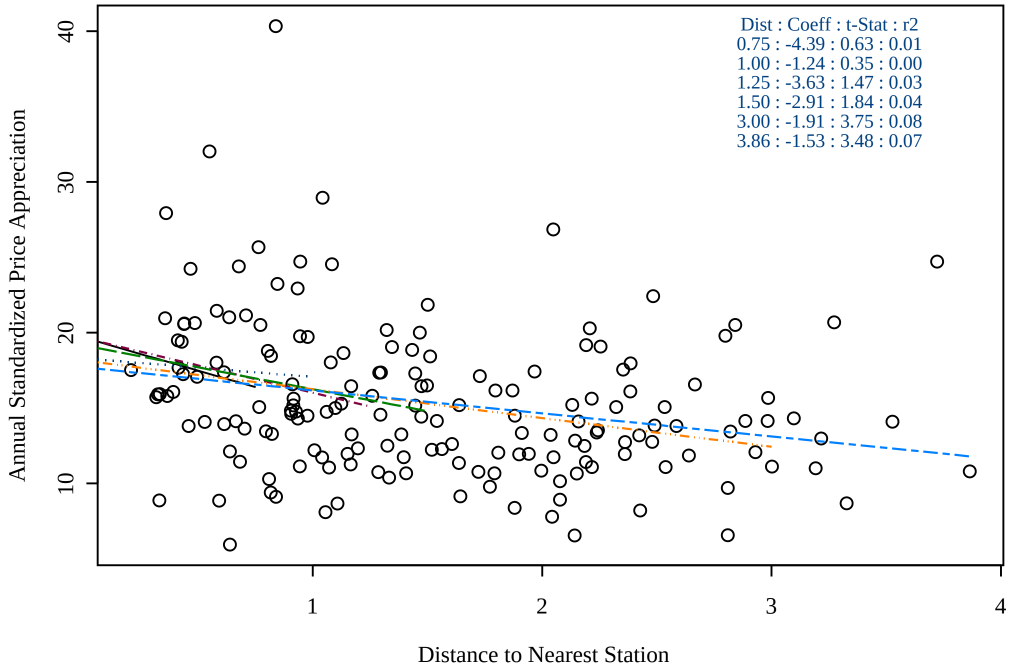
This second approach is based on an estimated price appreciation surface over a catchment area around the stations. Using predicted prices – for the standard attribute set – it is possible to estimate a surface of prices using simple spatial averaging. Differencing standard dwelling price surfaces before and after station opening creates a third surface that can be examined for systematic price appreciation that is a function of proximity. This second capitalization test lets the data determine the locale of the point that best describes the center of a negative exponential model.[18] If improved access to light rail via the introduction of a new station were indeed the cause of higher appreciation, then this second approach should locate the center of the appreciation at the station's locale.

[17]Tract-level analysis is undertaken rather than employing individual dwelling appreciation because the use of the standardized dwelling explicitly holds constant the attribute sets over time. Note that the temporal evolution of implicit prices invalidates a basic assumption of the repeat sales estimators.

[18]Several different parameterizations of a distance decay function were attempted. All yielded the sample qualitative result.

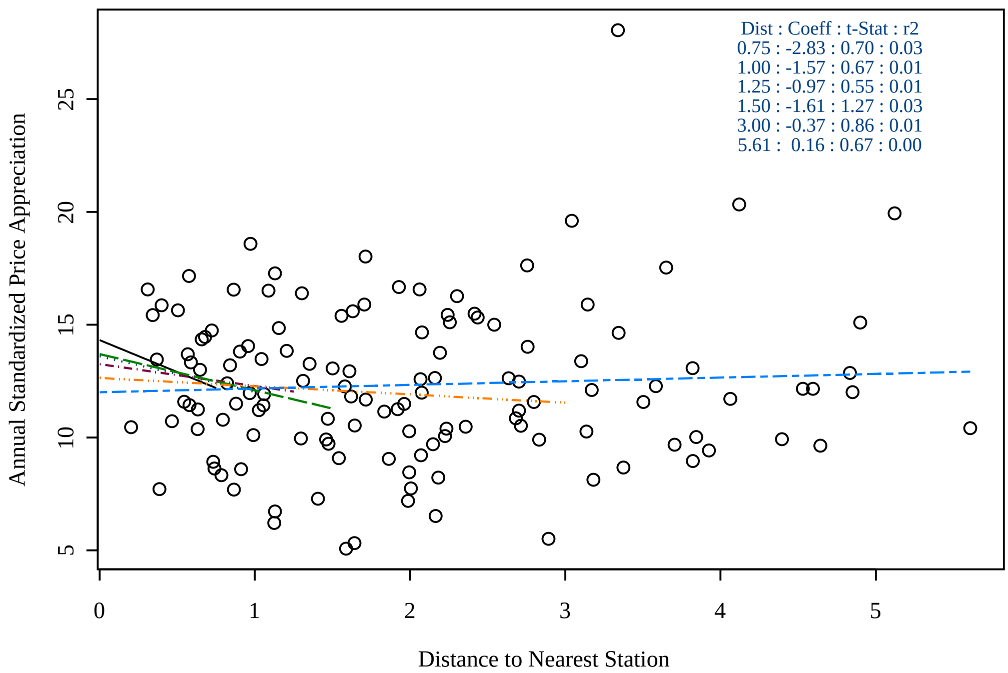
Figures 11 and 12 plot median tract appreciation against the distance to the nearest

Figure 11: Median Tract Price Appreciation & Distance to Station: Red Line



light rail station for the Gold and Red lines, respectively. To the extent that the new station advantages proximal locations, there should be a significant downward slope away from light rail stations reflecting that the newly capitalized amenity. The figures reveals no clear trend. The lines superimposed on the scatter plot are regression lines in which price appreciation is regressed on distance to the nearest light rail station over a number of different catchment areas. None of the regressions along the Gold Line have a significantly negative slope. Along the Red Line, only the largest catchment areas reveal a significant decline in relative appreciation with distance from the station. This is not compelling evidence for the positive capitalization of light rail. None of typically-sized catchment areas – those within walking distance – reveal a significantly negative slope. The slope calculated using the largest areas is likely to reflect economics wholly distinct from some new service flow to dwellings from access to light rail. This is suggested by the low explanatory power of all the regressions. Even in the case where the slopes are significant, over 90% of the variation in dwelling price appreciation is unaccounted for.

Figure 12: Median Tract Price Appreciation & Distance to Station: Gold Line



The second approach assessing capitalization looks for other point sources for appreciation. Again, in a complex urban setting, it is likely that local amenities are scattered throughout the sample – local amenities which are generally not included in traditional regressions. To the extent that stations are near these other amenities and the station location is used as the origin in the empirical analysis, it may be that average appreciation declines with distance from the station. However, using another location may provide better explanatory power. Figures 13 and 14 plot the results of these explorations. The outcomes in each figure are strongly suggestive that it is not the systematic introduction of new stations that triggers higher local price appreciation among residential properties. Along the Red Line, the entire region from Wilshire Boulevard to Hollywood Boulevard experienced above normal appreciation, but the point sources that best fit the appreciation surface around each station are typically well away from the stations themselves. Moreover, of the two pockets of highest appreciation may best be explained by alternative hypotheses that are not tested using traditional analysis. For example, one of these cluster of maxima – south of Wilshire – is located where stations had been in place well before the appreciation occurred. There

Figure 13: Price Appreciation & Alternate Point Sources: Red Line

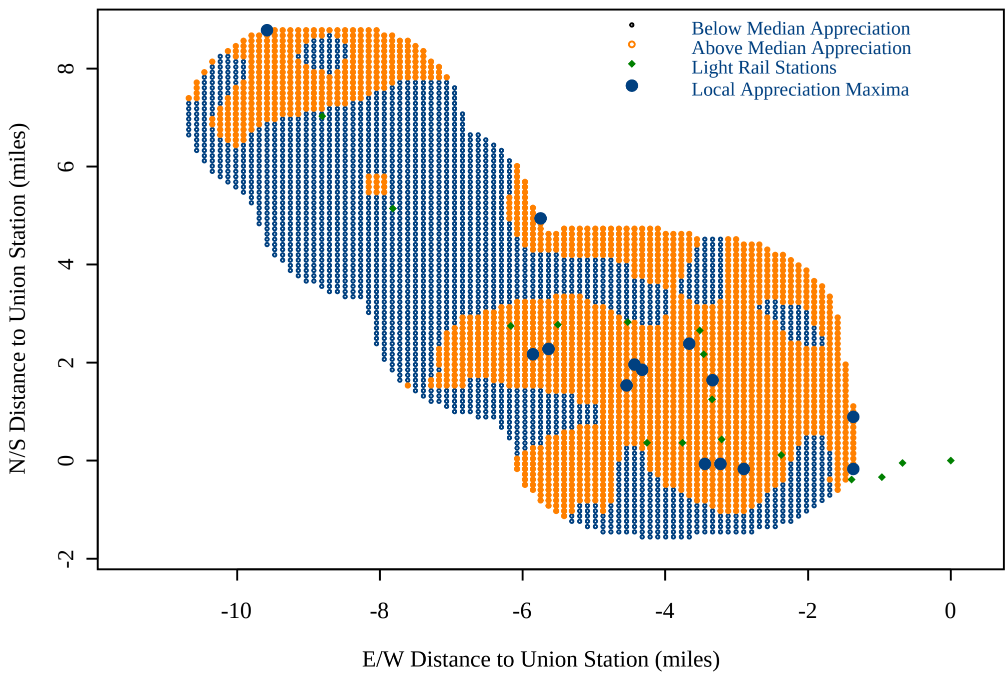
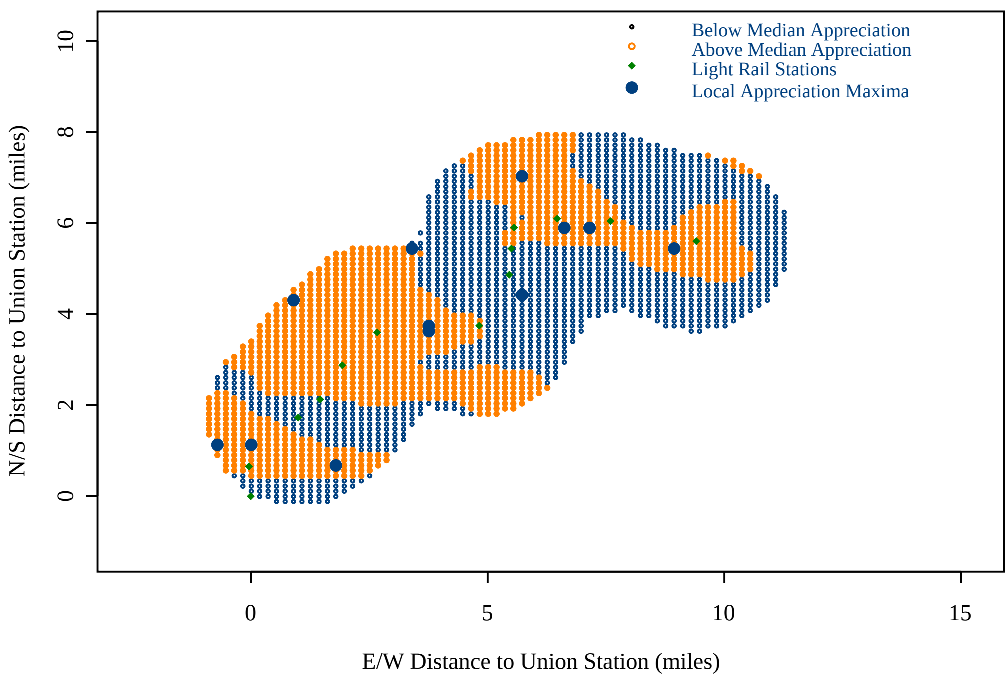


Figure 14: Price Appreciation & Alternate Point Sources: Gold Line



are several alternative maxima in the general location and orientation of Melrose Avenue, suggesting that neighborhood turnaround may be a better explanation for the asymmetric appreciation than the new access to alternative form of transit. The Gold Line results are similar in that, while there are stations around which price appreciation is above normal, there is no systematic evidence that stations are a general source of local change in demand for housing.

This observation raises the significant issue of how empirical work in urban areas is undertaken. Traditional hedonic regressions execute a simple t-test of significant – testing whether or not the estimated coefficient on proximity is significantly different than zero. Figures 13 and 14 suggest that these are weak tests of of the relevant point source of local appreciation. That is, where amenities are correlated spatially, the traditional interpretation of the coefficient can't differentiate between the null hypothesis that it is the station that is the cause of the significance, or whether other amenities, omitted and proximal, are responsible.

4.1. Traditional Hedonic Analysis & External Heterogeneity

Given the extensive discussion regarding problems with traditional hedonic approaches to assessing capitalization in a complex urban setting, it may be useful to see whether or not the coefficients they produce are, in fact, sensitive to sampling regime and to specification of the distance variables. To explore this, the same data used in the examination of the external heterogeneity and the locally-weighted regression analyses can be used in various traditional specifications. Figures 15 and 16 report these coefficients.

The top panel of Figure 15 plots the coefficient on the distance to the nearest light rail station in traditional hedonic regressions of four specifications using observations drawn from a series of concentric rings around the stations. "Model 3" regresses the log of observed sale price on the full set of characteristics reported in the previous tables using only the distance to the station to capture external heterogeneity. "Model 4" adds an additional distance variable capturing distance to the nearest highway on/off ramp. "Model 5" exchanges this variable for a set of dummies, one for each light rail station. "Model 6" uses both distance measures and the station dummies. In both figures, the symbols are hollow where coefficients

Figure 15: Coefficients on Distance to Gold Line Stations, by Sample and Specification Panels 1: Linear Dist., Panel 2: Log Dist., Panel 3: Quadratic Dist.

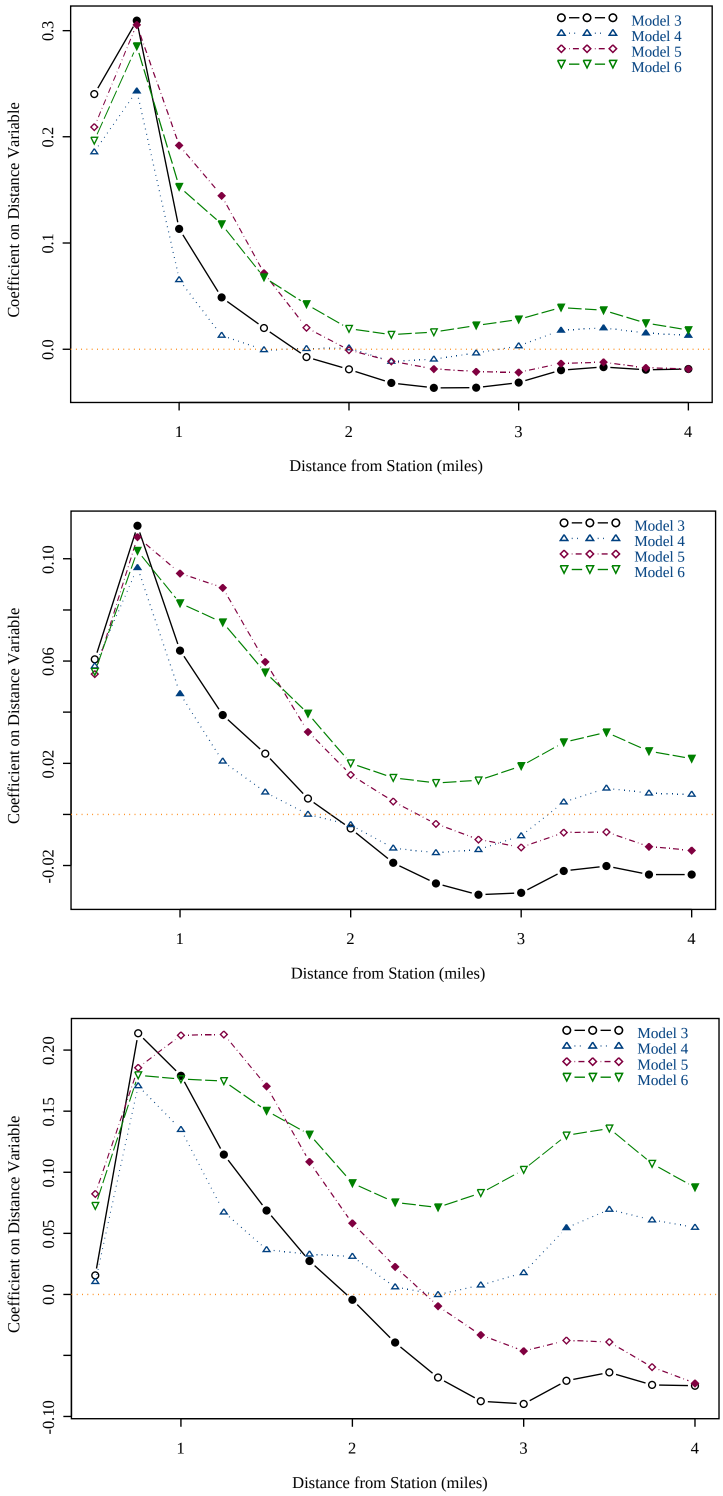
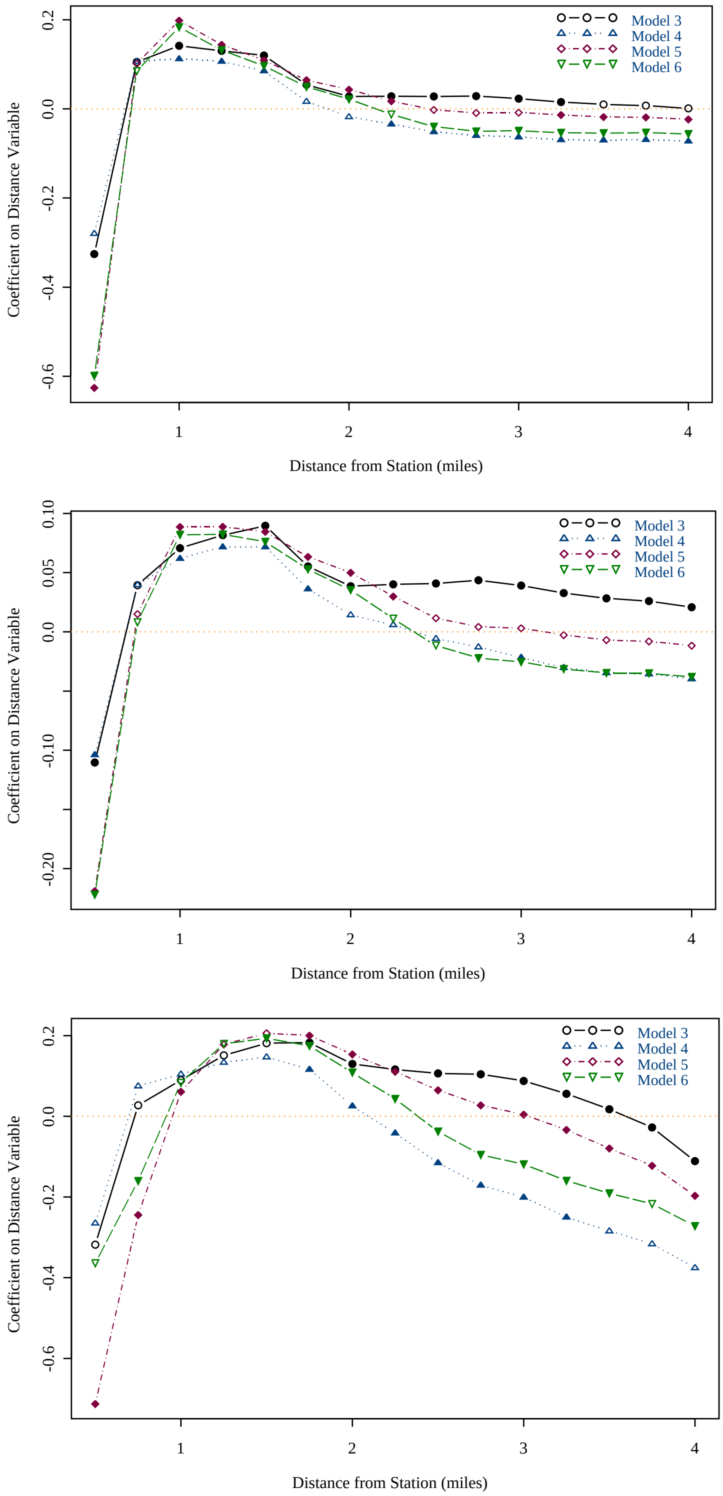


Figure 16: Coefficients on Distance to Red Line Stations, by Sample and Specification Panels 1: Linear Dist., Panel 2: Log Dist., Panel 3: Quadratic Dist.



are not significant at the 5 percent level, and solid where they are.

The difference between Models 3 and 4 is striking in all three panels. This difference amounts to the difference between a model which implicitly posits that all other spatial amenities are uncorrelated with access to light rail and a model that allows for the possibility of spatial correlation in at least one other local amenity. The difference in the linear models is particularly pronounced using the larger samples. For example, the coefficients on the distance to the nearest light rail station in Models 3 and 4 vary between highly significant and negative (indicating positive valuation of access to light rail) and highly significant and positive. In this case, the simple addition of another spatial amenity completely reverses the interpretation of light rail as a social cost or benefit. This pattern holds broadly across all three panels. The parallel in the second panel, which reports coefficients on the natural log of distance, is stronger than in the third panel, which reports the net effect of distance to the nearest station from the two parameters of a quadratic specification.

Models 5 and 6 add dummies for each station along the lines – allowing for shifts in local intercepts, but maintaining fixed coefficients on the structural and parcel characteristics. Adding these dummies to the simpler station-distance only model (Model 3) appears to shift the measured effect of distance upward. But even this added level of sophistication is still highly sensitive to sample size. Where the sample is drawn from less than two miles from the stations, the estimated effect of distance is positive and generally statistically significant. In the case of quadratic specification, the seemingly benign choice of sample perimeter moving from 2.25 miles to 2.50 miles changes the sign from positive and significant to negative and significant.[19]

Figure 16 repeats the same sensitivity of traditional hedonic models to choices of specification and sample for the Red Line data. The choice of either implies an outcome – there is no robustness. Moreover, the pattern of differences between Gold Line and Red Line results is not consistent. Unlike the Gold Line tendency of the station-distance only model to produce smaller estimates than the others, the Red Line data returns just the opposite. This suggests that the biases are a function of local external heterogeneity, not some regularity

[19] In the case of the quadratic specification, the symbols are filled-in when both linear and quadratic terms are significant at the 10% level.

that might be accounted for with some standard correction.

In short, these sets of traditional hedonic indexes strongly suggest that no single estimate should be viewed without suspicion. These results point strongly to the need for a great deal of experimentation in both sample and specification, but not for the usual reasons. Where it is common to use the best overall fit of the variation in the dependent variables to choose the "right" model, it may be that the most robust result is the one that should be reported. More appropriate, however, may be moving away from models that rely on strong and untested assumptions. The loess model developed in this paper relaxes the assumptions that do not hold in the data. The results presented used locally linear models, but trials with fewer parameters, different specifications of the continuous variables, and with some interactions yielded qualitatively similar results. The problems with the fixed-coefficient specifications are apparently avoided with any of the local regression specifications that offer a greater measure of flexibility in parsing the observed sales prices from an exceedingly diverse urban housing market.

5. Conclusion & Extensions

That house prices vary is well understood. However, the sources of this variation – and its impact on urban empirical research – may be more complicated than is typically assumed. Where a great deal of attention has been focused on *internal* sources of variation – parcel size, living area, kitchen quality, etc. – less consistent rigor has been applied to sources of *external heterogeneity*. This has led to statistical models in which omitted variables act through a number of channels to bias individual parameter estimates. This paper demonstrates the extent to which the presence of external heterogeneity complicates the interpretation of coefficients in a number of traditional hedonic analyses. The pronounced sensitivity of these models to relatively innocuous choices of specification and sample suggests the need for a more robust alternative. The locally-weighted regression approach demonstrated here is far less sensitive to the specification of the local regression. Furthermore, because each regression is local by construction, the unused remainder of the sample had essentially no effect on local prices.

The origin of the asymmetry in the attention to internal and external price variation may simply be the late availability of geocoded sales data. Structural and parcel data are routinely collected by multiple-listing services, tax assessors, and planning departments. But, data on amenities and disamenities beyond parcel boundaries are gathered on a more *ad hoc* basis. For example, the Los Angeles Assessor's data used in this research contains only a property's address and census tract number – providing possible links to other data, but offering no direct information regarding the variables that influence price that exist beyond a property's boundaries. Access to highway ramps and light rail stations, to give two examples, are not found in the Assessor's data. They are, instead, added through conscious merger with other data sets using common coordinate systems. Beyond these two variables, what other amenities and disamenities were overlooked? The list is likely quite long, including schools, parks, weather, and access to employment, consumption, etc. Moreover, other sources of heterogeneity are likely to be unknown to the researcher and likely as problematic, if not more so. Something as ill-defined or unmeasurable as "neighborhood quality" or "architectural cohesiveness" may be equally confounding for traditional hedonic analysis when coefficients are fixed. Urban land and housing markets are complex. The extent of the external heterogeneity that may be impossible to control for in traditional hedonic analysis should give pause to researchers and policy makers alike.

Gathering the "complete" list of relevant variables is not generally feasible. Responding to this reality by assuming that what is omitted will wash out in the error term appears dangerous. Variation in implicit prices appears to cluster spatially and in regularly irregular patterns. The processes that generate local attribute prices remain a black box in this research, but their variation has been clearly demonstrated. This implies that pooling dwellings without regard for the underlying differences in how they are priced across space and time is likely to lead to unstable parameter estimates.

The extent of this problem for the empirics of urban issues remains an open question. Clearly for the case of access to light rail, no one combination of sample and specification in a series of typical hedonic regression can be credibly generalized to a larger population: none provide solid footing for answering the important question of the capitalization of access to light rail into local house prices. The comparisons between the traditional hedonic models and the more flexible local regressions were striking. Not only did the local regressions prove more robust to choice of specification and sample, they provided the opportunity to examine two important aspects of urban research. The first is the response to local variations in housing markets. It is common to acknowledge segmented housing markets with the inclusion of geographic dummies, to allow for individual intercepts across submarkets. This is a half measure that was solidly rejected by the data and failed to overcome the lack of robustness across several specifications and samples. This is because spatial and temporal variation in the slope parameters is an essential part of explaining house price variation.

The second issue is more general: the desirability of parsimonious models needs to be balanced with the robustness and interpretability of their outcomes. The setting for the empirical examples used in this research is the natural catchment areas for an existing light rail line. That is, there is no reason to believe that this is an exceptional case of extreme values derived from small and particularly odd housing markets and an unusual spatial amenity. Rather, the results and comparisons presented here underscore the difficulty in identifying individual parameters in a complex urban setting. Indeed, clean identification in a context in which there is large internal and external variation – and where the variables of interest may be spatially correlated with any number of other amenities and disamenities and/or submarkets – may only be possible with the sorts of quasi-natural experiments exploited in Baum-Snow and Kahn (2000) and Gibbons and Machin (2005). Their examples motivated the use of before and after comparisons of dwelling price appreciation in the areas around light rail stations.

Using this framework and the more flexible loess approach, light rail stations appear to be weak negative externalities in their immediate vicinity. Beyond this small radius, the data tell us little regarding the capitalization of access. Indeed, in many cases where stations appear to offer positive capitalization, the data suggest that some other spatially proximal amenity is driving the results. In light of these results, cost/benefit analyses that have incorporated significant capitalization based on traditional hedonic analyses should be reconsidered. More generally, analyses in complex urban land markets need to be careful not to overlook the underlying sources of variation and how their empirical approaches incorporate them.

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