The Price Elasticity of the Demand for Residential Land

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Abstract

The price elasticity of demand for residential land is estimated using a suburban Philadelphia data base that includes appropriate instruments to deal with the simultaneity issues raised by Bartik (1987) and Epple (1987) when estimating demand functions for bundled goods. We find that the price elasticity is fairly high, -1.6 in our preferred specification, and that OLS estimates of the price elasticity (based on estimates of inverse demand schedules) are biased upward substantially as predicted by Bartik (1987) and Epple (1987). Because the demand for residential land is so elastic, it has important implications for a host of urban issues and the emerging ‘smart growth’ debate. In particular, ‘smart growth’ policies–most of which would raise the price of residential land–could lead to much increased residential densities. The high elasticity also implies that other policies, such as the federal tax treatment of housing which lower the relative price of land primarily for higher income households, could increase the incentives for residential sorting.

I. Introduction

A host of metropolitan issues ranging from central city decline to suburban traffic congestion and the perception of disappearing green space are hotly debated in academia and the press. These issues tend to be covered under the rubric of 'smart growth' initiatives which are being taken up by politicians ranging from local zoning boards to Vice President Al Gore. The emerging 'smart growth' debate is intimately related to society's adoption of less dense land usage patterns. At least to date, the discussion does not appear to recognize that the impact of any policy designed to alter land use patterns is dependent, at least in part, upon the nature of the demand for land.

Analysis of the demand for land has a long tradition and received increased scrutiny in urban economics when the now standard Mills-Muth-Alonso city model was developed in the 1960s. Muth (1964, 1969, 1971) in particular, provided a simplified framework in which to evaluate the demand for residential land. In contrast to Alonso (1964), who viewed residential land as a good over which consumers held preferences, Muth argued that the demand for residential land was derived solely from its role as a factor of production in housing. Muth's empirical estimates of the derived demand for residential land in his 1971 article helped establish a concensus that the price elasticity of demand for land was in the -0.8 to -1.0 range. Subsequent advances in applied econometric theory by Bartik (1987) and Epple (1987) imply that these estimates are biased downward. The primary contribution of this paper is to provide an unbiased estimate of the price elasticity. Our findings confirm Bartik's and Epple's insights and bring new evidence to bear on the nature of the demand for residential land.

Because residential land is typically bundled with housing, its price is seldom directly observed. Although residential land prices can be estimated using standard hedonic techniques, the bundled aspect of residential land introduces additional econometric issues that make estimating its price elasticity of demand a very difficult task. Bartik (1987) and Epple (1987) showed that the nonlinearity of the underlying hedonic price function relating house value to a trait bundle effectively allows consumers to choose both quantities and marginal prices of all traits--including lot size. Under these circumstances, ordinary least squares (OLS) estimation of an inverse (regular) demand schedule is likely to result in an upwardly (downwardly) biased price elasticity. Moreover, identification of the underlying demand function places onerous requirements on the data that seldom are satisfied. First, repeated observations on the market of interest are needed. Second, the distribution of preferences must not change across the repeated observations of the market. Third, the data must include instruments that shift the household's budget constraint but which are uncorrelated with unobserved tastes that could be influencing the consumed trait set. If these conditions are satisfied, consistent estimates of the parameters of the demand function can be obtained using the two-stage least squares (2SLS), instrumental variable (IV) procedure described by Bartik (1987) and Epple (1987).

Fortunately, we are able to address these issues with a unique data set on house transactions from Montgomery County, PA. This data base includes virtually all single family housing transactions spanning a nearly 30-year period from 1970-1997 in the most populous suburban county in the Philadelphia metropolitan area. All observations have been geocoded so that street addresses are known in addition to a wealth of structural trait data.

Our identification strategy treats each year as a single observation on the market and makes the assumption that the distribution of preferences does not change across years–at least in ways that we cannot control for. The results confirm Bartik's (1987) and Epple's (1987) conclusion that OLS estimates of price elasticities arising from inverse demand schedules are biased upward. In our preferred specification, the OLS-based price elasticity of about -2.5 is about 50 percent higher than the -1.6 figure resulting from the 2SLS estimation.

Our finding that the price elasticity of demand for residential land is relatively high is important for two reasons. First, it has powerful implications for how various public policies can affect urban form. Simply put, if the price elasticity is high, policies that affect land price can materially affect residential density and in some cases residential sorting by income. Second, in contrast to Muth's (1964, 1969, 1971) view that the demand for residential land can be described solely as a derived demand based on its role as a factor of production in housing, our findings suggest there is an independent demand for land as was postulated by Alonso (1964).

The remainder of the paper is organized as follows. The next section outlines the econometric issues first raised by Bartik (1987) and Epple (1987) involved in estimating the price elasticity of demand for a single trait such as residential lot size. Section III then describes the Montgomery County, PA, data base in more detail. This is followed with Section IV's presentation of the specifications estimated and a discussion of key results. Section V outlines the implications of our findings for how policy that changes land prices might impact urban form and for the nature of the demand for residential land. A brief summary concludes the paper.

II. Econometric Issues

Using hedonic techniques to estimate market prices of individual traits in bundled goods is standard fare in empirical studies of housing markets, but estimates of the underlying demand functions for these traits are rare. Determining the price elasticity of demand for a single trait such as residential lot size is fraught with more than the typical identification problems involved in any situation in which demand (or supply) must be estimated. Bartik (1987) and Epple (1987) pointed out the unique identification problems in their critique of Rosen's (1974) suggested methodology for estimating the supply and demand schedules for bundled traits.

Rosen (1974) analyzed the issue as a standard identification problem and suggested the following two-step procedure for estimating the supply and demand functions for traits of bundled goods. First, compute individual equilibrium trait prices based on estimates of a hedonic price function such as that for housing shown in equation (1):

(1) $V_i = f(Z_{ik}; \beta_k) + \varepsilon_i$,

where: V_i is the observed value of house i;

Z_{ik} is a vector of housing traits;

β_k is vector of parameters;

ε_i is the random error term.

The market price of a trait in the bundle such as residential land, *l*, is given by $p_{il} = \partial V_i/\partial Z_{il}$. Note that if the hedonic price function is nonlinear, the price of residential land will vary across houses.

The second step is to estimate an inverse demand or marginal bid function using the trait price as the dependent variable:

(2) $p_{il} = \partial V_i/\partial Z_{il} = h(Z_{il}, E_i, D_i; \gamma_1, \gamma_2, \gamma_3) + \mu_i$,

where: Z_{il}, is the amount of residential land;

E_i is non-housing expenditure;

D_i is a vector demand shifters;

$(_j$ are coefficient vectors; and

μ_i is an error term.

A companion marginal offer function would be estimated along with (2) and would contain individual supplier traits (S_i). Rosen (1974) suggested that two-stage least squares (2SLS) be employed, with the supplier traits being appropriate instruments for the endogenous Z and E vectors in the marginal bid function.

Bartik (1987) and Epple (1987) pointed out that the most difficult issue in estimating individual trait demand parameters does not lie in traditional supply-demand interaction, as no individual consumer's behavior can affect suppliers because a single consumer cannot influence the hedonic price function itself. Rather, the crux of the problem lies in the nonlinearity of the hedonic price function which implies that consumers simultaneously choose both quantity and marginal price of the housing trait. Epple (1987) illustrated this with a graph similar to that in Figure 1 which has the hedonic price of the trait on the vertical axis and the quantity of the trait on the horizontal axis. Even though the distribution of supply is exogenously given in this example, the nonlinearity of the hedonic price function means that the price changes with any quantity chosen as indicated by the two tangencies in the figure. Hence, a choice of price necessarily implies a choice of quantity (and *vice versa*). In this situation, OLS estimates of the parameters of the inverse demand function given in equation (2) imply a greater price elasticity than the true price elasticity.[1] Conversely, OLS estimates of a regular demand function in would yield parameters that imply a result less than the true price elasticity.

The solution to this problem is an instrumental variables estimation, but of a different type than that employed for the standard supply-demand identification problem. Appropriate instruments are those that exogenously shift the household budget constraint yet are uncorrelated with unobserved tastes. The reason is that a shift in the budget constraint will be correlated with the observed Z (and E) vectors, yet uncorrelated with tastes. Thus, it deals with the underlying omitted variables problem because it allows estimation of the response to changes in quantity holding constant the unobserved tastes. Bartik and Epple recommend two classes of factors that can shift the budget constraint exogenously as candidate instruments. One is income or wealth. The other is the set of variables that shift the hedonic price function, assuming that average tastes do not change across those shifts. This assumption is very important because of what it requires of the data. In particular, it suggests that multiple observations on the market that satisfy two conditions are needed. First, the distribution of tastes must be unchanged across observations on the market. And, second there must be forces that shift individuals' budget constraints across observations on the market.

We are fortunate to have a unique data base to deal with both requirements. Our data are from

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[1]The problem essentially is one of omitted variables. Unobserved individual tastes that are positively correlated with both price and quantity are omitted from the estimation, causing the estimated responses of marginal bids to the quantity consumed to be biased upward (toward zero in this case). Stated differently, a household with a strong preference for a given trait in the Z vector will choose more of it and be willing to pay a higher price for it (*cet. par.)*. Note that if equation (2) were linear, the price elasticity would be $0 = (1/(_{1})p_{l}/Z_{l}$, and since $(_{1}$ is biased upward toward zero, it implies an estimated elasticity greater than the true price elasticity.

tax assessment files containing observations on transactions of single family detached homes in Montgomery County, PA, over the period 1970-1997. We treat sales in each year as an observation on the market for homes, with the maintained hypothesis being that the distribution of preferences in the county does not change over time (or at least does not change in a way that we cannot control for in the estimation).

Given the importance of the assumption, some discussion of it is useful. Across Montgomery County there are small lots and big lots, and preferences certainly differ over this trait. However, the key issue for us is that the county-wide distribution of preferences over time does not change much–again, in ways we cannot control for. A look at key demographics that are known to influence the rent-own decision and to affect the demand for housing suggests great stability over time in Montgomery County. For example, even though the population in the county has risen by 55,000 from 623,799 in 1970 to 678,111 in 1990, the fraction of males has changed by only 0.1 percent. The percentage of adults (i.e., those at least 18 years of age) has barely risen–from 66.3 percent in 1970 to 68.8 percent in 1990. The median age was 31 in 1970 and 33 in 1990. The county was and still is overwhelmingly white, being 96.1 percent white in 1970 and 91.5 percent white in 1990. And, in 1990 Montgomery County's mean and median income still was the highest among all suburban Philadelphia counties. Thus, in many ways the demographic make-up of the county looks the same in 1990 as it did in 1970, providing support for our assumption that the distribution of preferences is not changing much over time.[2]

[2]Because the 2000 census has not been taken, we do not have more recent data but we expect more of the same in terms of the county's demographics. Note that the assumption the distribution of

Given our assumption that an annual cross section of sales constitutes one observation on the market, hedonic regressions of the type illustrated in equation (1) are estimated by year to determine annual market prices of a square foot of lot size (p_l). Were we not concerned with the price of residential land and residential lot size being simultaneously determined, an inverse demand function (or marginal bid) could be estimated via OLS with the price of land, p_{il}, regressed on the quantity of land, Z_{il} , and other appropriate terms such as demand shifters (denoted D) and non-housing expenditures (E). Because of the simultaneity problem, however, we must estimate the marginal bid function via 2SLS in which Z_{il} and E_i are instrumented for by a set of variables that shift the household's budget constraint without being correlated with tastes. Thus, the specification we estimate via 2SLS is of the form described by equation (3),

(3) $p_{il,t} = h(\hat{Z}_{il,t}, \hat{E}_{it}, D_{it}; "_1, "_2, "_3) + >_{il,t}$

where $"_j$ are coefficient vectors;

$>_{it}$ is the error term; and

$\hat{Z}_{il,t}$, and $\hat{E}_{it}$ are instruments generated from equations (4) and (5) below.

(4) $\hat{Z}_{il,t} = g_z (D_{it}, S_{it}; ._D, ._S) + <_{it}$

(5) $\hat{E}_{it} = g_E (D_{it}, S_{it}; 2_D, 2_S) + L_{it}$

where: S_{it} is a vector of variables that shift supply or both supply and demand;

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tastes is unchanged across observations on the market would be much more tenuous if we took individual suburbs as our markets. In that case, hedonic prices would be estimated for each locality, with the assumption being that the preference distribution is the same across localities. It strikes us that the distribution well could be different in a large lot suburb on the urban fringe versus a small lot, inner-ring suburb. Hence, our choice of sales throughout the county in a given year as an observation on the market.

$._k$ and 2_k are parameters of the instrument equations; and

$<_{it}$ and L_{it} are the error terms and all other terms are defined as above.

The price elasticity of most interest to us can be computed from the $"_1$ coefficient. Before getting to the specifics of the estimation and the results, the next section more fully describes the data employed in estimating equations (1) as well as instrument equations (4) and (5).

III. Data

The core data base was created from tax assessment files for Montgomery County, PA, the most populous suburban county adjacent to the city of Philadelphia. The data begin in 1970 and end in 1997. Montgomery County extends from the Philadelphia border to the metropolitan fringe. All observations are geocoded so that precise location within the county is known, allowing matching of observations to census tracts and local jurisdictions. There are 53 such jurisdictions in our sample. The tax assessment data cover all properties in the county and include information on a variety of housing characteristics in addition to sales price. We focus our attention on the nearly 100,000 observations on sales transactions of single family homes.

<u>Housing Traits, Neighborhood Characteristics and House Prices</u>

Tables 1 and 2 report summary statistics on structural traits and neighborhood characteristics used in the hedonic equation. Full sample means over 1972-1997 are reported along with minimum and maximum values across all cross sections.[3]

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[3]While our data begin in 1970, lagging in the regression analysis reported below results in the loss of the first two years of data. To maintain consistency with the regression analysis, we report summary statistics for the 1972-1997 period throughout the paper.

The values of the housing traits themselves are quite stable over time. Even with building on the suburban fringe, Montgomery County housing has not changed all that much over time, with average housing quality being fairly high at the beginning of the sample. The maximum living area (LVSQFT) of 2,130ft^2 in 1997 is only 16 percent higher than the minimum of 1,828ft^2 in 1977. Lot size (LOTSQFT) also has increased only slightly on average, with the maximum mean size of 19,859ft^2 in 1995 versus a minimum mean size of 17,874ft^2 earlier in 1979.[4] Central air conditioning (CENTAIR) is more prevalent over time, increasing from being in only 21 percent of sold homes in 1977 to 47 percent in 1996. However, the biggest change is in the age of the stock (AGE). It is getting older. The mean age was 21 in 1977, while in 1997 the mean age of a house that sold was 47. The vast majority of sales in Montgomery County clearly are not new homes constructed on the urban fringe. In addition to the housing traits listed above, we also have data on a number of other features of the properties, including a dummy variables for the presence of a garage (GARAGE), a pool (POOL), or fireplace (FIREPL).

Neighborhood characteristics also are quite stable over time. The biggest change is in population density of the census tract where sales are occurring (POPDENS), which has fallen nearly 20 percent from its peak in 1977. This undoubtedly reflects the expansion to the northern and western parts of the county which are on the urban fringe. The fraction of a census tract covered by single family housing (LANDDENS) is between 14 and 17 percent, depending upon the year. In addition to density variables, we also have data that measure accessibility to center city Philadelphia. Commute time to Philadelphia's central business district (HTIME) is very stable because it is not measured

[4]Median values obviously are lower, with the median lot size in 1972 and 1997 being just under 15,000 square feet. Hence, the median sale was on a house with about one-third of an acre of land.

annually, but only at one point in time (1987). Changes in that variable's mean arise because the spatial distribution of sales varies across years. Commuter train access to Philadelphia's CBD is measured by a dummy variable for the presence of a train station in the neighborhood (STATION). In most years, forty percent or more of homes in our sample are in communities with train stations connecting to the central city of Philadelphia.

Mean and median sales prices by year are reported in Figure 2. This and all other monetary values always are in 1990 dollars. The table depicts the large changes in real prices that have buffeted the Philadelphia market in general and Montgomery County in particular. For example, there was an 80% real increase in mean price from the 1982 recession to the peak in 1988-89. Since then mean home prices have trended down over 15%. Median prices move by almost as much. Both mean and median figures are well above national averages for existing homes as reported by the National Association of Realtors, reflecting the above average quality of the county's housing stock.

Finally, the number of observations each year are reported in the Appendix. Observations generally increase over time, although there is a clear cyclical pattern to the number of sales. The fewest number of observations in any year is 1,532 in 1972 versus a maximum number of 7,063 in 1986.

Supply and Demand Shifters: Instruments for Lot Size and Non-Housing Expenditure

Table 3 reports the full list of variables used as instruments for lotsize (Z_l) and non-housing expenditures (E) in the 2SLS demand estimation. Summary statistics on the variables are reported in Table 4. Recall that candidate instruments are those which shift the household's budget constraint without being correlated with tastes. It is noteworthy that the restriction instruments not be correlated with tastes effectively rules out a strategy of using lagged values of regressors as instruments. It also prevents use of previous sale prices, which is unfortunate because there are many repeat sales observations in our data. The previous sales price is likely to incorporate information about the tastes of the current occupant.

Fortunately, we are able to amass a considerable number of demand and supply shifters that reasonably could be thought to shift the budget constraint exogenously. Those variables likely to work through supply are listed in the top panel of Table 3. Supply shifters include a variety of new construction, tract size, and vacant land measures that capture actual and potential changes in housing activity across individual census tracts. These variables reflect the number of new homes built in the tract each year (NEWHOMES), how extensive is new construction as measured by the fraction of homes in the tract that are new in any given year (%NEWHOMES), census tract size in square miles (TRCTAREA), and the amount of vacant land available for residential development in each year (VACLAND). Except for TRCTAREA which is measured only in 1980, each of these variables varies over time.

Table 4 shows that the mean number of new homes per year in a tract over the full sample is 9.2. This variable is cyclical as indicated by the low of 3.2 in 1975 and the high of 16.8 in 1996. New homes as a fraction of all homes in the tract averages 2.2 percent over the sample, with the annual means varying from one to three percent. The mean tract size (TRCTAREA) is 2.9 square miles. While there is no intertemporal variance in this variable, there is considerable variance across tracts as the standard deviation is 3.5 square miles. The mean fraction of vacant land available for residential development (VACLAND) does not vary much over time, averaging from 25 to 30 percent depending upon the year. As with tract size, there is much more cross sectional variance.

The instruments likely to work only through the demand side, listed in the middle panel of Table 3, are employment growth in the city of Philadelphia (PEMPG) and employment growth in the suburbs of Philadelphia (SEMPG). Employment growth is likely to increase housing demand in communities in close proximity to the location of the employment growth. Over the full sample period, the city's employment growth averaged just under -1% per year, with the suburban growth exceeding 2% per year on average.[5] Table 4 shows that there is substantial variance in these data over time. We use two annual lags of these variables and interact them with locality dummies for the 53 municipalities in our sample. Interaction terms are included because the demand-side impact of city and suburban growth can shift the budget constraint differently in different parts of the metropolitan area. Using these data, Voith (1999) has shown that the housing market impacts of city employment growth differs markedly for that of suburban employment growth, and that the impacts of both city and suburban growth vary across location withing the county.

A final set of instruments includes demographic and financial variables whose impact on the budget constraint could work through both supply and demand. The thirty year mortgage interest rate (MORTRATE), for example, is likely to reflect both shifts in supplier and demander costs and hence shifts the budget constraint. The average loan rate for the sample period is 9.6 percent, although this varies widely over time as our series spans the high inflation late 1970s and early 1980s as well as the low inflation 1990s. The mortgage rate also is interacted with municipality dummies to capture

[5]The suburban growth rate is based on employment growth in all four Pennsylvania suburban counties of Philadelphia--Bucks, Chester, Delaware, and Montgomery.

differences in how the budget constraint shifts across location.

Demographic variables include a mobility measure, PCTMOVED, which reflects the fraction of households that moved between 1975 and 1980 and PCT35_54 which measures the fraction of household heads between the ages of 35 and 54. This age range spans the prime home owning years of the life cycle. These variables are computed from the STF3 files of the 1980 census and have no intertemporal variance. Mobility is relatively high as indicated by the fact that over 35 percent of households in our tracts had a different residence in 1980 versus 1975. Nearly a quarter of household heads in these tracts are between 35 and 54 years of age.[6] In addition to the mobility measures, we also have total sales in the tract each year (HOMESALE), which captures changes in the actual level of transactions over time. Sales of homes in a tract also are cyclical. For example, it bottoms out at 40 homes per tract during the 1982 recession before increasing to 78 in 1993.

<u>Non-Housing Expenditures</u>

While our data are very strong in terms of housing, location controls, and potential supply and demand shifters, the Montgomery County tax assessment files do not contain detailed information on household income. The only income data in the files is mean income at the tract level for 1980. Consequently, we use data from the *American Housing Surveys (AHS)* in conjunction with this figure to impute income at the household level. Using the observations on houses in the Philadelphia suburbs

[6]These two variables are highly correlated with the analogous figures from the 1990 census. The mean fraction of households that moved between 1985 and 1990 is 37 percent, or two points higher than found a decade earlier. The fraction of household heads between the ages of 35 and 54 also is marginally higher in 1990.

that can be identified from the *AHS*[7], we begin by defining household income (y) in deviation from mean form as shown in equation (6),

(6) $y_i = \ln Y_i - \ln Y$,

where Y_i is the income for household i and Y is the sample mean across all years. Income in deviation from mean form then is regressed on a set of housing traits ($x_i=X_i-X$, also in deviation from mean form) common to both the Montgomery County and *AHS* data sets and a set of time dummies as shown in equation (7),

(7) $y_i = x_i *_1 + \text{TimeDummies} *_2 + >_i$,

where > is an error term.

The coefficient vectors $*_1$ and $*_2$ are then used to impute household incomes in the Montgomery County data base. This is done in a way that incorporates the mean tract income information that is available. For the purposes of exposition, denote that tract mean value (which does not vary over time) as Y_c. An increment to that value is imputed, introducing time series and cross section variance from the *AHS*. This increment, denoted $y_{i,m}$, is imputed via the following equation,

(8) $y_{i,m} = x_{i,m} *_1 + \text{TimeDummies} *_2$,

where $x_{i,m}$ represents a housing trait vector in deviation from mean form analogous to that in equation

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[7]We use every available annual survey plus all special metropolitan surveys of the Philadelphia metropolitan area (done approximately every 4-6 years) in this effort.

(7), with $*_1$ and $*_2$ being the coefficient vectors estimated in equation (7) .

Imputed household income for the Montgomery County observations then is $\hat{Y}_i = Y_c + y_{i,m}$. Finally, non-housing expenditures (denoted E, which is what is required by theory for the demand estimation) is computed using a capitalization rate c to convert house values into service flows as in equation (9),

(9) $E_i = Y_i - cV$,

where V is house value (the sales price in the Montgomery County data) and the cap rate is assumed to be 7%.[8] The end result is a mean non-housing expenditure value of E=$38,885 with a standard deviation about that mean of $17,321.

IV. Specifications and Results

Hedonic Price Functions

The first task in determining the price elasticity of the demand for residential lot size is to estimate the hedonic price of an added square foot of lot size via a specification as in equation (1). Because we want to estimate the price of a square foot of a generic lot, our hedonic specification contains housing traits and neighborhood characteristics, including controls for density and location within the metropolitan area. The structural trait and neighborhood characteristics used include those listed above in Tables 1 and 2. Three of the housing traits were entered in quadratic form: age (AGE,

[8]The 7% rate is arbitrary in the sense it is not estimated, but it is within the range reported in the literature. We have experimented with small changes about this number. No result reported below is affected in any meaningful way by this.

AGE2), living area (LIVAREA, LIVAREA2), and lotsize (LOTSIZE, LOTSIZE2).

The specification of the hedonic employs a Box-Cox transformation of the dependent variable (real house price) as illustrated in equation (10).

$$(10)\ (V_i^{\lambda} -1)/\lambda = Z_i\beta + e_i,$$

where λ is the transformation parameter. This model is estimated on each annual cross section, although the time subscript is dropped for convenience sake.

We arrived at this specification after a full grid search of possible Box-Cox parameter values showed that the likelihood function was not sensitive to transformation of the right-hand side variables.[9] The transformation parameter is always significantly greater than zero and averages 0.316, with the vast majority of estimated values falling between 0.25 and 0.40. Thus, the Box-Cox parameters indicate that the data tend to favor something much closer to the semi-log functional form traditional in many housing studies over a linear functional form. That said, the data confidently reject the null that $\lambda=0$ in each cross section.

The equilibrium price of a square foot of lot can be calculated from (10) as

$$(11)\ p_{il} = \partial V_i/\partial N_{il} = \beta_l\, \hat{V}_i^{(1-\lambda)},$$

with the partial derivative evaluated using coefficients estimated in equation (10) and each observation's

[9]A full grid search was conducted because experimentation showed that results were sensitive to starting values. We approximated the likelihood and mapped out the surface for all possible combinations of the transformation parameters λ and (say) θ for the right-hand side variables. The likelihood proved to be very flat throughout the full range of θ values. Hence, we do not transform the independent variables. The likelihood proved much more sensitive to the value of λ. The results reported below are from an estimation that uses as a starting point for the Box-Cox estimation the λ value from our grid search that maximized the likelihood.

predicted value, $\hat{V}_i$ from the same equation.[10] The plot in Figure 3 shows that the price of a square foot of land varies considerably over time, but is without a discernable long term trend. The wide variance is not unexpected as land effectively is the residual claimant on house value. Casual observation of the time series shows that land prices fall substantially at the beginning of recessions and depressed housing markets and rise markedly just after the economic upturn begins. Land prices peaked in Montgomery County in the late 1980s, reaching $1.51/ft^2 in 1988. Since then prices have trended down roughly 30 percent in real terms, although the last year of data shows a marked upturn in price that the popular press suggests has continued into 1998 and 1999. As a percentage of house value, the prices in Figure 3 hover around 15 percent of mean house value in most years. In 1972, the $1.03 price per square foot implies land constitutes 17 percent of mean house value that year assuming the mean lot size of 19,856ft^2 for that year. The low is reached in 1992 when the $0.89 per square foot price implies land is only 10 percent of the mean house value that year.[11]

<u>Estimating the Price Elasticity of Demand Via 2SLS</u>

Using the estimate of p_l derived from equation (10)'s hedonic specification, an inverse demand function of the type illustrated above in equation (3) is estimated The results presented below are from a specification in which lot price (p_l), lot size $(Z_{l,})$, and non-housing expenditures (E) are all in log form.

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[10]The actual computation was slightly more complicated because the house value, lot size and lot size squared were scaled to facilitate the estimation.

[11]We experimented with a series of alternative specifications of equation (10). For example, allowing lot size to enter in cubic form has little impact on the results. If we do not perform a Box-Cox transformation of house price and estimate a traditional semi-log functional form, land prices are slightly higher on average. There also are more negative lot prices from that estimation. However, this has little impact on the 2SLS results and the price elasticity of demand estimates discussed in the next section.

Both the dependent variable and the independent variables are in log form, with the exception of the dichotomous variables and the growth rates of city and suburban employment. However, other functional forms were tried and we comment briefly on them below.

Formally, we estimate equation (12) below by 2SLS with Z and E being instrumented for with the supply and demand shifters described in Section III. The model estimated not only includes the instrumented (log) lot size and non-housing expenditure variables, but demand shifters themselves. In equation (12), these variables are represented by the D vector.

(12) $lnp_{l,\,i,} = {''}_{1,} \ln \hat{Z}_{l,\,i} + {''}_{DS} D_i + {''}_{y} \ln \hat{E}_i + D_i.$

All terms are as defined above, with D being the error term.[12]

In our specification of the equations for Z_l and E, the instrument set listed in Table 3 is expanded in two ways. First, the municipality dummies used in the employment growth and mortgage rate interactions are included themselves. Second, we include a vector of dichotomous year dummies to capture general supply or demand shifts that occur over time. The interaction terms and municipality dummies expand the number of instruments, but this is not a problem for our estimation given the very large sample size. There are 98,837 observations used in the estimation. Because the first and second lags of the employment growth variables are used, observations from 1970 and 1971 are dropped.

[12]It is important to note that because some estimated lot price values (the $p_{l,\,i}$ values) are negative, we added a constant equal to the most negative value observed in the data set (2.45 in this case) to each price. This preserves the relative ranking of prices across observations while allowing us to use all observations in the estimation. We also estimated a version in which all negative $p_{l,\,i}$ values are dropped and experimented with other functional forms, including a simple linear demand in which no terms are logged. As is discussed below, the findings are robust to those changes.

Our instrument set explains about 40 percent of the variance in (log) lot size and non-housing expenditures (adjusted R^2 for the lot size equation is 0.41, while that for the non-housing expenditures equation is 0.40). Given that our identification comes through the four supply shifters list in the top panel of Table 3, as only they are excluded from the demand equation, it is noteworthy that they are highly statistically significant individually and collectively in the two instrument equations. We can reject the null that they are jointly insignificant at better than the 1 percent level. Full regression results for the two instrument equations are available upon request.

The demand shifters included in the D vector in equation (12) include all variables from the middle and bottom panels of Table 3. That is, all pure demand shifters and those that could work through either supply or demand are included in the final specification of the inverse demand schedule. Table 5 reports regression summary statistics for the inverse demand equation, along with information on the coefficients on the two instrumented variables. The 2SLS results are in the top panel, with the OLS results included for comparison purposes in the bottom panel. The adjusted-R^2 from the 2SLS estimation is 0.41, with a mean square error of 0.098 and a dependent mean of 1.23 (recall that lot price is in log form). Full regression results for the 240 other regressors (most of which are interactions with the municipality dummies) are available upon request. As the results presented indicate, coefficients tend to be estimated fairly precisely, but that is not unexpected when one has almost 99,000 degrees of freedom.

The signs of the coefficients on the Z and E variables are the expected ones. The demand schedule does slope down as indicated by the negative relation between lot size on lot price. And, lot size held constant, more non-housing expenditures are associated with ownership of more expensive land. However, neither coefficient can immediately be transformed into an elasticity. This is obvious for E, as the income elasticity must arise from the estimation of a regular, not inverse, demand schedule. The price elasticity of demand also is not the inverse of the coefficient on Z, but it can be transformed into an elasticity estimate. Because the dependent variable has been transformed with the addition of a constant (2.45 in this case), it is easy to show that the price elasticity must be computed as $0_p=[(p_l/(p_l+c))*(1/{''}_{1,})]$, where p_l is the mean lot price per square foot, c is the constant value that was added to each price observation, and ${''}_1$ is the coefficient on Z_l from Table 5. The price elasticity resulting from the 2SLS estimation of the inverse bid function for residential lot size is -1.64.

It is especially noteworthy that this estimate is only 66 percent of the -2.48 elasticity resulting from a simple OLS estimate of the inverse demand. Thus, it appears that OLS estimates of the price elasticity of this particular trait are substantially biased upward for the reasons outlined in Bartik (1987) and Epple (1987). It is also worth emphasizing that the OLS estimate of a 'regular' demand curve that has lot size on the left hand side and lot price per square foot on the right is downward biased.[13] The price elasticity arising from a OLS estimation of a regular demand function with the identical functional form is -0.81, only one-half that found in the 2SLS model of the inverse demand function.

These general findings are robust to various specification and sample changes. For example, if we drop all negative lot price observations (i.e., if we do not add a constant so that all values are positive before the logging of price), the price elasticity from the 2SLS estimation is only marginally different at -1.78. The OLS-based price elasticity is -2.59 so that the upward bias still is a hefty 69

[13]That this is the case follows mathematically from inverting the inverse demand (presuming that is possible, which it is here).

percent. The implied elasticity from estimating a regular, as opposed to an inverse, demand is -0.70, also not very different from the findings reported for our preferred specification.

Estimating a purely linear 2SLS version of (12) so that no dependent or independent variable is logged does result in a higher price elasticity of -2.30. However, it still is less than the -2.56 value obtaining from an OLS estimation and greatly exceeds the -0.59 value associated with OLS estimation of a 'regular' demand schedule.[14]

In sum, our results suggest that the price elasticity of demand for land is fairly high, ranging from -1.64 to -2.3, with our preferred specification yielding results at the bottom end of that range. That said, OLS-based results are even higher, varying in a narrow band from -2.48 to -2.59. And, price elasticities arising from estimation of regular, not inverse, demand functions are biased downward–severely. Our findings there never exceeded -0.81.[15]

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[14]Tweaking the underlying hedonic specification does not change the tenor of the results either. For example, if lot size is entered in cubic, rather than quadratic, form in equation (9) and then equation (10) is estimated with the new implied lot prices, the 2SLS price elasticity is -1.56, barely different from the -1.64 figure from our preferred model. The upward bias associated with OLS estimation holds even if we do not use a Box-Cox transformation and estimate a simple semi-log hedonic. Given that the data clearly reject logging house price in the hedonic, we do not believe these estimates are relevant for gauging the true value of the price elasticity of demand. We note them only to emphasize that OLS price elasticity estimates are higher than the 2SLS estimates no matter what functional form one uses in the hedonic model.

[15]In the only other study that explicitly tries to deal with the issues raised by Bartik (1987) and Epple (1987), Cheshire & Sheppard (1998) report price elasticities of demand for land ranging from -0.6 to -1.6 for a variety of British cities they studied. Besides being at the high end of their range, an important difference between our findings and theirs is that Cheshire & Sheppard (1998) report no difference between OLS and 2SLS results. We believe that the reason they do not find OLS-based elasticities upwardly biased lies in their strategy for choosing instruments. The adopted a policy of employing lagged values of regressors as instruments. As discussed above, we rejected that approach because lagged regressors are unlikely to shift the budget constraint independent of preferences. Thus, we do not think their instrumental variables estimation effectively deals with the underlying specification

V. Implications for Urban Form and the Nature of the Demand for Land

An elastic demand for residential land has potentially important policy implications because policies that have or will influence the price of land could result in material changes in the quantity of land demanded, and in some instances, the extent to which high and low income households choose separate communities. That our estimate is higher than previously reported also may suggest that there is an independent demand for land beyond the derived demand suggested by Muth (1964, 1971). Both issues are considered more fully in this section.

<u>The Price Elasticity of Demand for Land and Urban Form</u>

If the price elasticity of demand for residential land is in the -1.6 range, policies that change the price of land materially can have very large impacts on urban density and on spatial sorting along income lines. To see this more clearly, first consider the federal tax treatment of housing which Poterba (1991) estimates provides benefits averaging 15 percent of user costs on an annual basis. If these benefits are not capitalized into the price of land (i.e., residential land is elastically supplied), our price elasticity estimate of -1.6 indicates that the tax treatment of housing could reduce residential density by up to 24 percent (i.e., 24=15*1.6). While this overstates the likely impact for obvious reasons[16], the

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bias issue.

[16]One reason is the no capitalization assumption. If the program benefits were fully capitalized into land prices, no behavioral effects on residential land usage would result. This may be closer to the truth in fully built-out cities and inner-ring suburbs where residential land may be in very inelastic supply, but certainly is not the case on the urban fringe. This suggests that, while a metropolitan-wide average effect may not have a clear meaning, the impact on density could be very large in communities in which land is in elastic supply. A second reason is that the program benefits need not all fall on land. However, our priors are that of all the traits the comprise the good called housing, physical structure attributes such as bathrooms, bedrooms, and roofs are much more likely to be in elastic supply than is land. To the extent this is not the case, the 15 percent change in price overstates the influence of the

perhaps obvious point we are trying to make—combining policies that have big effects on land prices with a big price elasticity can lead to big impacts on behavior—appears to have been largely overlooked in an urban literature dominated by a successful model that (not improperly by any means) focused attention on the trade-off between income and transportation/commuting costs.

The importance of a price elastic demand for residential land for spatial sorting along income lines that could result from a policy such as subsidizing home ownership through the tax code also can be highlighted within the traditional city model. Consider a standard spatial model with housing consumption given by q, land rent by r, non-housing consumption by c, commuting costs per mile by t, household income by y, distance from the urban core measured by x, and preferences given by v(c, q). Now, let the federal tax treatment of housing be modeled such that high income households (i.e., itemizers) receive a subsidy while low income households (i.e., non-itemizers) receive no subsidy. Thus, if J is the high income household's share of housing costs, with the government paying $1-J$, the budget constraint is given by $c + Jrq = y - tx$ for the household residing at location x. Substituting for non-housing consumption, the equal utility level U required across space in equilibrium requires that $Max_{\{q\}}v(y-tx-Jrq, q) = U$. The familiar bid-rent function of the high income household is determined by differentiating this expression, such that $Mr/Mx=-(t/Jq)$.

This bid-rent function tells us by how much rent must vary across locations (x's) for rich

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policy. Yet another reason is that our example abstracts from income effects. If the public subsidy were eliminated, government revenue would be higher so that taxes could be cut (other public outlays held constant, of course). Household incomes would be somewhat higher. Since the income elasticity of demand for land is positive, the net impact on density would be lower than our back-of-the-envelope calculation suggests.

households to be indifferent across sites. For the rich to sort into the suburbs and the poor into the central city, the bid-rent curve of the rich must be flatter than that of the poor. Stated differently, the slope of Mr/Mx must be smaller (in absolute value) than the corresponding slope for the low income group, with the appropriate comparison being made where their bid-rent curves intersect.

How sorting is affected by an increase in the tax subsidy (i.e., a decrease in J) depends critically upon the price elasticity of the demand for land. Specifically, if the price elasticity is greater than one (in absolute value), the policy increases spatial sorting along income lines.[17] The most realistic case to consider is one in which q adjusts in response to a decline in r. To analyze this situation, it is helpful to derive the J-induced change in the bid-rent function slope assuming that the height of the bid-rent curve stays constant. This can be done by differentiating the denominator (Jq) of the Mr/Mx expression with r held fixed. It turns out that $M(Jq)/MJ*_{r\ \mathrm{constant}}$ #0 if the price elasticity of the demand for land is greater than one. Thus, if the housing tax subsidy is increased for high income households (i.e., **J decreases**) and the demand for residential land is price elastic, the denominator of Mr/Mx increases, thereby flattening the bid-rent function for the rich. This strengthens tendencies towards income sorting.

Thus, both the extent of urban sprawl and the degree of suburbanization of the rich well may have been more influenced by public policies that have lowered land prices than is presently realized. We emphasize that this is not to say that population decentralization and spatial sorting along income lines would not have occurred in the absence of policies impacting land prices. Quite the contrary in

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[17]We are indebted to Jan Brueckner for pointing this out to us and for suggesting the example outlined immediately below.

fact, as we agree that the trade-off between land consumption and commuting costs emphasized in the traditional Mills-Muth-Alonso city model is an essential motivating force of the expansion of metropolitan areas and of spatial sorting along income lines. That said, our price elasticity results indicate that additional work is urgently needed to determine more precisely how public policies affecting the price of land may have influenced the nature of urban form in the United States independent of income growth and improvements in transportation technology. This is needed not just to improve our understanding of the forces that may have helped drive the low density suburban lifestyle that has come to dominate America's metropolitan areas, but also to better comprehend the impacts of smart growth policies for the future. Our findings indicate that anti-sprawl policies which increase the cost of using land can have meaningful impacts on the quantity of land demanded. Hence, a first point of departure should be to gauge the likely price effects of any such policies.[18]

The Price Elasticity of the Demand for Land: Implications for the Nature of Demand

Given the potential policy import of our price elasticity estimate and the fact that it is higher than most previous estimates in the literature, a careful comparison with previous research clearly is in order. Some background on how the demand for residential land is treated in the urban literature is very useful before delving into specific comparisons of estimates.

There are two distinct perspectives in the literature. One, epitomized by Alonso (1964), treats land very generally as an argument of the household's utility function. The demand for land is no

[18]This will also serve to emphasize that 'containing' sprawl is not free. Prices will have to be raised to achieve any increase in density. Indeed, one of the benefits of 'sprawling' is that land costs are lower to home owners.

different from the demand for any other good and it must obey only those restrictions applicable to any demand function. The other perspective, pioneered by Muth (1964, 1969, 1971), treats residential land and the physical buildings on it as inputs into the production of housing. From this viewpoint, the demand for land is derived solely from the demand for housing and the supply of built structures. More specifically, the parameters of the demand for land can be shown to depend upon the following: (a) the elasticity of housing demand; (b) the elasticity of supply of structures; (c) the relative importance of land; and (d) the elasticity of substitution of land for capital in the production of housing.[19]

This distinction between Alonso's and Muth's treatment of land is important for two reasons, one related to the analysis of urban issues in general and the other to our paper's elasticity estimate specifically. A key attraction of Muth's approach is that a variety of interesting urban issues ranging from the impact of improvements in the road infrastructure on aggregate urban land value (see Muth (1964), pp. 230-231) to estimation of the real resource cost of building public housing on slum versus non-slum land (see Muth (1971), pp. 252-253) are amenable to analysis based on knowledge of the price elasticity of demand for residential land and at least some of the variables enumerated in the previous paragraph. Alonso's more general treatment does not constrain the parameters of the demand for land nearly so nicely, and thus yields much weaker empirical predictions with respect to these and other policies.

At least partially because much urban policy analysis is made simpler if there is no independent demand for land beyond that associated with its role as a factor of production in the technology of

[19]See Muth (1964) for a brief and clear derivation. His book (1969) deals with many of the underlying issues in greater detail.

producing a commodity called housing, there has been more work trying to pin down the key parameters identified by Muth. With respect to our paper, it is noteworthy that the results of Muth and those who followed in his path suggest the price elasticity of demand for residential land is in the -0.8 to -1.0 range. Hence, is it with this work that a careful comparison of approaches and results needs to be made.

At its simplest, Muth (1964, eq. 18) shows that the price elasticity of demand for land (0_l) can be expressed as

(13) $0_l = -k_{nl}F + k_l 0_h$,[20]

where k_{nl} is the share of non-land factors in the production of housing, k_l is land's share in the production of housing, F is the elasticity of substitution between land and the non-land factor in the production of housing, and 0_h is the price elasticity of demand for housing. Typical estimates for F and 0_h reported in the literature are 1 and -1, respectively.[21] While one can quibble with these particular estimates, they indicate the price elasticity of demand for residential land cannot be more than -1 itself, assuming of course that the demand for land can be viewed entirely as derived from the demand for housing and the supply of physical structures.

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[20]Labor and non-land capital are assumed to be perfectly mobile in this case. If this assumption is abandoned, the expression for the price elasticity of demand becomes slightly more complex, with the elasticity of supply of housing entering the equation explicitly. The price elasticity of land still is a function of the elasticity of substitution, the price elasticity of housing, and the factor shares; however, the relation is non-linear. See equation 16 in Muth (1964) for the details.

[21]These also tend to be the most recent estimates, although that for the price elasticity of housing demand has a longer pedigree. See Thorsnes (1997) on the elasticity of substitution. Reid (1962) first concluded that the price elasticity of housing demand was about -1. A variety of other work reports slightly less elastic findings. However, Rosen (1979) reports a price elasticity of -1, using time series variation that we consider most appropriate for dealing with the issue.

Our interpretation of this branch of the literature is that estimates of the elasticity of substitution in production probably are biased down, so that Muth's derived demand perspective could lead to slightly higher estimates of the price elasticity of demand for land. McDonald's (1981) review of the elasticity of substitution literature came to the same conclusion based on a combination of classic errors-in-variables and endogeneity problems. Thorsnes (1997) most recently tries to deal with these issues and reports estimates of F as high at 1.08 (but statistically indistinguishable from 1).

It is worth noting that larger elasticities of substitution result from instrumental variables (IV) specifications. Most estimates of F essentially derive from a specification akin to the following

(14) Non-Land Housing Expenditure/Land = " + $*Land Price + ...,

Typically, the dependent variable in (14) is computed as {(property value/land area) - price of land}. The fact that the price of land is used to compute the dependent variable can lead to obvious problems. Instrumenting for the price of a unit of land generally leads to larger estimates for $ (and thereby, F, which is function of $).

Even with improvements in data reducing measurement error and providing better instruments, we suspect that the elasticity of substitution in production is higher than that reported by Thorsnes (1997). The primary reason is that the potential impact of zoning has not been (and perhaps cannot be) fully controlled for. On the production side, zoning must constrain the extent to which developers can substitute land for capital (and *vice versa*) in housing. Within a given platt of homes, developers may have limited substitution possibilities for regulatory reasons. However, in a technological sense, the scope for substitution almost certainly is much larger.

We do not know precisely how large any remaining bias is, but equation (13) can be used to gauge how much higher F would have to be to generate a price elasticity of land demand of -1.6. Using a land share of 15 percent which is what we find for our suburban Philadelphia data (i.e., k_{nl} = .85 and k_l = .15) and a price elasticity of housing demand of -1, the elasticity of substitution must be 1.7 for the implied price elasticity of demand for residential land to equal -1.6. If the true F equals 1.35 (midway between Thornses' (1997) recent estimate and 1.7), the implied demand price elasticity for residential land is -1.3.

While some might find it conceivable that correcting remaining biases would lead to a 70 percent increase in the estimated elasticity of substitution, good reason exists to believe there is a demand for land independent of its use as a factor in the production of housing. In fact, Muth (1971, Table 3) reports results from an OLS estimation of an ordinary demand function for land (i.e., quantity of land regressed on price of land) supporting just such a conclusion.

Muth's estimated price elasticity is virtually identical to that implied by his theoretical framework in which the demand for land is derived solely from its use as a factor in the production of housing. Given that Muth (1971) wrote well before Bartik (1987) and Epple (1987) informed us about the biases inherent in OLS estimation of demands for bundled traits, it was reasonable for him to interpret this as evidence that his approach captured all that was essential about the demand for residential land. We now know that the price elasticity of such a trait is biased down when estimating a 'regular' demand schedule (i.e., Q on P).[22] Recall from Table 5 that we found the OLS-based elasticity from a

[22]The underlying process giving rise to Muth's data still is one of consumers choosing land as part of a bundled good. Hence, price and quantity are being chosen simultaneously. Because unobserved individual tastes are likely to be correlated with both price and quantity of residential land, the economic issues raised by Bartik (1987) and Epple (1987) apply.

‘regular’ demand estimation was only 50 percent of that resulting from a 2SLS-based estimate of an inverse demand estimation.

Beyond these results, we think there are compelling economic reasons to believe that some land usage is purely for consumption and is not needed to produce a physical structure of a given quality. That is, we find it easy to imagine that some people like to garden and that gardens will be bigger the lower the price of land—independent of the technology of producing housing. If land prices increase (or cross sectionally, are higher in some areas), people will substitute toward other goods. We also think the price elasticity associated with such ‘consumption demand’ might be fairly high. A garden is not likely to be as critical as a roof or a kitchen. A house is not a really a house (as least as defined in America) without a roof or kitchen. Thus, if the price of a roof rises, it is impossible to do without a roof. This is not the case for gardens (or other consumption uses of land). If your garden is (say) 5 percent of total land area, your house is still pretty much the same house if you substitute away from the garden towards big screen televisions or a better car.

While identifying this particular effect is well beyond the scope of this paper, we conclude that there is good reason to believe that the price elasticity of demand should be higher than that implied by a perspective that views the demand for land solely as derived from its use in the production of housing. More specifically, we see no reason to rule our relatively high price elasticity estimate as out of order, or in any sense not to be credible. That said, our finding is based on an application of new and complex technology involving the analysis of bundled traits. It also is based on data from one suburban county. Given the potential importance our findings have for the emerging Smart Growth debate, it is critical that other estimates be made with other data.[23]

VI. Conclusions

This paper presented new evidence on the price elasticity of residential land. A data base spanning 28 years of single family, detached home sales in Montgomery County, PA, is used to provide the needed repeated observations on a single market that Bartik (1987) and Epple (1987) show are required to deal with the special endogeneity problems that arise when consumers effectively choose both the price and quantity of a given trait. Our results show that the price elasticity of demand for land is fairly high, with our preferred estimate being -1.6. Our analysis also shows that OLS estimates are substantially upward biased, as anticipated by Bartik (1987) and Epple (1987). That the demand for residential land is fairly elastic has potentially important implications for a variety of urban issues and policy discussions. Absent full capitalization, housing-related tax expenditures which are estimated to lower user costs by 15 percent may have led to substantially lower densities in our urban areas. And, smart growth policies being debated in the current political arena well may lead to higher residential densities over time given how price elastic the demand for residential land appears to be.

[23] Witte, *et. al.* (1979) is the only other study of which we are aware that estimates the price elasticity of land as a disaggregated attribute. They report a very low elasticity estimate of -0.32. However, that work uses data on rental buildings (including assessed values for prices) and does not employ the same econometric approach because it was written before Bartik (1987) and Epple (1987). Thus, it does not provide an especially appropriate comparison.

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Table 1: Summary Statistics on Continuously Measured House and Neighborhood Traits Used in the First-Stage Hedonic Estimation			
Variable	Full Sample Mean (Full Sample Standard Deviation)	Minimum Cross Section Mean (Year)	Maximum Cross Section Mean (Year)
AGE (Age of Property)	33 (28)	23 (1972)	39 (1997)
LVSQFT (Living area square footage)	1,967 (795)	1,828 (1977)	2,130 (1997)
LOTSQFT (Lot size square footage)	18,966 (14,780)	17,874 (1979)	19,859 (1995)
POPDENS (Population per square mile)	2,939 (2,380)	2,634 (1996)	3,232 (1977)
LANDDENS (Fraction of tract covered by single family homes)	15.8% (6.4)	14.2% (1973)	17.1% (1996)
HTIME[a] (Travel time by road to central city in minutes)	56 (19)	54 (1972, 74, 75, 80, 81, 82)	57 (1992-1997)

Notes:
[a]HTIME is measured only 1987. Hence, all variance arises from changes in the spatial distribution of home sales.

Table 2: Summary Statistics on Discretely Measured House and Neighborhood Traits Used in the First-Stage Hedonic Estimation

Variable	Full Sample Percentage	Minimum Cross Section Percentage (Year)	Maximum Cross Section Percentage (Year)
CENTAIR (% with central air)	34	21 (1977)	47 (1996)
FIREPL (% with fire place)	59	54 (1979)	64 (1997)
GARAGE (% with garage)	79	74 (1977)	82 (1994-96)
POOL (% with pool)	6	4 (1976-77)	7 (1972, 1989-90)
STATION (% with train station in census tract)	42	48 (1975)	37 (1996)

Table 3: Variable Set Used to Instrument for Lot Size (Z) and Non-Housing Expenditures (E)
Supply Shifters
NEWHOMES–# of new homes built in the tract each year
%NEWHOMES–fraction of homes in a tract each year that are new
TRCTAREA--census tract size in square miles
VACLAND–vacant land in the tract available for residential development
Demand Shifters
$SEMPG_{-1}$--suburban employment growth lagged one year
$SEMPG_{-2}$--suburban employment growth lagged two years
$PEMPG_{-1}$--Philadelphia employment growth lagged one year
$PEMPG_{-2}$--Philadelphia employment growth lagged two years
$SEMPG_{-1}$*Municipality Dummies–suburban employment growth rate lagged one year interacted with municipality dummies
$SEMPG_{-2}$*Municipality Dummies–suburban employment growth rate lagged two years interacted with municipality dummies
$PEMPG_{-1}$*Municipality Dummies–Philadelphia employment growth rate lagged one year interacted with municipality dummies
$PEMPG_{-2}$*Municipality Dummies–Philadelphia employment growth rate lagged two years interacted with municipality dummies
Supply and Demand Shifters
PCTMOVED–fraction of households that moved between 1975 and 1980
PCT35_54–fraction of household heads between the ages of 35 and 54
MORTRATE–annual mortgage rate
MORTRATE*Municipality Dummies–annual mortgage interest rate interacted with municipality dummies
HOMESALE–total # of sales in the tract each year
YEARS–dichotomous year dummies

Table 4: Summary Statistics on Supply and Demand Shifters Used in the Instrument Equations			
Variable	Full Sample Mean (Standard Deviation)	Minimum Cross Section Mean (Year)	Maximum Cross Section Mean (Year)
MORTRATE (Mortgage Rate)	9.6% (1.9)	7.1% (1993)	15.0% (1981)
NEWHOMES (# new homes in tract)	9.2 (18.7)	3.2 (1975)	16.8 (1996)
%NEWHOMES (% new homes in tract)	2.2% (4.2)	0.8% (1997)	3.1% (1972)
SALES (# sales in tract)	64 (38)	40 (1982)	78 (1993)
PEMPG (Philadelphia Employment Growth Rate)	-0.8% (1.6)	-4.4% (1991)	1.2% (1984)
SEMPG (Suburban Employment Growth Rate)	2.3% (2.0)	-2.9% (1991)	5.1% (1978)
VACLAND (% tract land zoned residential that is vacant)	28.0% (51)	25.0% (1997)	30.9% (1973)
PCTMOVED (%moved between 1975-1980)	35.7% (10.7)	Not Applicable	Not Applicable
PCT35_54 (% household heads aged 35-54)	24.3% (3.6)	Not Applicable	Not Applicable
TRCTAREA (Tract area in square miles)	2.9 (3.5)	Not Applicable	Not Applicable

Table 5: Inverse Demand Schedule, 2SLS Instrumental Variables Estimation		
Dependent Variable: Ln Lot Price per Square Foot (Ln p_l)		
Independent Variable	Coefficient	Standard Error
Intercept	1.585	0.090
Ln Z-log lot size	-0.178	0.002
Ln E-log non-housing expenditures	0.118	0.010
. Demand Shifters .	Available Upon Request	Available Upon Request
Adjusted R^2	0.41	
Root Mean Square Error	0.098	
Dependent Mean	1.23	
Inverse Demand Schedule, OLS Estimation		
Independent Variable	Coefficient	Standard Error
Intercept	1.493	0.012
Ln Z-log lot size	-0.118	0.001
LN E-log non-housing expenditures	0.078	0.001
Demand Shifters	Available Upon Request	Available Upon Request
Adjusted R^2	0.56	
Root MSE	0.092	
Dependent Mean	1.23	

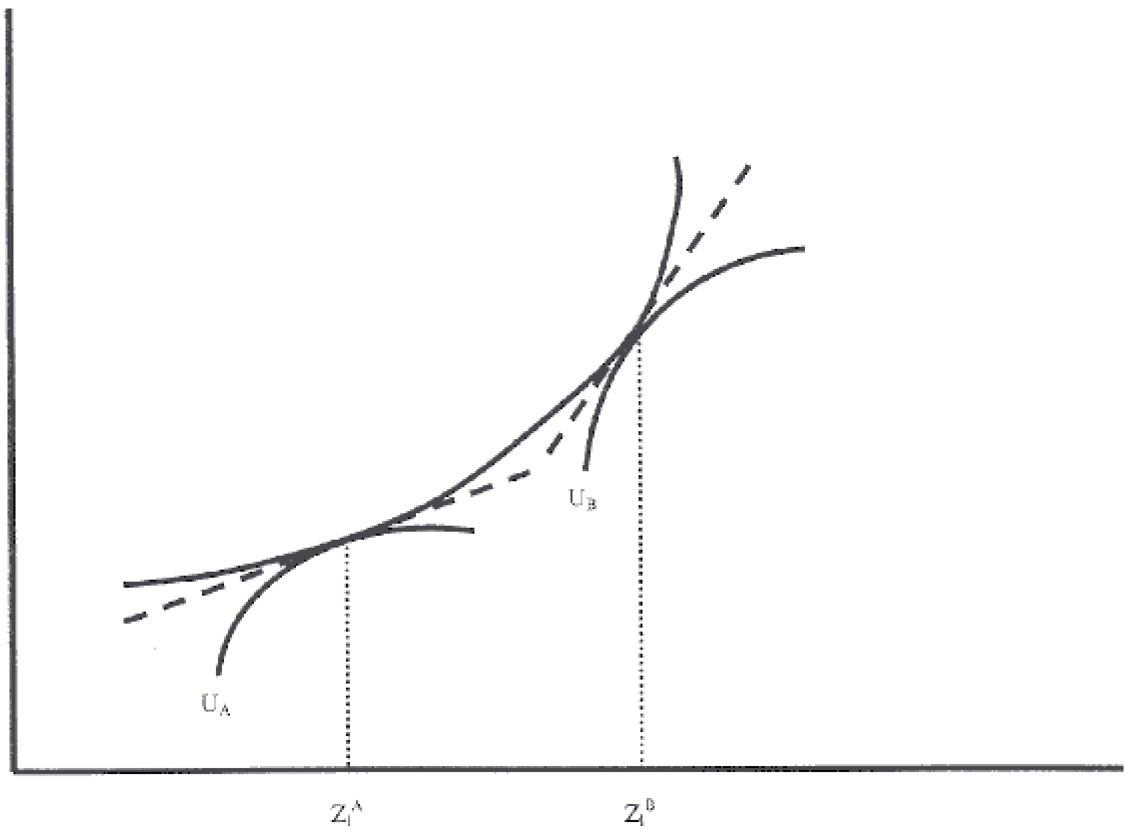
Appendix

Appendix Table A.1: House Price Observations By Year

Year	Number of Observations
1970	451
1971	1486
1972	1734
1973	1843
1974	1760
1975	1840
1976	2464
1977	2963
1978	3324
1979	3351
1980	2524
1981	2138
1982	1976
1983	3070
1984	3315
1985	3909
1986	7211
1987	5936
1988	5794
1989	5259
1990	4830

1991	4864
1992	5461
Appendix Table A.1 (cont'd.)	
1993	5498
1994	5779
1995	5265
1996	5939
1997	2102

$$P_1 = \frac{\partial HV_1}{\partial Z_1}$$



Z_1

Figure 1

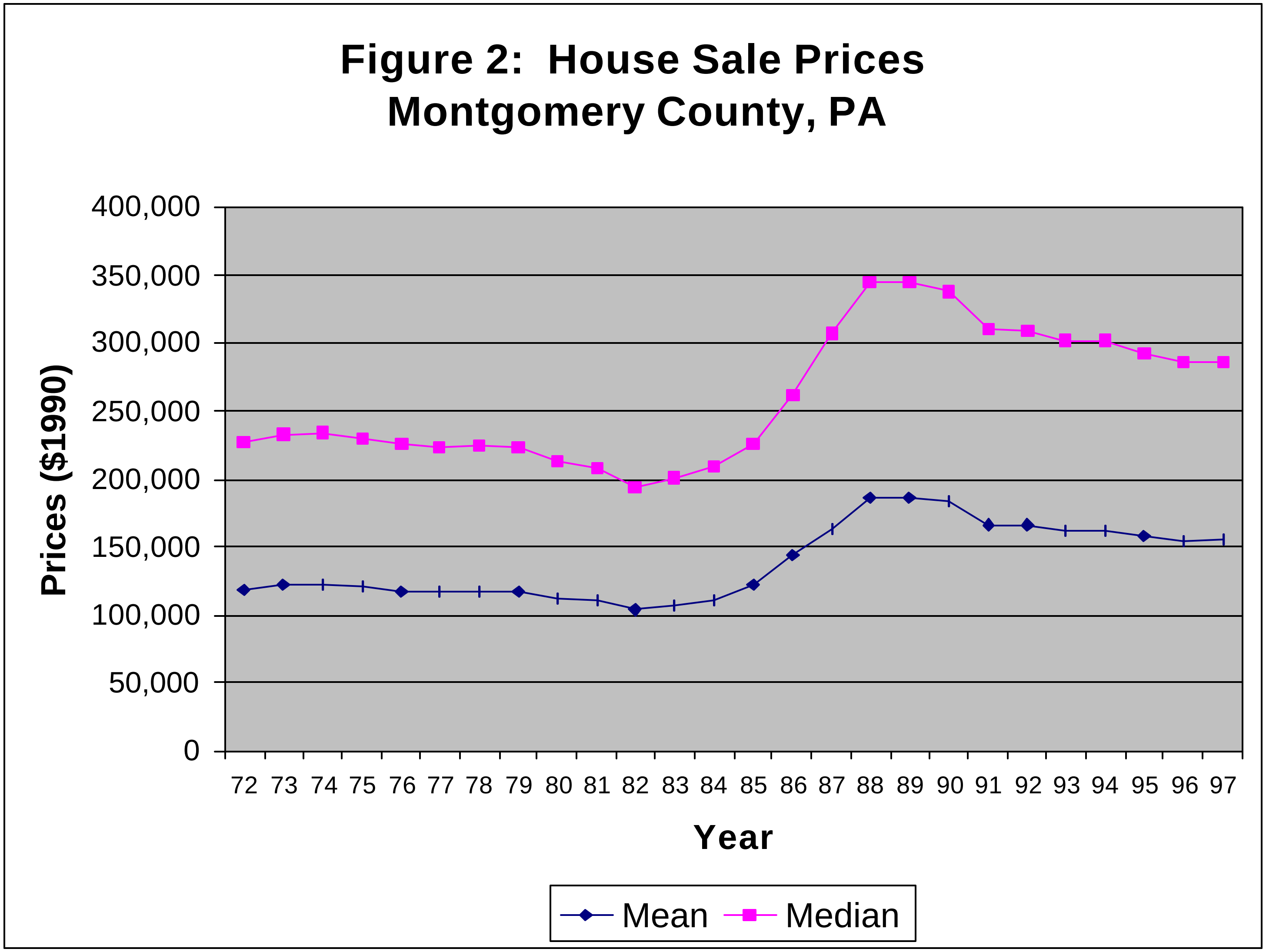


Figure 2: House Sale Prices
Montgomery County, PA
400,000
350,000
300,000
250,000
200,000
150,000
100,000
50,000
0
Prices ($1990)
72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97
Year
Mean
Median

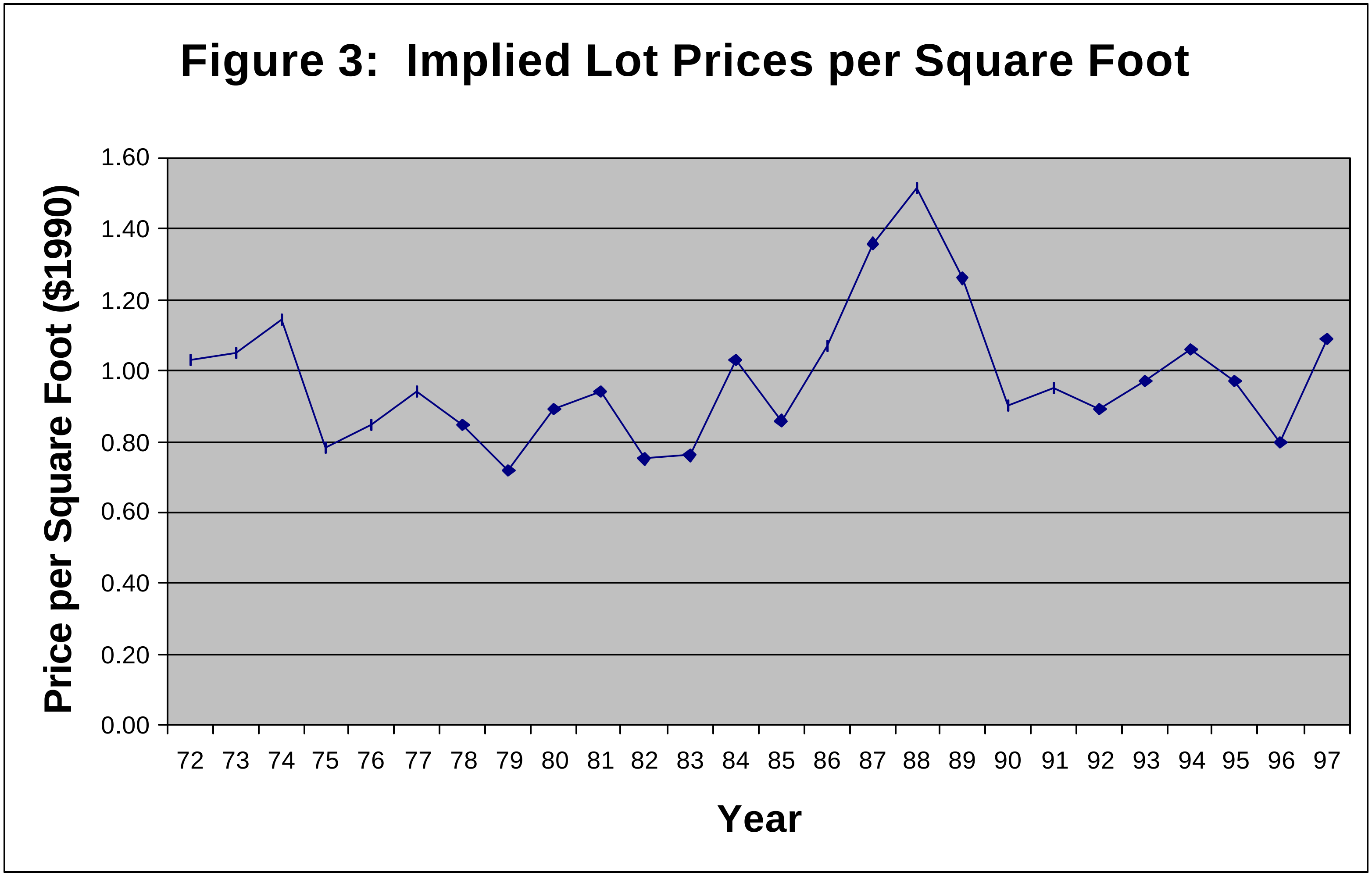


Figure 3: Implied Lot Prices per Square Foot
Price per Square Foot ($1990)
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97
Year