PRICE BASED POLICIES FOR MANAGING RESIDENTIAL DEVELOPMENT AND IMPACTS ON WATER QUALITY

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Abstract: We combine results from an instrumental variable duration model of residential development with a water quality model to examine how price-based policies impact urban development and nitrogen and phosphorus loads. Our duration model uses a control function approach to instrument for housing prices using spatial equilibrium linkages in the urban housing market. We combine the IV model with a water quality model to examine several price-based policies in a series of land-use simulations. Our results show that ignoring price endogeneity substantially underestimates the impact of price-based policies on residential development and nutrient loads. The policy simulations also reveal important tradeoffs between objectives for managing residential development and water quality. A uniform tax on development significantly reduces acreage developed, but increases nitrogen and phosphorus loads relative to a baseline scenario. A green tax for development on forested parcels is the most effective to mitigate water quality impacts, albeit with the lowest reduction of acreage developed.

Keywords: Land Use, Water Quality, Duration Models, Price Endogeneity, Residential Development JEL Codes: Q24, Q25, Q53, Q58

1. INTRODUCTION

Urban land-use change plays a critical role in determining the health of ecosystems (Glaeser and Kahn, 2004; Wu, 2008). Urban development patterns are the result of supply and demand forces that give rise to market clearing prices, which influence individual development decisions. Price-based policies, such as impact fees and green taxes, are becoming increasingly popular as policy options for managing urban land use and its impact on environmental outcomes (Brueckner, 2000; Burge and Ihlanfeldt, 2006). Understanding the relative effectiveness of specific policies depends on having economic models that can consistently estimate the responsiveness of individual landowner conversion decisions to changes in prices.

Choice models are frequently used to analyze spatially explicit micro-level land conversion decisions (e.g., Irwin and Bockstael, 2002; Cunningham, 2007; Towe et al. 2008; Lewis et al. 2009; Wrenn and Irwin, 2015). Operating at the landowner or parcel level, these models incorporate spatially and temporally varying parcel and neighborhood attributes, including prices, which impact development decisions. In several recent studies, econometric land-use change models have been used to conduct spatial simulations to analyze the effectiveness of incentive-based policies on environmental outcomes related to carbon sequestration (Lubowski et al. 2006), water quality (Langpap et al. 2008), biodiversity (Lewis et al. 2011), and tradeoffs with multiple ecosystem services (Nelson et al. 2008; Lawler et al. 2014). An econometric challenge in all of these models is that equilibrium prices, or rents, for urban development are functions of both observable and unobservable attributes. Thus, the inclusion of price or rent variables requires accounting for endogeneity concerns in order to precisely identify the effectiveness of incentive-based land use policies.

In this paper, we combine an instrumental variable (IV) duration model of residential land conversion with a watershed model to examine how price-induced changes in residential

development patterns impact nitrogen and phosphorus loading in the Baltimore metro region. The objectives of this study are to: (1) econometrically identify the responsiveness of residential development to changes in housing prices; (2) combine the results from an econometric land-use change model with pollution loading rates from a water quality model to develop a simulation framework suitable for analyzing price-based land-use policies; and (3) use the simulation framework to analyze policy scenarios designed to manage both residential land development and water quality outcomes.

To address these objectives, we estimate a parcel-level duration model that addresses price endogeneity using a unique dataset on residential subdivision development in the Baltimore metro region. Our residential subdivision data are manually reconstructed using information from historic subdivision plat maps entered into parcel GIS shapefiles to produce the residential development activity in the Baltimore metro region from 1994-2007. These data include information on the size and location of the original parent parcel for each subdivision as well as information on the number of residential lots created, zoning, and other characteristics of the parcels. Our duration model accounts for price endogeneity to produce a consistent estimate of the price elasticity of residential land conversion. To instrument for price, we use a control function approach appropriate for instrumentation in a nonlinear model (Papke and Wooldridge, 2008; Petrin and Train, 2010; Wrenn et al. 2017) and combine it with the spatial equilibrium logic used in developing instruments within demand-side urban location choice models (Bayer and Timmins, 2007; Bayer et al. 2007; Klaiber and Kuminoff, 2014).

To analyze the effectiveness of price-based policies that influence residential development and water quality outcomes, we combine the results from our duration model of residential conversion with land cover data and nitrogen and phosphorus loading rates from the Chesapeake Bay Program (CBP) watershed model in a series of land use simulations. The CBP watershed model

is the most policy relevant model in our study region as it is used by the EPA and all jurisdictions in the watershed to evaluate compliance with the Chesapeake Bay total maximum daily load (TMDL) requirements. We focus on nitrogen and phosphorus loads as measures of water quality impacts because the EPA regulates both nutrients under the Chesapeake Bay TMDL, and both of these nutrients have also served as the primary water quality measures in the region since the Chesapeake Bay Agreement was initiated in 1983.

We use our model to analyze three specific policies which are both relevant to the Baltimore region and generally applicable for land-use planning in other regions. Specifically, we focus on three price-based policies designed to manage residential development and water quality. In Scenario 1, we implement a uniform tax on all parcels. This scenario reflects the uniform manner in which property tax policies and development impact fees are often implemented in urban areas in the United States to be considered equitable. In Scenario 2, we implement a tax increase on parcels in rural areas without municipal sewer service and a subsidy on parcels in designated urban areas with municipal sewer service. This "compact development" scenario aims to reduce sprawl in rural areas, while using incentives to encourage infill development in designated urban areas with existing infrastructure capacity. Finally, in Scenario 3 we implement a "green tax" based on the existing forest cover on each parcel as a means of preserving parcels with large amounts of forest cover. For each policy scenario, we conduct simulations based on tax and subsidy rates for a 1% and 2% change in housing prices. We then compare the simulation results for land development outcomes (number of subdivision developments and total acreage developed) and water quality impacts (total nitrogen and phosphorus loads) relative to a set of baseline simulation results where prices are held fixed at their initial levels.

Our econometric model and policy simulations provide several important results and contributions to the literature. First, we demonstrate that failure to account for price endogeneity

produces biased and inconsistent elasticity values and leads to incorrect conclusions about the effectiveness of price-based policies. Using our preferred IV model, we find that the elasticity values in the IV model are 2.4 times larger than those in the non-IV model. The policy simulations for the non-IV model suggest that not accounting for price endogeneity has important implications when evaluating the effectiveness of price-based policies on land development and the concomitant environmental impacts.

Next, we find that our price-based policy simulations lead to explicit tradeoffs between policies seeking to manage the spatial pattern and amount of residential land conversion and those seeking to manage water quality. The uniform tax increase (Scenario 1) leads to a large overall reduction in both the number of residential developments and total acreage developed, relative to the baseline simulation; however, this policy leads to a perverse effect on water quality since it increases both nitrogen and phosphorus loads. The key mechanism behind this result is that, while the uniform tax reduces the total acreage developed, the majority of this reduced land conversion would occur on existing agricultural land in rural areas which has higher baseline nutrient loads relative to rural residential development.

The compact development policy (Scenario 2), which attempts to limit urban spatial expansion and concentrate development in areas with public sewer, leads to a similar outcome – a decrease in both the number of developments created and total acreage developed and an increase in nitrogen and phosphorus loads. Finally, the green tax policy (Scenario 3), which is designed to preserve forest cover, produces significant reductions in both nitrogen and phosphorus loads, albeit with the lowest overall reduction in acreage developed. Hence, our simulations indicate that price-based policies which limit forest loss are the most effective at mitigating the water quality impacts from residential development in our study region. Given the increasing availability of micro-level data on residential development and housing prices, our novel approach is particularly useful both as

a method for controlling for price endogeneity in land-use change models and as a means of analyzing price-based policies aimed at managing urban growth and environmental impacts.

2. ECONOMETRIC MODEL

Housing supply outcomes impacting ecosystem functioning and water quality are a result of many individual landowner decisions linked through market processes. As an individual landowner decides to convert an undeveloped parcel to residential use, they consider not only attributes of their own parcel but also the likely prices and subsequent revenues this conversion will provide (Capozza and Helsley, 1989). Housing prices are spatially varying equilibrium outcomes arising from many individual transactions. The equilibrium prices are functions of both observable and unobservable attributes, to the researcher, which introduces econometric challenges when including prices in supply and demand models. The inclusion of prices in housing demand and supply estimation requires accounting for the potential that omitted variables create endogeneity concerns. In nonlinear models, handling these types of endogenous attributes is a longstanding challenge.

Nonlinear duration models are frequently used to capture housing supply decisions in a reduced-form setting (Irwin and Bockstael, 2002; Newburn and Berck, 2006; Cunningham, 2007; Towe et al. 2008; Lewis et al. 2009; Wrenn and Irwin, 2015; Newburn and Ferris, 2017). Operating at the parcel level, these models easily accommodate micro-level land use features that vary spatially as well as temporally. We extend the standard duration modeling framework by combining a nonlinear IV technique to instrument for price using a control function methodology (Rivers and Vuong, 1988; Papke and Wooldridge, 2008; Petrin and Train, 2010; Wrenn et al. 2017). The instruments used in this control function model are formed from equilibrium relationships – a method commonly used in structural models of housing demand (Bayer et al. 2007; Walsh, 2007; Klaiber and Phaneuf, 2010).

Duration models of land conversion assume that in each period t the landowner of an undeveloped parcel i located in neighborhood j decides whether or not to convert their parcel to a residential subdivision. Conversion decisions depend on parcel-level attributes I_{it} and neighborhood-level attributes X_{jt} where we define neighborhoods as Census 2000 block groups. We use discrete annual time-steps to define the time dimension of our duration model consistent with much of the empirical housing supply literature. To operationalize the model, we specify a reduced-form latent profit function underlying the duration model as

$$\Pi_{it}^* = I_{it}'\beta + X_{it}'\alpha + P_{it}'\gamma + u_{it} \tag{1}$$

where Π_{it}^* is the latent profitability on parcel i, I_{it} and X_{jt} are parcel and neighborhood characteristics affecting profitability, respectively, P_{jt} is the price of housing services at the neighborhood level, and u_{it} is an idiosyncratic error term. Based on equation (1), the parametric proportional hazard we adopt is

$$h(t) = h_0(t)h(I'_{it}\beta + X'_{it}\alpha + P'_{it}\gamma)$$
(2)

where $h_0(t)$ is the baseline hazard, which is shifted proportionally by changes in the variables in the model.

To address endogeneity of housing prices, a proxy for expected revenues, we adopt a control function approach. This approach uses a two-step estimation procedure to instrument for endogenous variables using residual variation derived from a first-stage regression that includes exclusionary instrumental variables Z_{jt} that control for the correlation between price and the error term. The first-stage OLS regression is specified as

$$P_{jt} = X'_{jt}\beta + Z'_{jt}\delta + v_{jt} \tag{3}$$

where the exogenous neighborhood variables, Z_{jt} are a set of excluded variables that affect price, but not latent profit Π_{it}^* , and v_{jt} is an idiosyncratic error term.¹

In the presence of endogeneity, the error term from equation (1) is given as

$$u_{it} = v'_{it}\theta + e_{it}. (4)$$

Assuming joint normality between u_{it} and v_{jt} , the residual vector, \hat{v}_{jt} from the first stage is added to the second-stage duration model as an additional covariate. Assuming that the instruments in the first stage are valid, we rewrite equation (1) as

$$\Pi_{it}^* = I_{it}'\beta + X_{it}'\alpha + P_{it}'\gamma + v_{it}'\theta + e_{it}$$
(5)

where assuming joint normality between the errors in both stages results in a discrete-time duration model as

$$P(\Pi_{it}^* = 1 | I_{it}, X_{jt}, P_{jt}, v_{jt}) = \Phi\left[\frac{I_{it}'\beta + X_{jt}'\alpha + P_{jt}'\gamma + v_{jt}'\theta + \tau_{t-t_0}}{\sqrt{1-\rho^2}}\right].$$
(6)

We include a set of time fixed effects τ_{t-t_0} to model the baseline hazard.

The price instruments we construct to include in the first stage borrow from the intuition developed in structural urban demand models of location choice. These models use the logic of Nash equilibrium to form instruments in a residential sorting context. The primary insight from this literature is that distant attributes impact prices in focal neighborhoods through spatial equilibrium – i.e., they impact demand and price in distant locations and thus impact the overall equilibrium price level in the urban area. By isolating these distant, exogenous attributes it is possible to form instruments that are uncorrelated with unobservables in the focal neighborhood. We adopt this same methodology in the Baltimore metro region.

9

¹ As is the case in a standard 2SLS IV model, identification depends on having at least as many excluded variables in the first stage (Z_{jt}) as there are endogenous regressors in the main model.

Figure 2 shows a map of our study region displaying both county and neighborhood (2000 census block group) boundaries to provide the intuition for our instrumentation procedure. As an example, this figure depicts a single "focal" neighborhood with a seven-mile distance ring drawn around the centroid of the focal neighborhood. Our instrumentation strategy uses variation in exogenous attributes from "distant" neighborhoods located outside the distance cutoff defined by this ring as a means of controlling for price endogeneity. "Local" neighborhoods are defined as those that are located within the distance cutoff, but not including the focal neighborhood. To determine the extent of local versus distant neighborhoods, we use a series of statistical tests to examine the validity of our distance thresholds. To do this, we exclude an increasing number of local neighborhoods around each focal neighborhood and create an IV matrix (Z_{jt}^n) that consists of weighted average values of exogenous attributes from neighborhoods outside of the boundaries defined by these local neighborhoods, where the superscript n indexes the distance cutoff used in forming the Z matrix. We add these weighted instrumental variables to the right-hand side of equation (3) and estimate

$$P_{jt} = X'_{jt}\beta + Z^n_{jt}\delta + v_{jt}. \tag{7}$$

For each of these models, we use overidentification tests and choose the optimal model (optimal distance cutoff used in forming our instruments) based on the Chi-squared values from these tests (Stock et al. 2002; Wooldridge, 2010). By increasing the distance used in forming our instruments, we are able to net out local sources of variation, while retaining the power of the instrument, a result that is predicted by urban spatial theory (Bayer and Timmins, 2007).

3. DATA AND CONSTRUCTION OF VARIABLES

The data used in our models covers the three counties in the Baltimore metro region: Baltimore, Carroll and Harford counties (Figure 1). To produce subdivision data, we obtained GIS parcel data and the historical archive of subdivision plat maps for the three counties from the Maryland Department of Planning (MDP). Using the scanned images of subdivision plat maps, we manually reconstructed the panel of residential subdivisions for the years 1994-2007. The subdivision reconstruction process allowed us to determine all the individual residential lots in the original "parent" parcels. The year of subdivision approval for each plat is used to determine the timing of each conversion event. From this process, we reconstruct the landscape for the parcel boundaries as they were at the beginning of the study period in 1994.

In addition to the creation of subdivision data, we obtained historical information on zoning boundaries and municipal sewer service availability for each county. Using these zoning data, we calculate the number of residential lots permitted on each parcel. This process provides a micro-level land use dataset for the panel of developable parcels that are eligible for residential subdivision development from 1994 through 2007. For the econometric model, we define subdivision eligibility as any parcel that can, according to zoning, accommodate a subdivision development of two or more residential lots. Because our focus is on modeling the subdivision conversion process for single-family residential development, we screened out parcels zoned for commercial, industrial, multi-family dwellings (apartments), and institutional uses as well as parcels in protected status for parks and conservation easements. Combining our subdivision data with our method of determining subdivision eligibility results in a dataset of 15,015 parcels that were developable as of 1994. Among

² Plat maps are the residential subdivision plan that the developer submits for approval to the local government. It includes the location and exact boundaries of each residential lot as well as other information, such as year of subdivisions.

includes the location and exact boundaries of each residential lot as well as other information, such as year of subdivision approval.

these parcels, there were 2,394 residential subdivision events during our study period in 1994-2007, and the other parcels remained undeveloped (censored) at the end of 2007.

To develop an empirical strategy for handling price endogeneity, we begin by adopting the intuition underlying the spatial residential market structure from the urban location choice literature whereby households, or housing units, are nested within larger neighborhoods (Tiebout, 1956; Epple and Sieg, 1999; Bayer et al. 2007; Klaiber and Phaneuf, 2010). We assume that each of the 15,015 parcels in our data is nested within one of 667 neighborhoods, where neighborhoods in our context are defined based on Census 2000 block-group boundaries. Figure 1 provides the distribution of parcels and neighborhoods underlying the basic intuition for this process. As with the urban location choice literature, we assume that factors varying at both the parcel and neighborhood level impact the probability of conversion to a residential development in each time period.

Summary statistics for the variables used in our model are given in Table 1. The variables are separated based on their level of spatial variation. The top portion of Table 1 lists the variables that control for parcel-level characteristics. First, to control for locational parcel attributes, we include the distance, in kilometers, from each parcel to the center of Baltimore City (Dist), which reflects accessibility to the largest employment center in the region. We also include the distance to the closest major highway (DistMajRoad) as a measure of accessibility to transportation infrastructure. Both of these variables are expected to decrease the value of the parcel and its propensity to develop the farther the parcel is to the central business district (CBD) or major highway.

Zoning is also expected to play a role in determining the likelihood of conversion as the more densely zoned a parcel is the greater the number of building lots allowed. We obtained historic zoning maps for each county from the Maryland archives and overlaid these maps with our parcel data. The variable ZndLots captures the zoned lot capacity for each parcel based on parcel size, zoning type, and maximum density regulations. While zoning did change slightly in Baltimore

County during our study period, these changes were relatively small with most zoning designations for the entire region established in the mid-1970s. To account for the slight changes in zoning during our study period, we obtained the set of all historic zoning boundary maps for Baltimore County that enabled us to accurately calculate the zoned capacity for each parcel and each year in our data. We use historic sewer boundary maps for each county and create an indicator variable (Sewer) for parcels with municipal sewer services. Using the set of historic zoning and sewer boundary maps, the zoned capacity and sewer variables are temporally lagged to represent these variables prior to the development decision in each year. We expect that parcels that have more development rights or with sewer service are likely more valuable and thus more likely to develop.

The final set of parcel-level variables control for the physical features of the parcel. These include variables for the land area in acres for each parcel and soil quality characteristics derived from the SSURGO data provided by the Natural Resource Conservation Service (NRCS). We expect larger parcels are more likely to develop due to economies of scale. The NRCS soil classifications capture the hydrology, slope, percolation rate, and permeability of the soil. By combining these factors we construct development suitability measures for each parcel. First, to proxy for septic systems and basement suitability, we develop a septic suitability indicator (SepticSuit) based on soil permeability and percolation. We expect that parcels with a value of one will be more likely to develop as the soils on the parcel are more suitable for installation of septic systems and basements. Second, we use the slope classification for each parcel to develop a variable (Slope) for the percentage of each parcel that has a slope of more than 15%. We also overlay our parcel data with maps for 100-year floodplains from the Federal Emergency Management Agency

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³ Zoning designations were created for the entire region in the mid-1970s—Baltimore (1976), Harford (1977), and Carroll (1978). Zoning GIS shapefiles were also obtained to capture the minor zoning revisions that occurred in 2000 and 2004 for Baltimore County. The number of zoned lots on developable parcels in Baltimore County changed by less than 1 percent between 1994 and 2007. Sewer service boundaries were also created historically in Baltimore County (1967) and Harford County (1977) and have remained unchanged, thereby effectively act as urban growth boundaries to limit sewer service.

(FEMA) and create an indicator variable for whether the parcel is located in a floodplain zone (FloodPlain). We expect that parcels with steeper slopes or those located in floodplains are less likely to develop due to development limitations. Finally, we include an indicator variable for whether the parcel has an existing structure (ExHouse) as well as a variable for percentage of the parcel with forest cover (ForestPrcnt).

The neighborhood-level variables in Table 1 comprise time-varying factors most likely to influence the probability of development in each neighborhood and year. First, we develop measures of the percentage of land in each neighborhood that is either preserved or protected from development (Preservation). Maryland has an extensive farmland preservation program which we use to develop a time-varying measure for the percentage of land area in each neighborhood and year that is preserved. We also control for the percentage of land area in each neighborhood that remains undeveloped and developable (UDArea). Second, we capture competitive effects among developers using a one-year lag of subdivision activity (total lots approved) at the neighborhood level (ApprvLots). Finally, we estimate neighborhood land (LandPrice) and housing (HousePrice) prices using auxiliary regressions. Both the land and house-price variables are created by estimating a series of yearly hedonic models on arms-length land and housing transactions obtained from a statewide database of sales provided in the Maryland Property View (MDPV) database. Each model includes, among other controls, a set of block-group fixed effects which serve as our quality adjusted neighborhood land and housing-price indices (Sieg et al. 2002). The details of the data and estimation procedures for our housing and land-price variables are given in the Appendix. It is the housing-price variable produced from this process that is the focus of our econometric model and subsequent policy simulations.

⁴ This method of estimating prices is commonly used in the urban demand and supply literature (Walsh, 2007).

4. MODEL RESULTS

4.1 Control Function Estimation

The control function residual is obtained by estimating a pooled OLS regression in the first stage based on equation (7). This first-stage regression includes all exogenous neighborhood characteristics for the focal neighborhood, time and county fixed effects, and a set of instrumental variables based on average values of exogenous, demand-side attributes from distant neighborhoods. The instruments used include the percentage of land in each neighborhood that is preserved from development (PreservationAvg) and the percentage of land that is undeveloped (UndevelopedAvg).⁵ We expect each variable to impact the location choices of households and developers in distant neighborhoods, thereby influencing the equilibrium price, but we do not expect these distant measures to directly impact developer decision-making in the focal neighborhood (Bayer et al. 2007; Petrin and Train, 2010; Wrenn et al. 2017).

Using equation (7), we generate neighborhood-level residuals based on different distance bands and include them as additional variables in the duration model. To account for any nonlinear impacts associated with the control function, we also include a quadratic term for the residual in the model (Papke and Wooldridge, 2008). For robustness, we also estimate models based on omission of local neighborhoods falling within the distance cutoffs ranging from four to six miles.

Results from the first stage of our control function model are presented in Table 2. The distance cutoffs used in forming the instruments are shown along the top of Table 2; Panel A presents parameter estimates for the instrumental variables as well as estimates for the parameters of those same variables in focal neighborhoods; and Panel B presents results for a set of joint

⁵ Our instruments are broadly based on a traditional Hausman-type price instrumentation strategy (Hausman, 1997). Specifically, we assume that exogenous attributes in distant neighborhoods impact housing prices in those neighborhoods which in turn impact housing prices in focal neighborhoods via the spatial equilibrium outcome in the urban housing market. This is similar to using prices in distant markets as instruments for local prices in the industrial organization literature.

hypothesis tests that the coefficients on our instruments are equal to zero in the first stage. Based on the *F*-statistics in Panel B, it is clear that our instruments pass the first-stage tests for each of the distance bands in the duration models; *F*-statistics far exceed the rule-of-thumb exclusion threshold of 10 needed for inference based on the 2SLS estimator (Stock et al. 2002). We also find that our instrumental variables are statistically significant and have opposite signs from those same variables in focal neighborhoods which suggests that they serve as credible sources of exogenous variation (Bayer et al. 2007).

Based on our IV strategy, using increasingly distant neighborhoods to generate instrumental variables in equation (7) should isolate plausibly exogenous competitive effects on price, while reducing the potential for direct price impacts from local neighborhoods. The remaining residual variation in the first-stage models introduced by our instrumental variables, after purging local effects, serves as a control function for price endogeneity. We conduct overidentification tests based on the methodology described in Wooldridge (2010) that is similar to a Hansen's *J* overidentification statistic used in GMM models. Specifically, in addition to the residuals generated from the first-stage OLS model, we add one of the two excluded instruments to the right-hand side of the duration model, where we use the variable on the percentage of preserved land area as our excluded instrument, and perform a series of Chi-squared joint hypothesis tests.

The results from our overidentification tests and parameter estimates for price and controlfunctions variables are presented in columns (2)-(4) in Table 3. The distance cutoffs, ranging from
four to six miles, used for instrument formation are shown in column 1. For each model, we report
nonparametric block bootstrapped standard errors (300 replications) with bootstrapped samples
drawn based on neighborhood ID numbers. Overidentification tests show that we reject the null
hypothesis that the excluded variables are not correlated with the error terms in each of the models.

As we exclude additional neighborhoods in the first-stage regressions based on distance cutoffs, the

p-values for these tests rise and become less significant. This result reflects the spatial equilibrium nature of our IV strategy – as increasingly distant neighborhoods are used in constructing our instruments, the competitive impact of distant attributes on housing prices in a focal neighborhood are purged of local sources of variation that may directly impact prices in a focal neighborhood.

Lastly, column (4) of Table 3 presents the control function residual and it squared term, which both have the expected negative sign. This indicates that failure to control for endogeneity of prices is likely to lead to an understated price elasticity of land conversion.

4.2 Duration Model Estimation

Estimation results for both the non-IV and IV duration models are shown in Table 4. We separate the results into parcel and neighborhood characteristics. Standard errors are based on a nonparametric block bootstrap procedure with blocks based on parcel ID numbers. Examining these results, we find similar signs and significance in models with and without instrumentation. We now provide a brief review of the main findings in Table 4, followed by an analysis of the coefficients on housing price in each model.

For the parcel-level characteristics, the coefficient estimate on zoned lot capacity (ZndLots), which accounts for the number of allowable lots based on the zoning designation of the parcel, is positive and significant in both models, which suggests that zoned capacity play a key role in determining the likelihood of development. The coefficient on distance to nearest major highway is positive and significant in both models. The coefficient on floodplain is negative and significant in both models, suggesting that development is less likely in areas prone to flood risk. The coefficient

⁶ We also examined the distance cutoffs below four miles, but found that the *p*-values were either significant or close to significant in many of these cases.

on septic suitability is positive and significant in both models, indicating that development is more likely on parcels with suitable soils to allow septic systems.

For the neighborhood-level characteristics, we find that an increase in the number of prior lots approved at the neighborhood level has a positive impact, but only in the non-IV model. The coefficient on preservation is negative and significant, but only for the IV model. Finally, the coefficient on land price is negative and significant in both models, which is as expected if land serves as an input in the production of housing.

Turning attention to our primary interest, the estimated coefficients on the housing-price variable are positive and significant in both the non-IV and IV models. The coefficients for the housing price residuals are negative and significant in all models indicating a downward bias in price in models without instrumentation. Finally, the price coefficients in the IV models are substantially larger in magnitude than those in the non-IV models, which suggests that not accounting for price endogeneity may significantly underestimate the impact of housing prices on the probability of conversion. To provide some intuition for both the sign and relative magnitude of our housing price coefficients, we convert these coefficients into elasticities in Table 5.7 Examining these values, the price elasticity in the IV model is 2.4 times larger than in the non-IV model.

The results in Tables 4 and 5 demonstrate that accounting for price endogeneity is important. The result also has important policy implications suggesting that land-use planners and policymakers may be able to use targeted, price-based policies to achieve their objectives. In Section 5, we explore these ideas further using the results from the IV and non-IV duration models in a series of land-use simulations, with an emphasis on the IV model results. Before proceeding, however, we first present several robustness checks for our IV duration model.

⁷ The point estimates are the average elasticity values calculated at each point in the sample, and they represent the "price elasticity of residential land conversion" and reflect the long-run price elasticity of land supply in our three-county metro region (Wooldridge, 2010).

4.3 Robustness Checks

Here, we provide a brief discussion of the results for several robustness checks. For further details, the results for all robustness checks are contained in Appendix B. All models use an identical dataset to the previous subsection with a six-mile distance cutoff for instrument creation.

The first model addresses the concern that land prices, in addition to house prices, may be endogenous. To address this, we assume endogeneity for land prices and include them as a second equation in our first-stage regression model. This implies that we will have two sets of controls – one set of residuals for the housing-price regression and another set for the land-price regression. Each can be used to test for endogeneity. The results from this model are shown in Tables B1 and B2 in Appendix B. Based on these tables, we find that: (1) land prices do not appear to be endogenous, at least after controlling for housing prices; and (2) the results for our housing-price variable continue to hold.

The second robustness check addresses a concern that our results may be driven by development outcomes in the abnormal housing market boom from 2005 through 2007. To address this concern, we drop these years from the data and re-estimate the entire model using only the data from 1994 through 2004. The results based on the abridged data are shown in Table B3. The results remain largely the same as the model using the full dataset.

The third robustness check addresses the potential issue of spatial error autocorrelation. While spatial error autocorrelation is an efficiency issue in linear spatial models, in nonlinear models it represents both a consistency and an efficiency issue (McMillen, 1992). To address this concern, we (1) implement a spatial sampling procedure on our data to reduce the impact of local spatial effects (Carrion-Flores and Irwin, 2004) and (2) run a spatial autocorrelation test designed for nonlinear panel models to test for spatial error autocorrelation. For the spatial sampling procedure,

we create 100 and 200-meter buffers around each of the parcels in our data. We then sequentially sample parcels based on parcel IDs and drop all parcels that fall within the distance cutoffs defined by our two buffers. We continue this procedure until there are no remaining parcels to drop. That is, we create two samples: one sample where each observation has no neighbors within 100 meters and a second sample with no neighbors within 200 meters. Using the two abridged samples, we reestimate our primary model. Additionally, we conduct a series of spatial error autocorrelation tests for nonlinear panel models (LM tests) using the generalized residuals from the probit to test for spatial error correlation (Pinkse and Slade, 1998; Baltagi et al. 2003).

The results from our spatial error models are shown in Table B4, where Panel A1 presents results from the sample data constructed using a 100-meter buffer and Panel B1 from the sample data constructed using a 200-meter buffer. The LM tests in Panels A2 and B2 are based on two different specifications for the spatial weights matrix: a 100-nearest neighbor specification and an 800-meter distance cutoff. Based on these results, we find that our findings continue to hold.

For the final robustness check, we address the concern of a violation of the joint normality assumption (an assumption of the control-function method) and examine how a nonlinear functional form may impact our results. To address this, we reclassify our model in linear form and estimate a generalized method of moments linear probability model (GMM LPM) with the instruments from our control-function model used as instruments in the GMM model.

The results from our GMM LPM model are shown in Table B5.8 The results for the first-stage *F*-stat and second-stage *J*-stat are very similar to those produced by the control-function model. We also observe that the GMM test of endogeneity is significant at the 10% level. Finally, we see that the elasticity value produced in the LPM model is similar to the IV model. Based on these

⁸ We only present results for the IV model. The non-IV LPM results are available upon request.

results and the other robustness checks in Appendix B, we feel confident in proceeding with our policy simulation analysis.

5. POLICY SIMULATIONS AND WATER QUALITY OUTCOMES

We now present our results from the policy simulations where we combine our duration model with parameters on nutrient loading rates from the CBP watershed model. The purpose of this analysis is to examine how different price-based land-use policies alter development patterns and water quality outcomes. For each of our three policy scenarios, we compare simulation results relative to a baseline simulation where housing prices remain at their original baseline levels. For each simulation, we employ a nested looping structure where the outer loop is over the parameter distribution from the duration model and the inner loop is over time in yearly time steps. Across each simulation, we highlight the important role of accounting for price endogeneity in obtaining measures of both urban development and environmental outcomes. Simulations proceed using the following steps.

5.1 Simulating Development Patterns

First, we use the data from our duration model to establish a baseline set of at-risk parcels for each time period in the model. In other words, the simulations use the 15,015 developable parcels from the original data, where each parcel is initially assumed to be developable in each time period. We use this set of parcels that were developable as of 1994 and overlay the parcel data in GIS with the 1992 USGS land cover data for the Baltimore region. For each developable parcel, we determine the baseline land cover with particular emphasis on the percentage of agricultural and forest land cover of each parcel. We use the USGS Chesapeake Bay Watershed Land Cover data from 1992, which is

derived from Landsat satellite imagery. To determine forest cover, we combine all forest cover types (deciduous, evergreen, mixed forest, and shrub) into a single land cover type. To determine agricultural land cover, we combine hay, pasture, and cultivated crops. To account for potential urban infill development, we also determine the 1992 baseline land cover in very-low and low-density development. We use the 1992 land cover data because it is the baseline land cover that is available immediately prior to the beginning of our study period in 1994. For the developable parcels, the baseline land cover is primarily in agriculture (55%) and forest (39%) with a smaller amount in very low density development (4%) and low density development (2%) occurring mainly inside sewer service areas.

The second step of our simulation procedure, the outer loop, iterates over the parameter distribution from the duration model by taking a draw from the estimated $1,000 \, kx1$ parameter vectors from the bootstrapped matrix of estimated parameters. Each parameter draw is combined with the baseline land use data established in the first step above and a probit link function from the duration model to form a predicted probability of development for each parcel.

The third and final simulation step involves determining which parcels develop in each time period. To do this, we employ an accept/reject strategy by taking a random draw from a uniform distribution for each parcel and comparing it with the predicted probability of development for each parcel estimated in the second step above. We assume that a parcel is developed if the predicted probability of development for that parcel is larger than the draw from the uniform distribution. To replicate the dynamic nature of the development process in our original data, these probability comparisons take place sequentially. That is, for each iteration of the outer loop (each vector of parameters drawn from the bootstrapped parameter matrix), we iterate at annual time steps making

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⁹ The USGS Chesapeake Bay Watershed Land Cover data is derived from the USGS National Land Cover Dataset and NOAA's Coastal Change Analysis Program.

comparisons in each time period and drop the parcels from all subsequent time periods after they are developed, which effectively reflects the terminal nature of the conversion event process. We refer to this as the inner loop, where we step through time keeping track of which parcels are developed in each time period. We repeat this inner loop procedure for each of the 1,000 outer loop parameter vectors.

Each of the 1,000 iterations in our simulation produces a vector of parcel IDs for the residential conversion events – i.e., it provides the land development outcomes for the number of residential subdivision events that occur and the total acreage developed in each iteration. To use these events for policy evaluation on water quality impacts, we link each set of development outcomes (parcel IDs from GIS data) with information on existing land cover and nitrogen and phosphorus loading rates to generate measures for the change in loading rates for the implementation of a given policy scenario.

5.2 Simulating Water Quality Impacts

Assessing the water quality impacts involves combining the CBP model information on loading rates with our predicted changes in land cover due to residential development. This involves using the loading rates from the CBP watershed model to determine the baseline nitrogen and phosphorus loads on each developable parcel according to the baseline land cover prior to development. Specifically, we determine baseline nitrogen and phosphorus loads according to edge-of-stream loading rates and the acreage for each baseline land cover type on each developable parcel.

As the final step in the simulation process, we use the simulation predictions for all developed parcels to calculate the post-development loading rates based on the predicted density of development for each subdivision. The relationship between development density and loading rates for nitrogen and phosphorus is once again taken from the CBP watershed model, with loading rates

increasing for higher development density. The duration model, while effective at modeling the optimal timing decision, does not explicitly model density. In order to assign a density to each simulated development, we calculate average density values from our observed subdivision data. Specifically, we use the actual data for the 2,394 residential subdivision events observed from 1994-2007, where residential density is calculated using the number of residential lots and land area of the parent parcel. We then calculate the average density values for each year and county, which is done separately for areas with and without municipal sewer service. We use these density values to assign development densities to each predicted subdivision development based the timing and location of the development. Using this information, we calculate the post-subdivision loading rates for each developed parcel. This process is repeated for the 1,000 simulated development patterns, and we examine the distribution of these development and water quality outcomes for each policy scenario.

5.3 Policy Simulations

While there are numerous price-based policies that could be analyzed, our main interest is to examine the scenarios that provide policy relevant implications for the impacts on land development and water quality outcomes. Thus, we focus on three policy scenarios which are both relevant to the Baltimore metro region and are generally applicable for land-use planning in other regions.

In Scenario 1, we implement a uniform tax increase for housing development on all parcels. This uniform tax scenario reflects the manner in which most residential property taxes or development impact fees are implemented in the United States in consideration of being equitable. In Scenario 2, we implement a tax for development on all parcels located in areas without municipal sewer service and a subsidy for development on all parcels located in areas with municipal sewer service. This scenario reflects the approach used by land-use planners to charge an impact fee to reduce sprawl in rural areas without municipal services, while aiming to encourage infill development

in designated urban areas with existing municipal services. In Scenario 3, we implement a green tax based on the existing forest land cover on each parcel. The goal is to reduce forest conversion, which has the lowest nitrogen and phosphorus loading rate. Our specific policy is to implement a tax for development on parcels with greater than 50% forest cover. This last scenario is focused on enhancing water quality outcomes, as opposed to managing urban spatial expansion based on existing municipal services. In all three scenarios, we compare the simulation results for each price-based policy scenario relative to the baseline simulation results where prices remain unchanged from their initial levels. In each scenario, the tax and subsidy values are done for a 1% and 2% change in housing prices.

Before turning to the results from the policy simulations, it is important to assess how well the predicted simulation results correspond to the actual subdivision data. To do this, we compare the baseline simulation results where prices remain unchanged and the actual subdivision data. Based on the 1,000 iterations, the baseline simulation predicted that the mean number of subdivision developments is 2,396, with the bootstrapped 95% confidence intervals ranging from 2,283 to 2,518 subdivisions. Hence the mean number of subdivisions for the baseline simulation model is very close to the actual number of observed subdivisions (2,394 subdivision developments in 1994-2007).

Table 6 shows the simulation results for the IV model on land development outcomes: the predicted number of subdivisions created and the total acreage developed. The simulation results are reported for the mean difference in the number of subdivision developments and the mean difference in the total acreage developed for each policy scenario relative to the baseline simulation. Land development outcomes are also provided separately for developments occurring inside and outside of sewer service areas. The region with sewer service is a proxy for development in urban areas, while the region outside sewer service represents development in rural areas. Bootstrapped 95% confidence intervals (CIs) are included based on the 1,000 iterations, where the null hypothesis

is a test on whether the bootstrapped 95% CIs contain zero. The analogous simulation results for the non-IV model on land development outcomes are presented in Table A1 in Appendix A.

Our policy simulations yield several interesting results. First, the number of subdivision developments and acreage developed for the IV model (Table 6) are much larger in magnitude compared to those for the non-IV model (Table A1). This suggests that the duration model, without instrumentation, provides estimates for development and acreage conversion that are biased downward in magnitude for all policy scenarios. Second, the uniform tax in Scenario 1 reduces the number of developments and acreage developed for the IV model, particularly in the rural areas outside sewer service. A marginal 1% increase in the tax rate for the IV model reduces the total area developed by 1,393 acres, of which 91% of this acreage reduction is lower-density development located outside sewer service areas (Table 6). Third, the results for Scenario 2 indicate a net reduction in the total number of developments and acreage converted. This scenario leads to more compact and higher-density development because there is increased development for urban areas inside sewer service areas and an even larger decrease in acreage developed in rural areas. The green tax for existing forest in Scenario 3 leads to a reduction in the total number of subdivision developments. Scenario 3 also shows a decrease in total acreage developed, but the magnitude is smaller than the reduction in acreage converted in either Scenario 1 or 2. Based on these results in Tables 6 and A1, the non-IV model as a means of assessing development outcomes would likely result in policymakers determining that price-based policies have a limited effectiveness given the muted development responses arising due to lack of instrumentation.

Table 7 provides simulation results for the IV and non-IV models focused on water quality impacts. Simulation results are reported for our study region as the mean difference in the total nitrogen and phosphorus loads for each policy scenario relative to the baseline simulation. In Scenario 1, the results for the IV model indicate a statistically significant increase in nitrogen and

phosphorus loads for both tax rates. While the uniform tax in Scenario 1 decreases the acreage converted to residential development, it actually leads to a perverse effect of increasing nutrient loads. This result stems from the fact that most residential development in Scenario 1 occurs in rural areas outside sewer service, which is predominantly agricultural land. Because the nitrogen and phosphorus loads for agriculture are higher than residential development the reduction in the amount of residential development in Scenario 1 actually increases nutrient loads significantly relative to the baseline simulation (Table 7). The analogous results for the non-IV model have the same sign as the IV model, but are biased downward, and the changes in the nitrogen and phosphorus loads are only statistically significant for the 2% tax rate.

In Scenario 2, the results for the IV model indicate a significant increase in nitrogen and phosphorus loads for both tax rates (Table 7). The nutrient loads for Scenario 2 are similar to those in Scenario 1, though with a slightly larger increase in the nitrogen loads. One reason that Scenario 2 leads to higher loads is that this policy, relative to Scenario 1, is aimed at increasing residential development in areas with sewer service. The infill development at higher density that is incentivized in Scenario 2 is mainly converting either remnant forest cover or very-low-density residential land cover that leads to higher loads. ¹⁰

Scenario 3 is the price-based policy that most effectively mitigates the water quality impacts from residential development. The results for the IV model show a significant decrease in nitrogen and phosphorus loads for both tax rates. While the green tax on forest cover in Scenario 3 has the lowest reduction in acreage developed, it is the most targeted to achieve the goal of water quality improvements. The preservation of forest cover occurs at the expense of farmland loss in rural areas. In urban areas, the forest cover retained allows development to shift to create more infill development. Furthermore, in addition to water quality improvements, the preservation of forest

¹⁰ Agricultural land is less common inside the sewer service areas.

cover may have other public benefits such as carbon sequestration, enhanced wildlife habitat, and reduction in air pollution and urban heat island effects for the Baltimore metro region.

6. DISCUSSION AND CONCLUSIONS

In this paper, we estimate a parcel-level duration model of residential development and apply an innovative approach to control for price endogeneity based on the spatial equilibrium logic used in developing instruments in the urban sorting literature (Bayer and Timmins 2007). We combine our IV duration model on residential land conversion with nutrient loading rates from the CBP watershed model to analyze the influence of price-based policies on residential development patterns and water quality. Our policy simulation results suggest that land-use change models not accounting for price endogeneity, as commonly done in the literature, may provide a biased assessment of the land conversion and environmental impacts that differ substantially in magnitude compared to our preferred IV model.

Our results indicate that there are potential tradeoffs when seeking to manage urban growth and environmental objectives. For instance, the compact development policy (Scenario 2), which aims to reduce sprawl in rural areas and encourage infill development in urban areas, leads to a significant overall reduction in the amount of acreage converted to residential development. This policy reflects the smart-growth goals of limiting urban spatial expansion and leapfrog development, but it nonetheless increases the nitrogen and phosphorus loads entering local waterways and the Chesapeake Bay. The primary reason is that agricultural land has higher baseline loads than would occur if converted to residential development. Bigelow et al. (2017) find an analogous result for consumptive water usage when analyzing the effect of land-use policies for urban growth boundaries for three cities in Oregon. They find that in one simulation scenario the most sprawling development patterns leads to a reduction in water withdrawals because the increased residential

development removes irrigated agricultural land from production, which uses relatively more water than after converted to development.

Our results suggest that the price-based policies focused on forest preservation are the most effective in mitigating the water quality impacts. An important aspect in our analysis is that we estimate the relative amount of land-use conversion in rural and urban areas. The vast majority of acreage developed occurs as rural residential development outside sewer service areas. Our subdivision data, which is painstakingly reconstructed for the Baltimore metro region, allows us to represent the residential development activity more accurately and simulate both rural and urban land-use conversion under various price-based policies. By contrast, most prior literature on spatial policy simulations for land-use change and environmental impacts is modeled primarily for urban development, thereby not fully accounting for the amount of rural residential land conversion.

In conclusion, incentive-based policies are increasingly popular options for managing landuse change and the impacts on ecosystem services related to water quality, biodiversity, carbon
sequestration and others. Our analysis demonstrates that an accurate understanding of the
effectiveness for price-based land use policies depends on an empirical strategy that accounts for the
potential bias from price endogeneity. Due to the growing availability of micro-level data on
residential development and housing prices, we anticipate that this novel instrumentation strategy
may be applied in future research to analyze various policy options for spatial land-use simulation
and the associated environmental impacts in both the United States and elsewhere.

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Figures

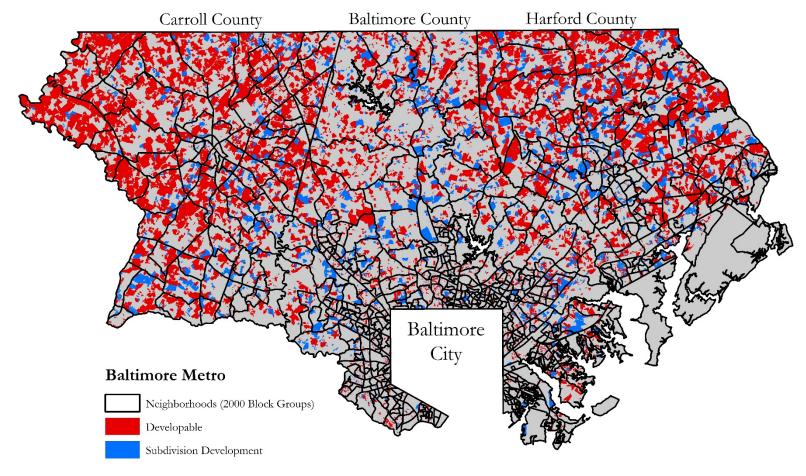


Figure 1. Baltimore metro region with subdivision development activity 1994-2007.

Note. – The figure shows the subdivision developments in 1994-2007 (blue), parcels that remain undeveloped in 2007 (red), and boundaries for each of the three counties. Neighborhoods are defined based on 2000 Census block group boundaries.

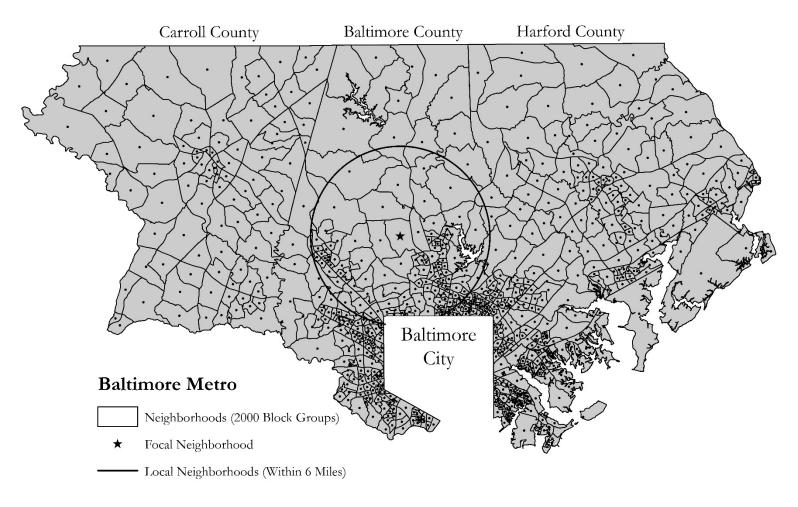


Figure 2. Instrumental variable strategy using exogenous variation in demand-side variables from "distant" neighborhoods.

Note. – Neighborhoods are defined based on 2000 Census block group boundaries. The "local" neighborhoods are those with centroids that fall within the 6-mile distance cutoff drawn around the centroid of the "focal" neighborhood; "distant" neighborhoods are those with centroids that fall outside of this circle.

TablesTable 1. Descriptive Statistics for Parcel and Neighborhood Variables

Variables		Mean	St. Dev.	Min.	Max.
Parcel					
Dist	Kilometers to Baltimore City	30.54	16.74	0.00	76.31
DistMajRoad	Kilometers to closest major highway	0.71	0.72	0.00	5.34
Area	Parcel area in acres	19.38	36.74	0.07	946.95
ZndLots	Count of zoned lots allowed	9.71	32.20	2.00	1378.00
Sewer	Indicator for municipal sewer service	0.46	0.50	0.00	1.00
FloodPlain	Located in 100-year flood plain	0.18	0.38	0.00	1.00
SepticSuit	Indicator for septic suitability	0.54	0.50	0.00	1.00
Slope	% of parcel with slope > 15%	9.81	23.22	0.00	100.00
ExHouse	Has an existing structure	0.54	0.50	0.00	1.00
ForestPrcnt	% of parcel with forest cover	38.77	34.98	0.00	100.00
<u>Neighborhood</u>					
Preservation	% of neighborhood in preservation	5.76	10.23	0.00	88.18
UDArea	% of neighborhood undeveloped	26.31	15.94	0.03	100.00
ApprvLots	Count of lots approved - 1-year lag	25.96	40.86	0.00	519.00
LandPrice	In \$1,000s per acre	77.21	66.02	4.22	718.84
HousePrice	In \$1,000s	128.42	44.68	20.25	493.73
Baltimore	Located in Baltimore County	0.58	0.47	0.00	1.00
Carroll	Located in Carroll County	0.24	0.43	0.00	1.00
Harford	Located in Harford County	0.19	0.39	0.00	1.00

Note - The statistics for the parcel variables are based on the 15,015 land parcels that were developable or developed during our study period (1994-2007). The statistics for the neighborhood variables are based on the 667 block groups (neighborhood boundaries) over the same time period.

Table 2. First-Stage Price Regression Results for Control Function Model

	Distance Cutoffs for Instrumental Varia			able Formation		
_	4 Mile	es	5 Miles		6 Miles	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
<u>Panel A</u>						
Neighborhood Characteristics						
PreservationArea (%)	0.0027 **	0.0011	0.0030 ***	0.0011	0.0034 ***	0.0011
UndevelopedArea (%)	0.0020 ***	0.0007	0.0021 ***	0.0007	0.0022 ***	0.0007
Instruments						
PreservationAreaAvg (%)	-0.5893 ***	0.0727	-0.3864 ***	0.0477	-0.2533 ***	0.0370
UndevelopedAreaAvg (%)	-0.0490 *	0.0303	-0.0311 *	0.0182	-0.0329 *	0.0182
<u>Panel B</u>						
First-Stage F-Statistic	54.03	3	48.08	3	37.45	•

Note - This table presents first-stage price regression results with different distance cutoffs used in forming the instrumental variables. The dependent variable in each model is the natural log of the quality-adjusted hedonic price index for each focal neighborhood in each time period. The instrumental variables for the focal neighborhoods are area-weighted averages based on values in distant neighborhoods with distance defined by miles from the border of each focal neighborhood. All models include time and county fixed effects. The top portion of the table specifies the distance cutoffs used in constructing the instrumental variables. Panel A presents results for the neighborhood and instrumental variables in each model. Panel B presents results for joint hypothesis tests of statistical significance for the instrumental variables in each model. N = 9,213

^{*} Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 3. Diagnostics Tests of Price Endogeneity

(1)	(2)	(3)	(4)
Distance	OverID		Control
Cutoff for	Test	Price	Function
Instrument	(⊅-value)	Coefficient	Coefficients
4 Miles	0.6531	0.7081 ***	-0.2572
5 3 61	0.7077	0.0025 ***	-0.3729 ***
5 Miles	0.7967	0.8835 ***	-0.4389 * -0.3910 ***
6 Miles	0.9811	1.0070 ***	-0.5660 ** -0.3859 ***
			-0.3037

Note - This table presents statistical tests and coefficient estimates from main duration equation using different distance cutoffs used in forming the instruments. Column (2) is an overidentification test (*p*-value) of the instruments; column (3) provides coefficient estimates and significance levels for the price coefficients, and column (4) presents coefficient values and significance levels for the control function variables (residuals and residuals squared) - a direct test of price endogeneity. The results on each line are based on the distance cutoff (column (1)) used in forming the instruments in the first-stage price regressions. The residuals from each first-stage model are included as controls (Wooldridge, 2010) in the duration model. All results are based on a bootstrapped model with 300 reps clustered at the neighborhood level.

^{*} Significant at 10% level

^{**} Significant at 5% level

^{***} Significant at 1% level

Table 4. Results from Duration Models (6-Mile Distance for Instrument in IV Model)

	Non-IV M	<u>lodel</u>	<u>IV Mod</u>	<u>lel</u>
	Coef.	St. Err.	Coef.	St. Err.
D 101 ::				
Parcel Characteristics				
Dist (km)	0.0008	0.0016	-0.0006	0.0017
DistMajRoad (km)	0.0422 ***	0.0158	0.0426 ***	0.0160
Area (acres)	0.0006	0.0004	0.0007 *	0.0004
ZndLots	0.0022 ***	0.0003	0.0022 ***	0.0003
Sewer	-0.0478	0.0395	-0.0299	0.0390
FloodPlain	-0.0656 **	0.0286	-0.0693 **	0.0285
SepticSuit	0.0637 **	0.0275	0.0535 *	0.0277
Slope	-0.0002	0.0005	-0.0002	0.0005
ExHouse	-0.0108	0.0324	-0.0054	0.0328
ForestPrcnt	-0.0018 ***	0.0003	-0.0018 ***	0.0003
Constant	-3.6846 ***	0.2737	-6.3427 ***	1.1827
Neighborhood Character	istics			
Preservation (%)	-0.0018	0.0016	-0.0040 **	0.0021
UDArea (%)	-0.0032 **	0.0013	-0.0043 ***	0.0013
ApprvLots	0.0006 **	3.0E-04	0.0000	0.0004
LandPrice	-0.1282 ***	0.0245	-0.1255 ***	0.0244
HousePrice	0.4179 ***	0.0529	1.0070 ***	0.2633
PriceResid			-0.5660 **	0.2689
PriceResid2			-0.3859 ***	0.1430
Log-Likelihood	-12375.3	11	-12362.04	42

Note - The table presents results for the non-IV and IV duration models. The IV results are produced using a control function methodology (Wooldridge, 2010). The residuals are generated using a 6-mile distance cutoff to form the price instruments. All models include time and county fixed effects. The standard errors are based on a block bootstrap procedure with 300 replications and clustered at the neighborhood level.

^{*} Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 5. Price Elasticity Estimates

	Coef.	St. Err.
Non-IV	1.1031 ***	0.1405
IV	2.6607 ***	0.6953

Note - The elasticity values are calculated using a marginal effects formula for probit model and represent the average percentage change in the probability of development (conversion) for a one percent change in price. The standard errors are calculated using the delta method and are based on the bootstrapped variance-covariance matrices from the duration model.

^{*} Significant at 10% level;

^{**} Significant at 5% level;

^{***} Significant at 1% level

Table 6. Results for IV Model on Number of Subdivision Developments and Acreage Developed

			IV Model	
	Tax/Subsidy			
	Rate	Inside Sewer	Outside Sewer	Total
Scenario 1				
Developments	1%	-19*	-33*	-52*
		[-17,-21]	[-30,-36]	[-49,-56]
	2%	-39*	-69*	-108*
		[-36,-41]	[-66,-72]	[-104,-112]
Acreage Developed	1%	-119*	-1274*	-1393*
		[-72,-165]	[-1073,-1475]	[-1183,-1602]
	2%	-216*	-2585*	-2802*
		[-169,-263]	[-2388,-2782]	[-2597,-3006]
Scenario 2				
Developments	1%	21*	-34*	-13*
		[19,23]	[-31,-37]	[-10,-17]
	2%	41*	-69*	-28*
		[39,43]	[-65,-72]	[-24,-31]
Acreage Developed	1%	131*	-1373*	-1243*
		[84,178]	[-1181,-1556]	[-1045,-1441]
	2%	278*	-2679*	-2410*
		[231,324]	[-2475,-2882]	[-2193,-2609]
Scenario 3				
Developments	1%	-7*	-15*	-21*
		[-5,-9]	[-12,-18]	[-18,-25]
	2%	-13*	-26*	-39*
		[-10,-15]	[-23,-29]	[-35,-42]
Acreage Developed	1%	-19	-437*	-456*
		[-67, 28]	[-242,-632]	[-253,-659]
	2%	-71*	-734*	-804*
		[-26,-117]	[-540,-927]	[-603,-1005]

Note - Asterisk (*) denotes statistical significance of the bootstrapped 95% confidence interval in brackets does not contain zero.

Table 7. Simulation Results for IV and Non-IV Models on Nitrogen and Phosphorus Loads

	Tax/Subsidy	NT 1873 5 1 1	TV 3.5 1.1
	Rate	Non-IV Model	IV Model
C : 1			
Scenario 1		4.00	
Nitrogen	1%	188	1610*
		[-872,1249]	[593,2626]
	2%	1599*	3374*
		[500,2698]	[2313,4436]
Phosphorus	1%	30	177*
1		[-45,105]	[104,250]
	2%	163*	368*
	_/~	[84,241]	[293,443]
		, , J	, , J
Scenario 2	107	407	10744
Nitrogen	1%	407	1864*
	20/	[-688,1502]	[842,2886]
	2%	1504*	3833*
		[458,2622]	[2769,4897]
Phosphorus	1%	37	164*
-		[-40,115]	[92,237]
	2%	132*	331*
		[55,209]	[255,407]
Scenario 3			
Nitrogen	1%	-1507*	-2197*
Muosen	1 / U		[-1144,-3250]
	20/	[-437,-2577]	
	2%	-2004*	-4527*
		[-913,-3095]	[-3463,-5591]
Phosphorus	1%	-97*	-125*
		[-21,-173]	[-50,-200]
	2%	-122*	-261*
		[-45,-200]	[-185,-337]

Note – All numbers are reported in pounds per year. Asterisk (*) denotes statistical significance of the bootstrapped 95% confidence interval in brackets does not contain zero.

Appendix ATable A1. Results for Non-IV Model on Number of Subdivisions and Acreage Developed

			Non-IV Model	
	Tax/Subsidy Rate	Inside Sewer	Outside Sewer	Total
Scenario 1				
Developments	1%	-7*	-14*	-21*
		[-4,-9]	[-11,-17]	[-17,-25]
	2%	-16*	-29*	-44*
		[-13,-18]	[-26,-32]	[-40,-48]
Acreage Developed	1%	-28	-487*	-515*
		[-74,17]	[-296,-679]	[-320,-711]
	2%	-68*	-1111*	-1179*
		[-22,-113]	[-925,-1297]	[-988,-1370]
Scenario 2				
Developments	1%	11*	-15*	-4
•		[9,13]	[-12,-18]	[0,-8]
	2%	19*	-29*	-10*
		[17,21]	[-26,-32]	[-6,-14]
Acreage Developed	1%	81*	-588*	-507*
O I		[35,127]	[-398,-778]	[-315,-699]
	2%	140*	-1066*	-966*
		[93,188]	[-919,-1294]	[-771,-1161]
Scenario 3				
Developments	1%	-1	-4*	-5*
1		[-3,2]	[-1,-7]	[-1,-9]
	2%	-3	-11*	-14*
		[0,-5]	[-9,-15]	[-10,-18]
Acreage Developed	1%	8	-72	-63
O F	•	[-37,54]	[-259,116]	[-257,130]
	2%	3	-318*	-316*
	270	[-43,49]	[-127,-509]	[-120,-511]

Note - Asterisk (*) denotes statistical significance of the bootstrapped 95% confidence interval in brackets does not contain zero.

Creation of Housing and Land Price Variables

Land Price Indices

To create our land-price variable we select all arms-length land transactions from the Maryland Property View (MDPV) databases that occur between 1994 and 2007. We further refine these data by excluding any parcels that already contained a farmland preservation easement on the property, which precludes it from being sold for development at full market value. We further exclude observations that were clearly not land sales based on the improvement value of the parcel. Finally, we exclude the top and bottom 1% of the sample based on the sale price per acre of the parcel to reduce the potential influence of outliers. The final data set on land transactions includes 10,669 arms-length land sales from 1994 to 2007.

To create our land price variable we estimate the following hedonic regression

$$ln(rlppacre_{lt}) = Par'_{lt}\beta + \delta_j + \tau + e_{lt}$$
(A1)

where rlppacre is the real land price per acre in year 2000 for land parcel l, Par_{lt} is a set of parcellevel controls, and δ and τ are block group and year fixed effects, respectively. The set of parcellevel controls includes the size of the parcel in acres as well as an indicator for whether the sale was for a previously subdivided lot, which controls for any differences in price between subdivided and unsubdivided parcels. We estimate the land price hedonic model using the pooled data set due to the limited number of land sales during our study period (Table A2 lists the number of arms-length land transactions for each year in our data). After controlling for land parcel characteristics, the year and block group fixed effects are used to construct an estimate of mean land price per acre in each neighborhood. For block groups and years without a sale we use a distanced weighted average of the values of the block group fixed effects for the closest five block groups in space in each year. Since land is an input in the production of housing we expect land prices to negatively affect latent profitability.

Year	Observations
1994	851
1995	754
1996	972
1997	922
1998	1047
1999	1035
2000	909
2001	795
2002	831
2003	617
2004	664
2005	572
2006	376
2007	354

Table A2. Number of arms-length land transactions by year

House Price Indices

The data used to generate our house-price variable also comes from MDPV. Similar to the approach for the land price data, we use only arm's-length single-family housing transactions between 1994 and 2007. After excluding the top and bottom 1% of the sample to remove outliers and removing any transactions that do not appear to be of single-family dwellings, such as multi-family dwellings and commercial structures, the final sample for 1994-2007 has 187,497 individual transactions. We convert the nominal sale price of each house to year 2000 dollars using the consumer price index (CPI) for the Baltimore metropolitan area.

To construct our housing price indices, we follow Sieg et al. (2002) and estimate a series of hedonic models that separate out the price of housing services at the neighborhood level from the quantity index of housing determined by structural and lot-specific characteristics of the house. To do this, we estimate the following house-price hedonic for each year

$$ln(rlhspr_h) = P_i + H'_h \beta + \epsilon_h \tag{A2}$$

where $rlhspr_h$ is the real transaction price for house h in census tract j, P_j is a fixed effect for the block group in which the house is located, and H'_h and ϵ_h are the observable and unobservable attributes for house h, respectively. We control for structure and lot-specific attributes of each house by combining our house price data with the tax assessor's data for each house. As shown in Sieg et al. (2002), P_j represents the price of housing services for each block group. Repeating the estimation

process in equation (A2) for each of the 14 years in our data provides a value for the price of housing services for each block group and year in our model.¹¹ This block group and year house price value is used in both our duration model and the first-stage regression as our measure of neighborhood house price.

One concern with the hedonic estimation strategy above is that by estimating yearly, instead of pooled, house price hedonics we implicitly assume that the quantity index is changing from year to year. However, estimating the quantity index (the coefficient on the housing characteristics) in each year comes at a price as sampling error is likely to increase statistical noise in the neighborhood fixed effects estimates. This extra noise is not likely to be a major issue in large samples, though it may affect the fixed effect estimates as yearly sample sizes decrease. Given that the sample sizes of our housing transactions data in each year are quite large (Table A3 lists the number of yearly armslength housing transactions in our data), we are able to run separate hedonic models for each year to generate our neighborhood-level house price indices. We did, however, run a pooled regression for the land price hedonic model in the previous section due to the smaller number of land transactions over time. This is an important consideration in applying our method in other settings.

Year	Observations
1994	11127
1995	11032
1996	12708
1997	12254
1998	13130
1999	14523
2000	12940
2001	13706
2002	14487
2003	14974
2004	16125
2005	14970
2006	14147
2007	11374

Table A3. Number of arms-length housing transactions by year

¹¹ A similar method for estimating the price of housing services has been applied in other structural models (see Klaiber and Phaneuf (2010) and Walsh (2007), among others).

Appendix B

Robustness Checks

Model Results on Tests for Land Price Endogeneity (First Stage)

Table B1. First-Stage Results for Land and Housing Price Regressions

	House Price Model		Land Price Model	
	Coef.	St. Err.	Coef.	St. Err.
<u>Panel A</u>				
Neighborhood Characteristics				
PreservationArea (%)	0.0032 **	* 0.0010	-0.0167 ***	0.0025
UndevelopedArea (%)	0.0022 **	* 0.0007	-0.0083 ***	0.0015
Instruments				
PreservationAreaAvg (%)	-0.1983 **	* 0.0292	0.3531 ***	0.0490
UndevelopedAreaAvg (%)	-0.0123	0.0177	0.2124 ***	0.0301
Panel B				
First-Stage F-Statistic	32.2	3	78.48	3

Note - This table provides results for land and house-price regressions estimated in the first stage of the IV duration model. The dependent variable in each model is the natural log of price (house and land) for each focal neighborhood in each time period. The instrumental variables for the focal neighborhoods are area-weighted averages based on values in neighborhoods outside of a 6-mile distance cutoff. All models include time and county fixed effects. The top portion of the table specifies the model based on the dependent variable. Panel A presents results for the neighborhood and instrumental variables in each model. Panel B presents results for joint hypothesis tests of statistical significance for the instrumental variables in each model. N=9,213

^{*} Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table B2. Duration Results Controlling for Land and Housing Price Endogeneity

_	Non-IV Model		IV Mod	<u>lel</u>
	Coef.	St. Err.	Coef.	St. Err.
LandPrice	-0.1282 ***	0.0245	-0.0639	0.1925
HousePrice	0.4179 ***	0.0529	1.0600 **	0.5513
PriceResid			-0.6050	0.6192
PriceResid2			-0.3964 ***	0.1508
LandPriceResid			-0.0526	0.1915
LandPriceResid2			-0.0088	0.0250
Log-Likelihood	-12375.3	11	-12364.0	40

Note - The table presents results for the non-IV and IV duration models with the IV model dealing with both housing and land price endogeneity issues. The IV results are produced using a control function methodology (Wooldridge, 2010). The residuals are generated using a 6-mile distance cutoff to form the price instruments for housing and land. All models include time and county fixed effects. The standard errors are based on a block bootstrap procedure with 300 replications and clustered at the neighborhood level.

^{*} Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Model with Alternative Time Period from 1994-2004 (Dropping Data from 2005-2007)

Table B3. Full Results for Model Estimated Using Data from 1994-2004

0.0044 ***	0.0012
0.0021 ***	0.0007
-0.3258 ***	0.0473
-0.0207	0.0188
36.53	
0.7493	
Coef.	St. Err.
0.7553 ***	0.2579
-0.2759	0.2672
-0.3208 **	0.1357
-9950.74	1 7
	0.0021 *** -0.3258 *** -0.0207 36.53 0.7493 Coef. 0.7553 *** -0.2759

Note - The table presents a full set of results for an IV duration model estimated using only data from 1994 through 2004. The residuals are generated using a 6-mile distance cutoff to form the price instruments for housing and land. All models include time and county fixed effects. The standard errors are based on a block bootstrap procedure with 300 replications and clustered at the neighborhood level.

Tests for Spatial Error Autocorrelation

^{*} Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table B4. Tests of Spatial Error Autocorrelation

	Non-IV Model	IV Model
Panel A. 100-Meter Distance Buffer		
1. Parameter Estimates	Coef. St. Err.	Coef. St. Err.
HousePrice PriceResid PriceResid2	0.4134 *** 0.0697	1.1134 *** 0.3566 -0.7300 ** 0.3640 -0.0563 0.1646
N	68143	
2. Autocorrelation Tests (p-value for LM Statistic)		
Weight Matrix Definition 100 Nearest Neighbor 800-Meter Distance Cutoff	0.1992 0.7029	0.1817 0.6595
Panel B. 200-Meter Distance Buffer		
1. Parameter Estimates	Coef. St. Err.	Coef. St. Err.
HousePrice PriceResid PriceResid2	0.3500 *** 0.0869	1.2319 *** 0.3783 -0.9170 ** 0.3916 -0.1372 0.1992
N	51211	
2. Autocorrelation Tests (p-value for LM Statistic)		
Weight Matrix Definition 100 Nearest Neighbor 800-Meter Distance Cutoff	0.8513 0.7485	0.9618 0.7119

Note - This table presents results from a series of models and statistical tests of spatial error autocorrelation for our duration models. All models and tests are developed based on the methods described in Carrion-Flores and Irwin (2004) where parcels are randomly sampled and surrounding parcels are dropped based on some pre-defined distance cutoff in order to reduce the influence of local unobservables. We use two distance cutoffs - 100 and 200 meters - based on distance buffers around each parcel in the data to select and drop parcels from the data. The results for the 100-meter models are shown in Panel A. and the results for the 200-meter models are shown in Panel B. In both panels, we display parameter estimates for the price and control function variables for the non-IV and IV models as well as results for a series of spatial error autocorrelation tests (LM statistics) based on two different weighting matrices. The LM test statistics in all models are developed based the theory in Pinkse and Slade (1998) and Baltagi et al. (2003) for nonlinear panel data models. The estimation for all models follows the procedure developed in the main part of the paper.

Generalized Method of Moments Linear Probability Model (GMM LPM)

^{*} Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table B5. Results for LPM Model

First-Stage F-Statistic	36.53
Hansen's J OverID Stat (p-value)	0.5738
GMM C-Stat Test of Endogeneity (p-value)	0.0597
HousePrice Elasticity	Coef. St. Err. 2.8999 *** 0.0093

Note - The table presents results for an IV linear probability model (GMM LPM) with endogeneous house prices. The instruments used in the model are the same as those used in the control function equation in the IV duration model with 6-mile distanced buffered used the create the instruments. The table presents results for a first-stage F-stat, a second-stage OverID test, an endogeneity test, and the coefficient value for the house-price elasticity produced from the GMM model. The model includes time and county fixed effects. The standard errors are clustered at the neighborhood level. * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level