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

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Abstract: Land plays a critical part in determining the health of an urban ecosystem. One of its key roles is regulation of nutrient delivery. In this paper, we combine results from an IV duration model with a water quality model in a series of land use simulations to examine the impact that different land use policies have in limiting or enhancing nutrient pollution in an urban setting. Our results reveal significant tradeoffs between objectives for managing urban growth and those for managing water quality. A uniform tax on development significantly reduces acreage developed, but increases nitrogen and phosphorus loads. A green tax for development on forested parcels is the most effective at mitigating water quality impacts, albeit with the lowest reduction of acreage developed. Our results suggest that policymakers and planners should use a multi-objective approach in designing land use policies.

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

1. INTRODUCTION

Land plays a critical part in determining ecosystem health. (Lawler et al. 2014). This is particularly true in urban environments where heterogeneous land uses can produce different environmental outcomes. One of the key roles played by land in an urban setting is in the regulation of nutrient delivery (e.g., nitrogen and phosphorus) to local waterbodies (Wu, 2008). Given this role, an important policy question relates to how, and to what extent, different policies land use policies may limit or enhance this association. One particularly important consideration is the extent to which urban land use policies – those designed to limit urban growth – may produce outcomes that are consistent with goals related to water quality management. Specifically, can anti-sprawl policies simultaneously reduce sprawl and nitrogen and phosphorus loadings, or should policymakers alter current policies to handle multi-objective outcomes?

To answer these questions, we develop a simulation framework and combine it with a model of nutrient pollution to examine how a common set of price-based land use policies, which lead to differential changes in residential development patterns, influence nitrogen and phosphorus loading in a large metro area. The specific objectives of this study are to: (1) estimate an instrumental variable land use model to identify the responsiveness of residential land use change to changes in housing prices; (2) combine model output with a water-quality model and develop a simulation framework suitable for analyzing policy; and (3) use the simulation framework to analyze the success of various land use policies in achieving water quality outcomes.

To address these objectives, we estimate an instrumental variable duration model using a unique dataset on residential subdivision development from the Baltimore, MD metro region.[1] Our

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[1] 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

residential subdivision data are manually reconstructed using information from historic subdivision plat maps and GIS parcel data. These data reproduce all residential development activity in the Baltimore metro region from 1994-2007 and include information on the size and location of the original parent parcel for each subdivision as well as information on zoning, the number of lots created, and various other parcel and neighborhood characteristics. To address price endogeneity and identify the response of land conversion to changes in housing prices, we use a control function methodology for nonlinear land use models developed in Wrenn et al. (2017).

To analyze the effectiveness of different types of land use policies in influencing residential development and water quality outcomes, we combine the results from our land use model 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 for our study region as it is used by both 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: (1) the EPA regulates both nutrients under the Chesapeake Bay TMDL and (2) these nutrients serve as the primary water quality measures in the region.

We use our model and simulation framework to analyze three tax policies which are both relevant to the Baltimore region and generally applicable for land use planning across the U.S. 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 mimics the uniform way in which property taxes and impact fees are implemented. In Scenario 2, we implement a tax on parcels in rural areas without municipal sewer service and a subsidy on parcels in designated

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).

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. Given that neither of these first two scenarios are specifically designed to manage water quality, our main interest is in evaluating how effective, indirectly, they are at doing so. Finally, in Scenario 3 we implement a "green tax" policy based on the existing forest cover on each parcel with the goal being to preserve large, contiguous chucks of forest cover as a means of reducing nitrogen and phosphorus runoff. For each policy, we implement land use simulations based on marginal (1%) changes to housing prices and compare our results with a baseline simulation where prices are held fixed. The outputs of interest from these simulations are changes in development outcomes – changes in the total number of number of subdivision created and changes in total acreage developed – and changes in water quality outcomes – total nitrogen and phosphorus delivered on a yearly basis.

Our model and simulations provide several key insights. Overall, we find that there is a clear tradeoff between traditional land use policies seeking to manage growth (anti-sprawl policies) and policies seeking to impact environmental outcomes, such as water quality. In the case of a uniform tax, while we observe a large reduction in both the number of developments created and total acreage developed this policy leads to an increase in annual nitrogen and phosphorus delivered. While this may seem counterintuitive, it has a clear explanation. The mechanism behind this result is that, while the uniform tax increase does reduce developed acreage overall, most of this reduction takes place on agricultural land parcels in rural areas of our study region which have higher baseline nutrient loads relative to rural residential development. Thus, the uniform tax policy effectively preserves, or maintains, many existing farm parcels, which contribute more to nitrogen and phosphorus pollution than low-density residential.

In the case of the compact development policy, which attempts to limit urban spatial expansion and concentrate development in areas with public sewer, we find a similarly perverse outcome as Scenario 1 – an overall decrease in both the number of developments created and total acreage developed, and an increase in nitrogen and phosphorus loadings. The mechanism behind this result is like that of Scenario 1. Finally, in the case of our green tax policy, which we designed to preserve forest cover and reduce nitrogen and phosphorus loads, we observe significant decreases in both nitrogen and phosphorus loadings, albeit with a lower overall reduction in acreage developed. Specifically, we find that while our green tax policy leads to a significant reduction in nitrogen and phosphorus, it results in only about a third as much of a reduction in acreage developed as Scenarios 1 and 2.

The previous results are policy relevant for several reasons. First, they suggest that the goal of traditional, anti-sprawl-type polices may not always be consistent the goals of more environmentally-minded policies. In our context, water quality outcomes are reduced in the case of the anti-sprawl policy. Second, they suggest that using targeted land use taxes (price-based land use policies) may be an effective tool for achieving environmental outcomes that are impacted by land use change. And finally, our results suggest that policymakers need to consider multiple objectives when designing land use policies – i.e., they need to optimize both anti-sprawl, tax, and environmental objectives when designing future policies. Our outcomes provide clear evidence that single-objective policies are unlikely to achieve the heterogeneous impacts desired of most land use outcomes.

The remainder of the paper is structured as follows. In Section 2, we present our econometric model and a brief overview of our instrumentation strategy. In Section 3, we present our data. Section 4 presents our results; Section 5 presents our policy simulations; and Section 6 provides some discussion and concludes.

2. ECONOMETRIC MODEL

Land use outcomes are the result of many individual land conversion decisions linked through market processes. As landowners decides to convert undeveloped land, they consider not only attributes of their own parcel but also the prices and subsequent revenues this conversion will provide (Capozza and Helsley, 1989). Housing prices are equilibrium outcomes and are functions of both observable and unobservable attributes. Thus, the inclusion of prices in housing supply models requires accounting for endogeneity problems generated by omitted variables. In nonlinear models, handling these types of endogenous attributes is a 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 (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 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

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

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

$$h(t) = h_0(t)h(I_{it}'\beta + X_{jt}'\alpha + P_{jt}'\gamma) \tag{2}$$

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

To address the endogeneity of housing prices, we apply 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 in our model 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.[2]

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

$$u_{it} = v_{jt}'\theta + e_{it}. \tag{4}$$

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. If the instruments in the first stage are valid, we can rewrite equation (1) as

[2] 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.

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

Where, assuming joint normality between the errors in both stages, we get the following discrete-time duration model

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

The inclusions of time fixed effects (τ_{t-t_0}) in model accounts for the baseline hazard function.

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.

Figure 1 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 six-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 area-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

$$P_{jt} = X_{jt}'\beta + Z_{jt}^{n}\delta + v_{jt}. \tag{7}$$

For each of these models, we use overidentification tests to choose the optimal distance cutoff used in forming our instruments based on the Chi-squared statistics (Stock et al. 2002; Wooldridge, 2010). By increasing the distance used in forming our instruments, we can 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 model covers a three-county region the Baltimore, MD metro: Baltimore, Carroll and Harford counties (Figure 2). To produce our 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.[3] 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.

[3] 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 subdivision approval.

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, based on 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 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.

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 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.[4] 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

[4] 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.

(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 (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.[5] It is the

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

housing-price variable produced from this process that is the focus of our econometric model and subsequent policy simulations.

4. MODEL RESULTS

4.1 Instrument Formation and Diagnostics

The control function residual used in our IV model is obtained by estimating the pooled OLS price regression in 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 in this paper are the percentage of land in each neighborhood that is preserved from development (PreservationAvg) and the percentage of land that is undeveloped (UndevelopedAvg).[6] These variables are assumed to impact the location choices of households and developers in distant neighborhoods, thereby influencing the equilibrium price, but not to directly impact developer decision-making in the focal neighborhoods. We estimate models based on the omission of local neighborhoods falling within the distance cutoffs ranging from four to six miles and use a series of diagnostics test to pick the optimal distance cutoff.

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 hypothesis tests that the coefficients on our instruments are equal to zero in the first stage. Based on the *F*-statistics in Panel B, our instruments pass the first-stage tests for all distance bands (Stock et

[6] 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 like using prices in distant markets as instruments for local prices in the industrial organization literature.

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).

Table 3 presents our overidentification tests. We use these to determine the optimal distance cutoff for our instrument. For these tests we include, in addition to the residuals generated from the first-stage OLS model, one of the two excluded instruments to the right-hand side of the duration model and perform a series of Chi-squared hypothesis tests. The results from these tests are presented in column (2) of Table 3 and 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, the *p*-values for these tests rise and become less significant. Based on these results, the optimal distance cutoff used in forming our instruments is six miles. We use the results from this six-mile model in the remainder of the paper.

<u>4.2 Duration Model Estimation</u>

Estimation results for the 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. 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 estimates 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, which suggests that zoned capacity plays a key role in determining the likelihood of development. The coefficient on distance to nearest major highway is positive and significant. The coefficient on floodplain is negative and significant suggesting that development is less likely in areas prone to flood risk. Finally, the coefficient on septic suitability is positive and significant 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 insignificant impact. The coefficient on preservation is negative and significant. Finally, the coefficient on land price is negative and significant, which is as expected if land serves as an input in the production of housing.

Turning attention to our primary variable of interest, the coefficient on the housing price, we find that it is both positive and significant. In addition, the coefficients for the housing price residuals (control functions) are negative and significant indicating a downward bias (endogeneity) in price in a model without instrumentation. These results demonstrate that accounting for price endogeneity is important.

4.3 Robustness Checks

Before proceeding with our land use simulation, we provide a brief discussion of several robustness checks of our IV model. Full results of these models are contained in Appendix B. All models use an identical dataset to the previous subsection with a six-mile distance cutoff for the instruments.

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 from the housing-price regression and another set from 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, we drop these years from our data and re-estimate the entire model using only the data for 1994-2004. The results based on these abbreviated data are shown in Table B3. The results remain largely the same as the model using the full dataset with the full study period.

Our third robustness check addresses the potential for spatial error autocorrelation to impact our results. 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 the two distance buffers (100 and 200 meters). 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 these two abridged samples, we re-estimate our main IV 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 our 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. 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. Based on these results, and the other robustness checks in Appendix B, we feel confident in proceeding with our policy simulation analysis using the results from our IV duration model.

5. POLICY SIMULATIONS AND WATER QUALITY OUTCOMES

We now describe the implementation and results from our policy simulations. The purpose of these simulations is to examine precisely how different land use policies impact development outcomes, land use patterns, and water quality indicators. For each policy we analyze, we compare simulation results for that policy with baseline results where housing prices remain fixed. 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.

5.1 Simulating Development Patterns

We begin by establishing a baseline set of at-risk parcels for each period (year) and baseline land cover. All simulations use the 15,015 developable parcels from the original data, where each parcel is assumed to be developable in period (year) of the simulation – i.e., all parcels that were developable at the beginning of our study period are used in the simulations and we assume each can be developed in each period. Using these data, we overlay them with a GIS shapefile of land cover for the Baltimore region in 1992. This overlay determines the baseline land cover for each at the beginning of our study period. We use the USGS Chesapeake Bay Watershed Land Cover data from 1992 because it is the baseline land cover that is available immediately prior to the beginning of our study period in 1994. From these data, we are interested in the percentage of agricultural and forest land cover on each parcel at the beginning of our study period. To determine forest cover, we combine all forest cover types (deciduous, evergreen, mixed forest, and shrub) into a single land cover class. 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. 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.

After setting up the data, we proceed with our nested simulation procedure. The outer loop is an iteration over the parameter distribution from the duration model. Specifically, for each outer iteration we take draws from the estimated 1,000 $kx1$ parameter vectors of the bootstrapped parameter matrix. Using these draws, we combine them with the data constructed above and the probit link function from the discrete-time duration model to form a predicted probability of development for each parcel. For each outer iteration, we step through time (the inner loop) and determine which parcels develop and which remain undeveloped. To do this, we employ an accept/reject strategy by taking a random draw from a uniform distribution for each parcel and comparing those draws with the predicted probability of development generated from the probit model, our data, and our bootstrapped parameter estimates. We assume that a parcel is developed if its predicted probability is larger than its random 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 we iterate over time at annual time steps making comparisons in each period and dropping parcels that are predicted to develop from all subsequent periods, which reflects the terminal nature of the residential development process in the raw subdivision data. 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 residential conversion events – i.e., each iteration provides the land development outcomes for the number of residential subdivision events that occur and thus the total acreage developed within each iteration. To use these events for policy evaluation on water quality outcomes, we link each set of development outcomes (parcel IDs from the GIS data) with information on existing land cover and nitrogen and phosphorus loading rates to generate measures for the change in loading rates following the implementation of a given policy scenario.

5.2 Simulating Water Quality Impacts

Assessing the water quality impacts of different post-policy land use outcomes involves combining the CBP model loading-rate data with the predicted changes in land use produced by our different policy simulations. This involves using the loading rates from the CBP watershed model to determine both the baseline nitrogen and phosphorus loads on each developable parcel and the predicted changes in loading rates following a policy-driven tax change. Specifically, we determine baseline nitrogen and phosphorus loads according to edge-of-stream loading rates and the acreage for each baseline land cover type and a post-policy loading-rate change based on predicted development density.

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. 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 in our raw subdivision data, 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-policy, post-development loading rates for each developed parcel and compare it to what would have happened had the parcel remained undeveloped. This comparison – of pre and post-policy outcomes – is repeated for each of the 1,000 simulated development patterns, and we examine the distribution of these outcomes for each policy scenario described below.

5.3 Policy Scenarios

While there are numerous policies that we could analyze with our model, our main interest is in examining and comparing water quality outcomes produced using standard land use policies – those focused on reducing sprawl and raising revenue – with water quality outcomes produced using some type of "green tax" policy. 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 1% property tax on all parcels. This uniform tax scenario reflects the way in which residential property taxes or impact fees are implemented in the United States. In Scenario 2, we implement a 1% tax on all parcels located in areas without municipal sewer service and a 1% subsidy on all parcels located in areas with municipal sewer service. This scenario reflects the approach used by planners whereby an impact fee is assessed 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 1% tax for development on parcels with 50% forest cover greater than 50%. 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 simulation results with baseline results where prices remain unchanged.

Before turning to our simulation results, it is important to assess how well our baseline simulation can predict development outcomes in the original subdivision data. To do this, we compare our baseline simulation results, where prices remain unchanged, with the original subdivision data. Based on the 1,000 iterations of our simulation, 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).

5.4 Simulation Results

In Table 5, we display the simulation results (changes) across all three policy scenarios for our land development outcomes (indicators) – changes in the number of subdivisions created and changes in total acreage developed. The results reported are for mean differences 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.

From Table 5, we first observe that for the uniform tax we get a significant reduction in both the number of developments created and in total acreage developed, particularly in the rural areas outside sewer service. For a 1% property tax on all parcel, we reduce the number of developments created by 52 and reduce the total amount of developed land by 1,393 acres, of which 91% of this acreage reduction is lower-density development located outside sewer service areas. The reduction of 52 subdivision events represents a 2.17% overall reduction in subdivision activity. Next, while the results for Scenario 2 also indicate a net reduction in both the total number of developments created and acreage converted, the total reduction in developments created is significantly lower than in the first scenario. This result is not surprising given that the purpose of this policy is not to reduce overall development, just to reduce acreage developed (reduce sprawl) and concentrate new development in areas with public sewer and water. Finally, the green tax in Scenario 3 also leads to a reduction in both the number of developments created and the total acreage developed. However, the total amount of acreage lost to development is about 33% lower than in the first scenarios.

Turning to Table 6, we present simulation output for our water quality indicators across each of the policy scenarios. The results reported are for mean differences, across the entire study region, in total nitrogen and phosphorus loads relative to a baseline scenario with no price change. In Scenario 1, the results indicate a statistically significant increase in nitrogen and phosphorus loads. While the uniform tax in Scenario 1 decreases the acreage converted to residential development, it 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 boundaries, which is predominantly agricultural land. Because the nitrogen and phosphorus loading from agricultural land is higher than for residential development the reduction in the amount of residential development in Scenario 1 increases nutrient loads significantly relative to the baseline simulation. This becomes particularly clear when looking at column (2) in Table 5 for this first scenario. From this column, we observe that following the uniform tax increase most of the reduction in development – counts and acreage – come from more rural areas without public sewer. The land that is being left undeveloped here is agriculture land, which contributes much more in terms of nitrogen and phosphorus loading than low-density, rural residential development does.

In Scenario 2, the results indicate a significant increase in nitrogen and phosphorus 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.[7] Specifically, this policy achieves both reduced low-density development – leaving agriculture land in production – and increased high-density urban development – which contributes more nitrogen and phosphorus than low-density residential development.

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

[7] Agricultural land is less common inside the sewer service areas.

of forest 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 combine our results with a nutrient loading rates from a watershed model to analyze the influence of price-based policies on residential development patterns and water quality. Our results indicate that there are potential tradeoffs when seeking to manage urban growth and environmental objectives. For instance, compact development policy (Scenario 2) we implement in our simulation framework, 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 for this result is that agricultural land has higher baseline loads than would occur if this land was converted to low-density residential development. Bigelow et al. (2017) find an analogous result for consumptive water use 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 lead to a reduction in consumptive water withdrawals because the increased residential development removes irrigated agricultural land from production, which uses relatively more water than low-density residential 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. Most 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 land-use 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

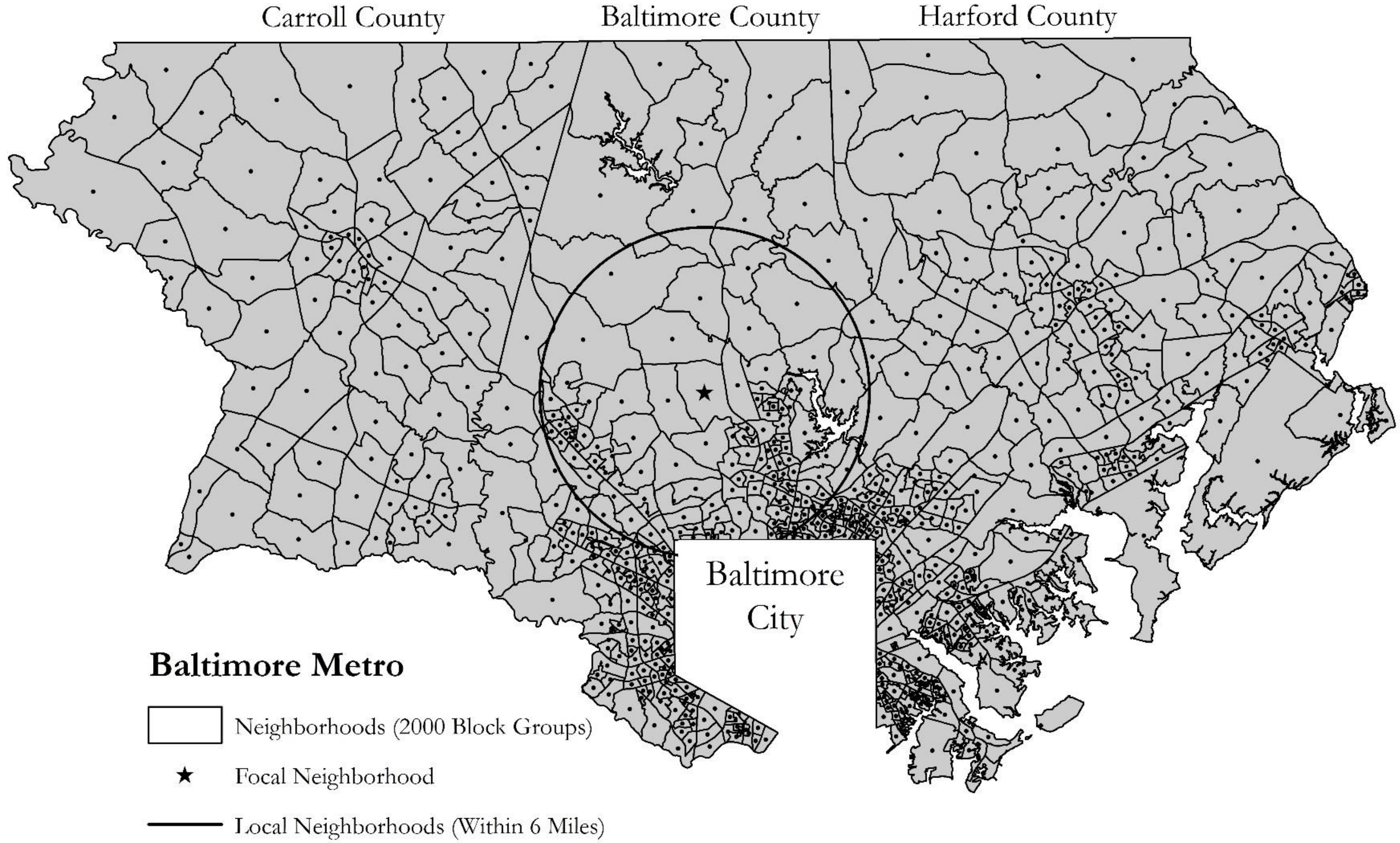

Figure 1. Instrumental variable strategy using exogenous variation in demand-side variables from "distant" neighborhoods.

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.

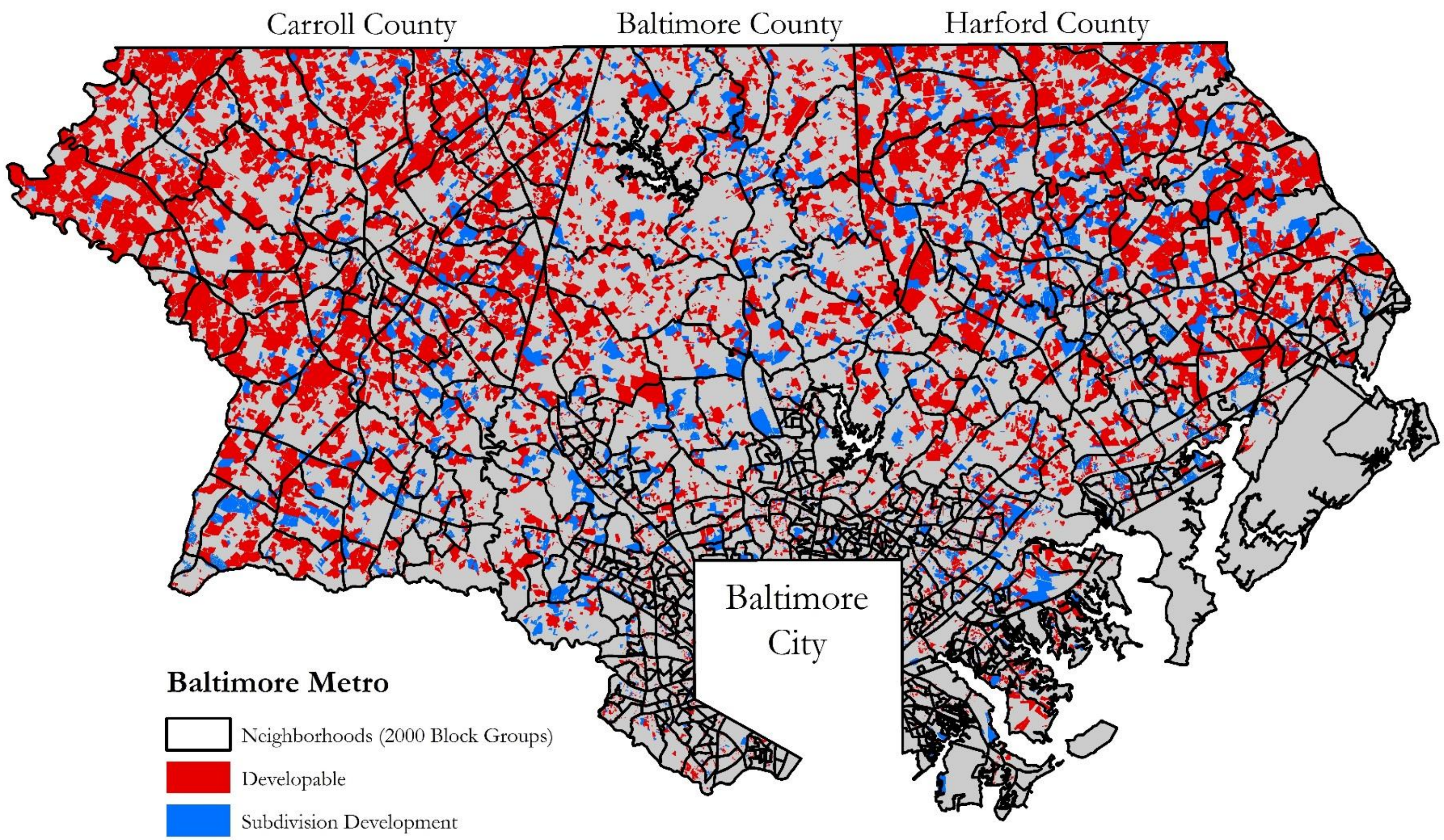

Figure 2. Baltimore metro region with subdivision development activity 1994-2007.

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.

Tables

Table 1. Descriptive Statistics for Parcel and Neighborhood Variables

Variables		Mean	St. Dev.	Min.	Max.
<u>Parcel</u>					
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 Variable Formation					
	4 Miles		5 Miles		6 Miles	
	Coef.	St. Err.	Coef.	St. Err.	Coef.	St. Err.
Panel A						
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
Panel B						
First-Stage *F*-Statistic	54.03		48.08		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 neighorbood. 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. Overidentification Test of Price Endogeneity

(1) Distance Cutoff for Instrument	(2) OverID Test (*p*-value)
4 Miles	0.6531
5 Miles	0.7967
6 Miles	0.9811

Note - This table presents overidentification using different distance cutoffs used in forming the instruments. Column (1) is the distance cutoff used in forming the instruments and column (2) is overidentification test (*p*-value) of the instruments.All results are based on a bootstrapped model with 300 reps clustered at the neighborhood
* Significant at 10% level
** Significant at 5% level
*** Significant at 1% level

Table 4. Results from IV Duration Model

	Coef.		St. Err.
Parcel Characteristics			
Dist (km)	-0.0006		0.0017
DistMajRoad (km)	0.0426	***	0.0160
Area (acres)	0.0007	*	0.0004
ZndLots	0.0022	***	0.0003
Sewer	-0.0299		0.0390
FloodPlain	-0.0693	**	0.0285
SepticSuit	0.0535	*	0.0277
Slope	-0.0002		0.0005
ExHouse	-0.0054		0.0328
ForestPrcnt	-0.0018	***	0.0003
Constant	-6.3427	***	1.1827
Neighborhood Characteristics			
Preservation (%)	-0.0040	**	0.0021
UDArea (%)	-0.0043	***	0.0013
ApprvLots	0.0000		0.0004
LandPrice	-0.1255	***	0.0244
HousePrice	1.0070	***	0.2633
PriceResid	-0.5660	**	0.2689
PriceResid2	-0.3859	***	0.1430
Log-Likelihood	-12362.042		

Note - The table presents results for the IV duration model. The results are produced using a control function methodology (Wrenn et al. 2017). The residuals are generated using a 6-mile distance cutoff to form the price instruments. The model includes 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. Simulation Results for Development Counts and Total Acres Developed

	(1) Sewer	(2) Non-Sewer	(3) Total
A: Uniform Tax (Scenario 1)			
Developments (Count)	-19	-33	-52
	[-17,-21]	[-30,-36]	[-49,-56]
Area (Acres)	-119	-1274	-1393
	[-72,-165]	[-1073,-1475]	[-1183,-1602]
B: Compact Development (Scenario 2)			
Developments (Count)	21	-34	-13
	[23,19]	[-31,-37]	[-10,-17]
Area (Acres)	131	-1373	-1243
	[178,84]	[-1181,-1566]	[-1045,-1441]
C: Green Tax (Scenario 3)			
Developments (Count)	-7	-15	-21
	[-5,-9]	[-12,-18]	[-18,-25]
Area (Acres)	-19	-437	-456
	[28,-67]	[-242,-632]	[-253,-659]

Note - This table presents results from a series of land use simulations using the results from the IV duration model. In Scenario 1 (A), we impose a uniform tax on all parcels in the data set. In Scenario 2 (B), we impose a tax on parcels in areas without public sewer and a subsidy on parcels in areas with public sewer. In Scenario 3 (C), we impose a tax on parcels with more than 50% forest cover. For each simulation, we impose either a 1% tax or subsidy on a parcel based on its location. The baseline land cover values are taken from the USGS land cover data for the Baltimore region. For each scenario, we present results for the change in the number of developments created and the change in total acres developed. We present results for these total broken out between areas with and without public sewer access (columns 1 and 2) and in total (column 3). All changes (comparisons) are made relative to a baseline land use simulation without a change in price. The mean values for each columns are shown beside of the tax rate and the 95% confidence intervals are shown in brackets.

Table 6. Simulation Results for Nitrogen and Phosphorus Loads

Scenario 1		Scenario 2		Scenario 3	
Nitrogen	Phosphorus	Nitrogen	Phosphorus	Nitrogen	Phosphorus
1610	177	1864	164	-2197	-125
[2626,593]	[250,104]	[2886,842]	[237,92]	[-1144,-3250]	[-50,-200]

Note - This table presents results from a series of land use simulations using the results from the IV duration model. In Scenario 1, we impose a uniform tax on all parcels in the data set. In Scenario 2, we impose a tax on parcels in areas without public sewer and a subsidy on parcels in areas with public sewer. In Scenario 3, we impose a tax on parcels with more than 50% forest cover. The baseline land cover values are taken from the USGS land cover data for the Baltimore region. For each scenario, we present results for the change in total nitrogen and phosphorus delivered in pounds. All changes (comparisons) are made relative to a baseline land use simulation without a change in price. The mean values for each columns are shown beside of the tax rate and the 95% confidence intervals are shown in brackets.

Appendix A – Creation of 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

$$ln(rlppacre_{lt}) = Par_{lt}'\beta + \delta_j + \tau + e_{lt} \quad \text{(A1)}$$

where $rlppacre$ is the real land price per acre in year 2000 for land parcel l, Par_{lt} is a set of parcel-level controls, and δ and τ are block group and year fixed effects, respectively. The set of parcel-level 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

$$ln(rlhspr_h) = P_j + H_h'\beta + \epsilon_h \tag{A2}$$

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.[8] 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 arms-length 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

[8] 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

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

	House Price Model			Land Price Model		
	Coef.		St. Err.	Coef.		St. Err.
Panel A						
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	32.23			78.48		

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

	Coef.		St. Err.
LandPrice	-0.0639		0.1925
HousePrice	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	-12364.040		

Note - The table presents results for theIV 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. 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

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

	Coef.		St. Err.
Panel A. First Stage Results			
Neighborhood Characteristics			
PreservationArea (%)	0.0044	***	0.0012
UndevelopedArea (%)	0.0021	***	0.0007
Instruments			
PreservationAreaAvg (%)	-0.3258	***	0.0473
UndevelopedAreaAvg (%)	-0.0207		0.0188
First-Stage *F*-Statistic	36.53		
Panel B. Overidentification Test			
p-Value	0.7493		
Panel C. IV Results			
HousePrice	0.7553	***	0.2579
PriceResid	-0.2759		0.2672
PriceResid2	-0.3208	**	0.1357
Log-Likelihood	-9950.747		

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.

* Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table B4. Tests of Spatial Error Autocorrelation

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

Note - This table presents results from a series of models and statistical tests of spatial error autocorrelation for our IV duration model. 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 IV model 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.
* 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	
	Coef.	St. Err.
HousePrice Elasticity	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