“How do land use policies influence fragmentation? An econometric model of land development with spatial simulation”

Environmental Economics, Volume 3, Issue 4, 2012

Douglas H. Wrenn (USA), Elena G. Irwin (USA)

How do land use policies influence fragmentation? An econometric model of land development with spatial simulation

Abstract

Land fragmentation generates a host of environmental impacts, including habitat degradation, biodiversity loss and a reduction in natural lands that filter nutrient and sediment run-off. The design of effective land use policies to reduce land fragmentation relies on an understanding of the economic decision-making of landowners, land developers and other actors and the factors that influence the spatial pattern of development. The authors investigate the effects of a market-based versus a regulatory policy instrument on land fragmentation using data from a rapidly urbanizing area of the U.S. The paper first estimates a discrete-time duration model of residential subdivision development and then uses Monte Carlo simulations that account for model uncertainty to generate spatially explicit predictions of land development outcomes under these two types of policies. The authors find that zoning regulations that constrain the supply of developable land generate much larger impacts on the predicted pattern of land fragmentation and that developers' demand for land is extremely inelastic. The paper concludes that, because of this highly inelastic demand for land, a zoning policy that restricts the density of development is a more effective policy for reducing land fragmentation than are market-based incentives. However, the results also imply that zoning controls that restrict the supply of developable land are likely to impose large welfare losses to developers.

Keywords: land use regulation, zoning, development fees, urban spatial structure.
JEL Classification: Q50, Q51.

Introduction

Human uses of land produce large social benefits in the form of food, fiber, shelter and other essential goods and services, but also generate a range of environmental impacts, including carbon emissions, soil and water degradation, alterations of habitat and hydrologic cycles and loss of biodiversity (Kalnay and Cai, 2003; Postel, Daily, and Ehrlich, 1996; Sala et al., 2000; Tilman, Fargione, and Wolff, 2001). The increasing rate of environmental impacts raises serious concerns regarding the sustainability of current land use practices. Reducing environmental impacts to achieve more sustainable land use outcomes relies on policies that can effectively manage land use processes at local, regional and global scales. However, because land use decisions are most often made locally by individuals or small groups of people, designing effective policies requires an understanding of the behavior of these local actors and the environmental, social, economic and institutional factors that influence their decisions.

Land change modeling is an important tool for analyzing the effects of policy on land use outcomes and for predicting the changes in land use patterns under baseline and alternative future scenarios (Turner, Lambin, and Reenberg, 2007). Generating landscape predictions relies on an understanding of human behavior to predict responses to policy changes and, in market-based economies, some representation of land markets to account for price effects. A range of models defined at varying spatial scales and geographic extents exist in the literature. At the most aggregate scale, sector-based models represent global input and output markets that are distinguished by large homogeneous regions. At the most disaggregate scale, spatial models of individual land use decisions are estimated using spatially contiguous microdata on land parcels with a geographic extent of a single county[1]. Spatially explicit models can account for a variety of local processes and their influence on land use outcomes, including land use externalities (Irwin and Bockstael, 2004, 2002), zoning and infrastructure (Butsic, Lewis and Ludwig, 2011; McConnell, Walls and Kopits, 2006; Newburn and Berck, 2006), open-space conservation policies (Lewis, Provencher and Butsic, 2009; Towe, Nickerson and Bockstael, 2008) and regulatory costs (Wrenn, 2012). The estimated parameters from these spatially explicit models can then be used with GIS to simulate policy effects and generate spatial landscape predictions that quantify how a policy change is predicted to influence the spatial pattern of land use (Lewis, 2010; Carrion-Flores and Irwin, 2004). This approach has been used to predict baseline and alternative landscapes for a variety of policy scenarios, most notably the influence of voluntary economic incentives for landowners on land conservation (Lewis et al., 2011; Lewis, Provencher, and Butsic, 2009; Nelson et al., 2008; Newburn and Berck, 2006). These and other studies evaluate in-

[1] More detailed reviews of sector-based models are available from Hertel, Rose, and Tol (2009). For more discussion of spatially disaggregate models see Brady and Irwin (2011); Irwin (2010) and the chapters by Irwin and Wrenn, Klaiber and Kuminoff, and Plantinga and Lewis in The Handbook of Land Economics (Duke and Wu, 2013).

dependently the effects and efficiency of various economic-based policies, e.g., in which landowners are compensated for conservation, or of quantity-based instruments that constrain land use, e.g., zoning, but do not compare the relative effectiveness of price-based versus quantity-based instruments.

We investigate the predicted effects of a market-based versus a regulatory policy instrument on land fragmentation by using spatial simulation methods and results from an econometric model of land development estimated with data on residential land development in a rapidly urbanizing county in the Baltimore, Maryland region. We investigate these policy effects by first estimating a discrete-time duration model of a land developer's decision to develop a land parcel as a residential subdivision. Subdivisions, in which a single land parcel is subdivided into two or more lots that are typically then used for single-family homes, are the most common form of residential land development in the U.S. We use parcel-level data on residential subdivision development over a 13-year time period from 1995 to 2007 from a fast-growing area in the Baltimore, Maryland region, which is located in the eastern U.S. Our dataset includes information on the location and price of land parcels and their physical characteristics. We also have information on spatially heterogeneous zoning regulations which restrict development and constrain a parcel's allowable density of development. The richness of the data enables us to identify the effect of expected land price and zoning on individual development decisions while controlling for other parcel-level variables, including soil type, slope and other variables that influence costs of development as well as key economic variables, including price drift and volatility, local competition and the opportunity cost of development. The estimates from the land development model are then used to conduct a series of policy simulations in which the pattern of land development is predicted under two types of policies: a land development fee, which increases the developer's cost, and a change in the allowable density of development, which alters the amount of development that is possible for any given parcel. The policy scenarios are designed with the goal of reducing the environmental impacts of land development by reducing the amount of development in the more rural areas of our study region, which in turn reduces land fragmentation by preserving larger areas of undeveloped land uses. We evaluate the predicted policy impacts by comparing the number of subdivisions that are predicted to occur in the higher density, more developed areas (suburban) versus more rural, less developed areas (exurban) of our study region.

Results show that, as expected, land costs have a negative effect on the timing of development and therefore, reduce the likelihood of development. We find that the maximum allowable number of lots that can be developed on a parcel, as determined by zoning regulations, has a positive effect on development timing and increases the likelihood of development. This effect is relatively constant across the different zoning classes, which range from the lowest allowable development density of one lot per 15 acres (agricultural zoning) to the highest allowable density of four lots per acre (R)10 zoning). The policy simulations reveal a highly inelastic demand for land by developers. We find that a development fee imposed on exurban land parcels that is equivalent to 20% of the land price only reduces the predicted amount of development in the exurban zone by 2%, which corresponds to an input demand elasticity for land of 0.1%. On the other hand, a zoning policy that decreases the maximum allowable density to one house per 20 acres, a decrease of about 33% compared to current exurban zoning, is found to decrease the amount of exurban development by 60%. We conclude that a zoning policy that restricts the density of development is a much more effective policy for reducing land fragmentation than is a price-based policy, but that this kind of quantity restriction also imposes potentially large welfare losses to developers.

These results provide an initial evaluation for the land development case of the two most common policies considered in environmental economics: price-based policies, in which the net returns are altered by a tax or subsidy that seeks to internalize an externality, versus quantity-based policies that constrain the amount of an externality-producing good. While we do not provide a formal welfare analysis of these policies, we predict their likely impacts on the spatial pattern of land development, which is a necessary first step towards assessing their relative efficiency. By accounting for the parcel-level variables that influence a developer's costs and returns from development and assuming profit-maximizing behavior, we are able to predict how a change in policy changes the likelihood that a parcel is developed. We do so in a spatially explicit way by using spatial simulation methods to predict the likely pattern of land development under the baseline and alternative policy scenario cases. Because environmental impacts are spatially heterogeneous, accounting for the change in the spatial pattern of land development is important for evaluating the welfare impacts of policies.

The remainder of the paper is structured as follows. Section 1 presents our random effects logit specification. Section 2 presents the data used in the model and the construction of our policy variables. Section 3 presents the discussion of the results and the policy simulations, and the final section concludes.

1. Model of residential subdivision development

Residential land development is a three-stage process in our study region. In the first stage, developers submit preliminary subdivision plans; in the second stage, they gain conditional approval from the planning board; and in the last stage, they obtain final approval to begin the development process. While the process officially has three stages, the first stage consists of only a preliminary hearing with no official approval given for the development[1]. As a result, in this paper we model the decision-making process of the developer beginning at the start of the second stage, where developers must commit funds and thus make predictions about future uncertainties during the development period.

Beginning with the second-stage conditional approval decision, we cast the developer's decision problem as one of choosing the optimal time, t^*, to file her application for development in order to maximize profits on her parcel. This optimal stopping decision is represented by the following profit maximization problem:

$$\max_{t^*} \pi_{it} = \int_0^{t^*} A\left(x_{it},\tau\right)e^{-r\tau} + d\tau + \\ +\left(R\left(x_{it},t^*\right) - C\left(x_{it},t^*\right)\right)e^{-rt^*}, \quad (1)$$

where r is the discount rate, A is the discounted value of agriculture rents on the parcel, R is the present discounted revenue generated from converting the parcel to a residential development and C is the present discounted cost of converting the parcel. Each of these inputs is impacted by numerous factors ranging from parcel-level characteristics such a slope, forest cover, zoning restrictions and the intertemporal price per acre of land to local and regional effects such as the distance to the city center or to primary roads. Conditional on these factors and their subsequent impact on the model inputs, developer chooses to convert her parcel when the developed value of the parcel in period t is greater than or equal to the value of development in time $t + 1$ plus the discounted one-period agricultural returns on the parcel[2].

$$Prob = \left(\pi\left(x_{it},t^*\right) + \varepsilon\left(t^*\right) \geq 0\right), \quad (2)$$

where $\pi_{it} = (rR(\bullet) - rC(\bullet) - A(\bullet))$. Equation (2) is a per-period binary choice model that takes on a value of one at the optimal development time for each parcel and zero otherwise. The vector of covariates, x_{it}, represent, once again, those factors most likely to impact the decision process, and ε represents the factors not observed by the researcher that impact the decision to develop such as land ownership issues, entrepreneurial skill and past development experience.

1.1. Empirical specification. To model the intertemporal development process, we follow Beck, Katz and Tucker (1998) and specify a binary time-series-cross-section model for discrete time or grouped-duration (event history) data. Duration data accounts for the elapsed time until an "event" occurs or is no longer observed. Such a specification models the entire process for each observation and captures the cumulative impact of the process and the variables on the decision-making process of the individual. Thus, an observation is at risk until it fails or an event occurs, and the model captures the hazard rate or probability of failure in any particular time period. The innovation of the Beck, Katz and Tucker (1998) paper is that for discrete-time or grouped-duration data, a continuous-time duration model can be approximated by specifying the binary stopping choice in each discrete-time interval by as an unbalanced binary panel data model, where the baseline hazard function is modeled by specifying time dummies for each period that an observation survives or is undeveloped. The coefficient values on the different time dummies provide for an explicit test of the temporal variation in the baseline hazard. The model also allows for the easy inclusion of time-varying covariates, which is particulary important in our case as a number of our variables such as the price per acre land, regulatory costs and local competition vary between parcels and over time.

The most common parametric specification for duration data is the continuous-time proportional hazard model:

$$h\left(t \mid x_{it}\right) = h_0\left(t\right)e^{x_{it}}\beta, \quad (3)$$

where the dependent variable is time, t, and x_{it} are independent variables at continuously measured time steps that impact the speed with which a particular event occurs. The hazard rate in the model depends on both the independent variables and the length of time that the observation has been at risk, $h_0(t)$[3]. Depending on the type of model estimated,

[1] During the first stage county planners determine if the landowner has permission to develop the parcel and whether it is located in a developable area. It is during the second stage that the official development plan is submitted and developers face uncertainty in gaining final approval.

[2] This theoretical specification is taken from the optimal timing model in Capozza and Helsley (1989).

[3] See Kalbfleisch and Prentice (1980) for a detailed survey of duration/survival data models and their empirical specifications.

the baseline hazard can take any number of different types of time dependence. Continuous-time duration models model the instantaneous probability of failure for each observation. In the case of grouped or discrete-time duration data, observations are only observed at discrete intervals. As a result, more than one event is observed in each period of time, and the model is simply the probability of a particular event occurring during a given time interval given that it has not occurred up to that point.

By letting y_{it}^{*} be a latent indicator variable of an event occurring to observation i in period t, the discrete-time hazard is simply $P\left(y_{it}=1 \mid x_{it}\right)$, which can be modeled using any binary panel data model. In this paper, however, we follow Beck, Katz and Tucker (1998) and model the intertemporal choice process for each parcel using a binary logit model[1]. Thus, the discrete-time duration model corresponding to equation (3) is given by the following probability model:

$$P\left(y_{it}=1 \mid x_{it}\right)=h\left(t \mid x_{i,t}\right)=\frac{e^{x_{it}\beta+p_{t-t_0}}}{1+e^{x_{it}\beta+p_{t-t_0}}}, \quad (4)$$

where x_{it} represents the value of the explanatory variables in interval t, and $p_t - t_0$ is a dummy variable indicating the time period in which the observation is being observed. The maximum likelihood specification of this model is as follows:

$$\sum_{i=1}^{n}\sum_{t=1}^{s}\left\{y_{it}\log\left(P_{it}\right)+\left(1-y_{it}\right)\log\left(1-y_{it}\right)\right\}, \quad (5)$$

where y_{it} is the binary decision in period t by developer i, and the P_{it} is the inverse logit link.

1.2. Unobserved heterogeneity. Despite the richness of our data and the covariates generated from it, there are still likely a significant number of unobservable factors that impact the decision to convert a parcel to a residential development. In the land use modeling context, these factors can be either parcel-level factors such as unobserved soil quality, slope or aesthetics on the parcel or individual-level factors such as the entrepreneurial skill or the debt level of the developer or ownership disputes between family members that jointly own a parcel. As a result of these factors, it is necessary to extend our previous empirical specification to make it robust to these influential unobservables or "random effects" factors.

In this paper, we incorporate unobserved heterogeneity by combining the discrete-time modeling approached described above with the "frailty" specification for handling unobserved heterogeneity in continuous-time duration models described in Kalbfleisch and Prentice (1980). This combination produces the following "random effects" logit model for discrete-time duration data:

$$P\left(y_{it}=1 \mid x_{it}\right)=h\left(t \mid x_{i,t},v_i\right)=\frac{e^{x_{it}\beta+p_{t-t_0}}}{1+e^{x_{it}\beta+v_i+p_{t-t_0}}}, \quad (6)$$

where the v_i are a series of time-invariant random error terms distributed i.i.d. standard normal, $N(0, \sigma^2)$, which capture the parcel and individual-specific unobservables. Combining the standard pooled logit model with the individual heterogeneity terms produces the following variance components model:

$$y_{it}=x_{it}\beta+v_i+\varepsilon_{it}>0, \quad (7)$$

where v_i is the same as before and ε_{it} are distributed logistically with mean zero and variance $\frac{\pi^2}{3}$. Combining the two variance components produces the correlation coefficient, ρ:

$$p=\frac{\sigma_v^2}{\sigma_v^2+\sigma_\varepsilon^2}, \quad (8)$$

which is a panel-level variance component that describes the portion of the total variance accounted for by time-invariant unobservables. The results for this and the other variables in the model are given in section 2. The entire model is estimated using Stata's random effects logit model, and the simulations in the results section are carried out using the free statistical software package *R*.

2. Description of data and covariates

2.1. Study region. Our study region is Carroll County, Maryland, an exurban county within the Baltimore metropolitan region that witnessed rapid population growth from the 1960's onward[2]. In response to burgeoning growth pressures, the county passed its first comprehensive zoning plan in 1963, which restricted development density to one house per acre in all areas of the county without public sewer facilities. Increased growth in the 1970's led to the passage of a second comprehensive plan in 1978, which included a massive down zoning of 70% of the land in the county to low-density agricultural zoning. This zoning class has a stated density of one house per 20 acres, but its actual effective density is closer to one house per 15 acres due to some leeway that was built into the law. Specifically, each parcel located in an agriculture zoning area and having at least six acres of land is allowed to create two buildable lots; each additional lot re-

[1] The most efficient link function for the binary choice model is the double-log logit model, but the authors show that for cases where the probabilities are small, the logit and the double-log models are virtually identical. Given that our data renders very small probabilities and the ease with which it can be interpreted, we choose to estimate a logit panel data model.

[2] A map of the county and our study region is shown in Appendix.

quires an addition 20 acres. Apart from several small adjustments made in 1989, these same restrictions have been in place in the county since 1978[1].

The 1963 comprehensive plan also provided the first formal procedure for the creation of large major and small minor residential subdivisions that is still in place today. Large subdivisions consist of any development with four or more buildable lots at the time of development and require the installation of streets, storm water management facilities and other infrastructure. Small developments are two or three lots and are not subject to any infrastructure requirements. In addition, while approval of large subdivisions requires a formal public hearing, small subdivisions can simply be approved by the chairmen of the planning board without a formal hearing. According to county planning officials, in most cases small developments can gain approval in less than two or three months; large developments, however, require an open public hearing as well as the approval of numerous county agencies, which can significantly increase the time until approval. While the combination of the exurban zoning policy and the creation of the formal subdivision policy was intended to control exurban and rural development and reduce the fragmentation the rural landscape, we find that over 60% of all subdivisions created from 1995 through 2007 were platted in exurban areas and of these, 82% were small minor developments (Wrenn, 2012).

2.2. Data construction and description. We constructed several micro panel datasets of residential subdivision at the parcel level to estimate the econometric model[2]. First, we constructed a panel of historical residential subdivision development, which we assembled by combining a current GIS parcel boundary file with the tax assessor's database and historical records of subdivision plats from the Maryland Archives. By matching the individual parcels in the parcel boundary shapefile with the plat maps, we determined all of the parcels in each development, assigned each development a unique ID number and a date when the subdivision first gained approval. Second, we constructed data on the historical evolution of land preservation and protected open space in the county. In 1980 Carroll County began its own purchase of development rights (PDR) program in an effort to protect farmland. Using state and county funding sources, the county has preserved over 54,000 acres of land in four different programs since 1980. We created the data for the history of these programs by matching data received from the county officials with the parcel boundary file using names and tax ID numbers. Finally, we reconstructed the history of the subdivision approval process for each of the subdivisions in our dataset by collecting the official minutes from the planning commission's monthly meetings. Using these data, we matched subdivision names with the information from the commission's database to provide dates for the stages of the development process for each of the developments.

The final dataset consists of all undeveloped parcels that, as of 1995, were eligible to be subdivided into at least two buildable lots according to the zoning regulations for the parcel. We use all parcels located in one of five zoning classes in the county: agriculture, conservation, and residential (specifically, R40, R20, or R10). This yields a total of 3,844 parcels of which a total 397 (or a little over 10% of the parcels in the county) gained final approval between 1995 and 2007. Another 343 were preserved during this period. We consider these parcels as undeveloped until the quarter they are preserved at which time they drop out of dataset. We assume that once a parcel reaches its full development potential it leaves our dataset. Thus, some parcels that are in the dataset at the beginning are not there in the final periods.

2.3. Covariates used in the empirical model. Table 1 defines all of the variables used in the estimation of our econometric land use model and gives their summary statistics. The first set of variables control for the location of the parcel and its accessibility relative to Baltimore city. *DisttoBalt* is the travel time, in minutes, from the edge of each parcel to the city limits of Baltimore city. This variable accounts for the broad impact of distance versus the city center on the likelihood of development. If the predictions of the urban monocentric model hold, then we would expect this variable to have a negative sign. The second accessibility variable, *DisttoPrimeroads*, is the distance, in meters, from the edge of each parcel to the closest primary or limited-access highway. This variable accounts for more localized accessibility effects, and it may be negative or positive depending on the tradeoffs between the benefits of accessibility and negative impacts of congestion and noise.

The second set of variables account for the impact of development costs on the timing decision. Most macro-level structural models have accounted for variable costs using a metro-level real building or development cost index. This, however, is not possible in our context as we are estimating the model in a single metro region. Moreover, because of the richness of our data-

[1] Given the amount of land in the county that falls within the agriculture zoning class and the drastic difference in density between this class and the other four zoning classes in the county, the estimation and analysis in the remainder of this paper will differentiate between these two areas by classifying all agricultural areas as low-density exurban development areas and the other four classes as higher-density suburban development areas.

[2] A full description of the data construction process for this paper is described in (Wrenn, 2012) and is reproduced in the Appendix.

set, we are able to capture a much more spatially explicit measure of local parcel costs and proxy for the most important factors that would impact this index in our region[1]. These costs are similar to building materials in the case of building construction. As with capital inputs to building construction, the market for labor and capital inputs for land excavation and conversion is competitive and the costs associated with development on any parcel, while they vary spatially, should be directly proportional to the characteristics of the parcel and not be uncertain from the point of view of the developer. The soils variables (*Soil*1 and *Soil*2) are the percentage of each type of soil on the parcel with *Soil*1 being the best soil. Their are three main types of soils, so both of these are relative to the excluded category or worst type, *Soil*3. *SteepSlp* is the percentage of the parcel that is over 15% slope and *FrstPrcnt* in the percentage of the parcel covered in forest. We expect better soils to speed up development and Slope and Forest to reduce it if they raise costs. The final variable, *FloodPlne*, is an indicator variable for whether a parcel is located in a 100-year flood plane[2]. All of these variables are constant across time.

The third set of variables captures the potential impacts of land use regulations on the development timing decision. The first variable, *ZonedLots*, accounts for the zoned maximum allowable density of development on each parcel. It is constructed by combining the acreage and zoning on each parcel to produce the maximum number of buildable lots for each parcel. Given that more buildable lots equal more revenue from the sale of the lots, we expect that this variable will have a positive impact on development. We use this variable in the policy simulations described in section 3.1 to simulate a policy change in the allowable density of development. The next four variables are indicators controlling for different types of zoning on the parcel. Carroll County has five major zoning classes in the county suitable for residential subdivision development. The first and the lowest density is the agricultural zoning region, which was described above. This is the excluded category in our land use model. The other four, *CnsvZone*, *R*40*Zone*, *R*20*Zone* and *R*10*Zone*, are higher density and designated as one house per three acres, one house per acre, two house per acre and four houses per acre, respectively. We include these variables to test whether different types of zoning have any additional effect on development outcomes beyond the difference in allowable density that is captured by the *ZonedLots* variable. The next variable, *EaseElig*, is time-varying indicator variable for whether a parcel is eligible for enrollment in a land preservation program in each time period. To be eligible for preservation, a parcel must be greater than 50 acres and have more than 50% of type 1 and 2 soils combined or be between 25 and 50 acres and border a previously preserved parcel. Thus, easement eligibly is based off of the size of the parcel, the percentage of certain soil types and the proximity of the parcel to other parcels that have preserved in the past. Because of this final clause, some parcels that are not eligible in one period may become eligible in latter periods as larger parcels around them preserve. Given the possibility of an alternative use (i.e., land preservation) that competes with the option to develop the parcel, we expect that this variable will have a negative influence on the likelihood of development. The last variable common *Approval* common captures the so-called implicit costs that arise from regulatory uncertainty which, in this case, are due to the uncertain amount of time that a developer must wait for approval of the subdivision plan by the local planning agency. As Wrenn (2012) shows, these implicit costs have a significant effect on development outcomes by reducing the likelihood and intensity of development and altering the spatial pattern. We follow Wrenn (2012) in the construction of this variable by using data on the length of time that it took each subdivision that we observe in our data to be approved. We use these data to model developer expectations over their own approval time by estimating a duration model for each year of our data, in which approval timing is modeled as a function of parcel characteristics using the observations on all previous development up until that year. We then use the parameter estimates to create an expected approval time for each undeveloped parcel that is eligible for development in each period[3].

The last section accounts for land market variables that are hypothesized to influence the development timing decision. The variable, *Compete*, is a proxy for the stock of existing developed lots in a local area around each parcel. We do not explicitly account for population growth in this model but, given the richness of the our subdivision and approval data, we can determine, in each time period, the number of buildable lots that have been approved based off of the dates from the plat maps. So, for each parcel in our data set, we calculate the number of approved buildable lots in a 10% region around each parcel in the previous two years. This variable proxies for both local competition and the local stock or existing supply of buildable lots for each parcel, in each time period. The last variable, *PricePerAcre*, is the predicted land price per acre in each period. We use this variable in the policy simula-

[1] This method of accounting for variable costs is similar to other land use models (Towe, Nickerson, and Bockstael, 2008; Newburn and Berck, 2006; Irwin and Bockstael, 2002).

[2] Given that some parcel straddle the flood zones, we give each parcel a value of one if the total area of the parcel within the flood zone is over 50%.

[3] For more details on the construction of this variable and for a full examination of how this type of uncertain regulatory cost influences development outcomes in this study region, see Wrenn (2012).

tions to capture the effect of a development fee that increases the costs of land development. The construction of this variable is described in the next section.

2.4. Proxy for land prices. The price of developable land is difficult to estimate due to data constraints. Ideally, the price of developable land would come from the repeated sale of undeveloped land parcels in a market between developers and landowners. However, our actual sample of raw land parcel transactions is quite small, even over a long period of time, making it difficult to use these transactions in any sort of predictive manner in an econometric analysis. So, in order to produce our estimate of the price per acre of developable land in each time period and on each parcel in our dataset, we use historical data on house prices and property characteristics collected from the state tax assessor's office to control for the added-value characteristics of the house and parcel and use the remaining coefficients for location and size to predict a yearly price per acre for each parcel in our dataset.

Table 1. Covariates used in land use model

Variables	Description	Mean	Std. dev.	Min.	Max.
Accessibility					
DisttoBalt	Travel time (min.)	41.02	8.05	23.18	65.51
DisttoPrimeroads	Dist. (meters)	1180.22	1130.36	5.25	9980.27
Development costs					
*Soil*1	Type 1 soils (%)	40.04	43.21	0.00	100.00
*Soil*2	Type 2 soils (%)	52.67	43.19	0.00	100.00
SteepSlp	Greater than 15%	17.27	29.21	0.00	100.00
FrstPrcnt	Forest cover (%)	33.50	32.21	0.00	100.00
FloodPlne	In a flood zone	0.25	0.43	0.00	1.00
Land use regulation					
ZonedLots	Zoned density	32.63	41.02	0	653
CnsvZone	Conservation zoning	0.18	0.38	0	1
*R*40*Zone*	R40 zoning	0.09	0.28	0	1
*R*20*Zone*	R20 zoning	0.08	0.27	0	1
*R*10*Zone*	R10 zoning	0.14	0.35	0	1
EaseElig	Easement eligibility	0.24	0.42	0.00	1.00
Approval	Subdivision approval time	10.64	5.15	1.98	95.39
Land market					
Compete	Local competition	13.95	21.19	1.00	135.00
PricePerAcre	Price per acre	1874.69	3130.04	28.82	37127.33

To create the data used in our house-price estimations, we matched housing transactions from the Maryland Property View (MDPV) Dataset from 1993 through the last quarter of 2007 with several other datasets containing the characteristics of the structure and the parcel. We kept only observations with price values within three standard deviations of the mean. We also threw out any houses with a square footage under 800 or over 10000 to remove outliers. The final dataset contained 34,311 arms-length transactions for the period 1993 through 2007. The descriptive statistics for the covariates used in each of the price index models are shown in Table 2.

To generate the coefficients necessary for our land-price predictions, we estimate the following hedonic model:

$$\log\left(P_i\right) = \alpha_j + \delta_z + \gamma_q + X_i'\beta + \varepsilon_i, \qquad (9)$$

where j is an indicator for the census tract in which the transaction occurred, z is an indicator for the zoning classification of the house and q is an indicator for the quarter of the transaction. This model is run for each of the 13 time periods of our model using the house-price transactions from the previous two years to estimate each model. For example, in 1995, we use the sales data from 1993 and 1994. The main reason we only use the two previous years is because we only have transactions data from 1993 onward and, as a result, we only have two years of data before the starting period of our model. However, given the linear nature of our price model and the large sample that is created using just two years of data, this technique is unlikely to cause any issues[1].

[1] We experimented with using three time periods for the hedonic estimation and running the main model from 1996-2007, but the results were the same. Thus, in order to increase efficiency in our main model, which is nonlinear, over the added the efficiency in the linear hedonic model, we chose to use two years of price data for the hedonic models and estimate the main model from 1995 forward.

Table 2. Summary statistics: hedonic price models

Variables	Mean	Std. dev.	Min.	Max.
Log real price (2000 dollars)	12.20	0.43	10.94	13.82
Travel time to Baltimore City (Kilometers)	36.81	6.73	22.72	64.49
Distance to primary road (Meter)	812.80	776.07	3.45	5000.00
Area	3.65	2.30	0.00	9.99
Square footage	1799.21	736.66	800.00	9600.00
Age of structure	18.67	24.77	1.00	150.00
New structure	0.22	0.41	0.00	1.00
Structure quality	3.54	0.76	1.00	8.00
Garage	0.61	0.0	0.00	1.00
Air conditioning	0.84	0.37	0.00	1.00
Brick	0.01	0.09	0.00	1.00
Number of full bathrooms	1.86	0.68	1.00	6.00
Townhouse	0.15	0.35	0.00	1.00
Inside of minor subdivision	0.02	0.15	0.00	1.00
Inside of major subdivision	0.79	0.41	0.00	1.00
Quarter 2	0.29	0.45	0.00	1.00
Quarter 3	0.26	0.44	0.00	1.00
Quarter 4	0.24	0.43	0.00	1.00
Conversation zoning	0.10	0.30	0.00	1.00
$R40$ zoning	0.11	0.32	0.00	1.00
$R20$ zoning	0.24	0.43	0.00	1.00
$R10$ zoning	0.38	0.50	0.00	1.00

Notes: N = 34,311. Each model has a full set of census tract indicators. All continuous variables are estimated in logarithmic form.

To produce our land-price predictions, we extract the coefficients for distance to Baltimore, distance to a primary road, the acreage of the housing lot, the indicators for zoning and the indicators for the census tract of the house from each of the 13 hedonic models. Then, using these coefficient values and the same variables for the developable parcels from our main model, we create a predicted land price for each parcel in our dataset for each of our 13 time periods. Finally, we divide this value by the total acreage on the parcel to generate a predicted price per acre for raw, developable land. By being able to control for all of the added value characteristics of the house and parcel, we are then able to use the remaining coefficients to produce a location and time value for the raw land on each parcel based on of its zoning, census-tract, size and relative-location characteristics.

One potential concern about our proposed method is whether the predictions it produces for land prices adhere to expectations in terms of value. Given the volume of data produced during this process, it is not possible present the results from each model in this paper. So, in order to give an indication that our predictions fit expectations, we present the means and standard deviations from each parcel divided out by zoning classes and years (Tables 3 and 4). Both of these tables show the efficacy of our prediction method. For zoning, we observe that as the density on the parcel increase, so does the price per acre, what we will expect if density translates into more buildable lots and potential revenue. Next, we see that the prices per acre follow the expected temporal trend as well. They were higher in 1995 than in 2000, when the US was in a recession, and then they recovered and grew during the housing boom in 2007. Both of these results provide evidence that our predictions for land prices are consistent with expectations and provide an efficient measure for use in our development timing model.

Table 3. Price per acre by zoning class

Zoning	Mean	Std. dev.
Agriculture zoning	501.43	480.00
Conversation zoning	660.62	454.43
$R40$ zoning	1635.60	1311.24
$R20$ zoning	3448.00	2519.64
$R10$ zoning	6832.83	4311.24

Note: Prices are in 2000 dollars.

Table 4. Price per acre by year

Year	Mean	Std. dev.
1995	1664.30	2653.14
2000	1563.64	2442.80
2007	3685.50	5468.91

Note: Prices are in 2000 dollars.

3. Results and discussion

The estimation results of the random effects logit model of land development are displayed in Table 4. We find that distance to Baltimore, the closest large urban center, has a negative and significant effect on the rate or likelihood of development. This is consistent with our expectations based on the urban economic model that predicts declining competition and returns for land development as transportation costs to the city increase. On the other hand, we find that distance to a major highway or road is positive, suggesting that there are negative externalities associated with being located near a major road that outweigh the benefits of greater accessibility. We find that the development cost variables all have the expected signs although some are not significant. Better soils increase the likelihood of development while steeper slopes and a greater proportion of forested area decrease development due to the higher costs of grading and preparing the land. Being located in a 100-year flood plane zone also decreases the likelihood of development.

We find some interesting results with respect to the impact of land use regulations on the timing of development. First, we find that the effect of the zoning density constraint, *ZonedLots*, is positive and significant, indicating that an increase in the allowable number of lots on a parcel increases its likelihood of development. In comparing development outcomes across the different zoning classes, neither of the more restrictive zoning types, *CnsvZone* and *R*40*Zone*, are found to have a significantly different effect from the omitted class, which is the most restrictive zoning. On the other hand, the two higher-density zoning classes, *R*20 and *R*10, are found to have a negative and significant effect on development timing. This results indicate the presence of other factors associated with developing parcels that are located in these zoned areas, which are the suburban areas of our study region, that slow development outcomes. This could be due to, for example, congestion effects or other negative externalities associated with new development in these areas. The option of land preservation, represented by the indicator variable *EaseElig*, is negative but not significant. The negative sign conforms with our expectations that having an additional land use alternative competes with the alternative to develop the parcel and therefore decreases the likelihood of developing these parcels (Towe, Nickerson and Bockstael, 2008). Finally, we find that an increase in approval time decreases the likelihood of development. This too is consistent with our expectations that an increase in approval time, which increases regulatory uncertainty and costs for the developer, will dampen the rate of development. This is also consistent with the findings of Wrenn (2012).

Finally, the two land market variables are also consistent with our expectations. Greater competition from a larger local stock of existing residential land decreases the likelihood that a parcel is developed (*Compete*). Likewise, higher land prices that increase the cost of land as an input into residential development are found to reduce the likelihood of development. Both results are consistent with basic economic theory and support our assumption of the profit-maximizing behavior of land developers.

While these estimated coefficients provide an indication of whether land use regulations and economic variables that are specific to individual land parcel will increase or decrease the likelihood of a parcel's development, they do not provide a full evaluation of the potential impacts of a land use regulation or economic policy on land development. Doing so requires a means of predicting the impact of a policy change on the changes in the quantity and pattern of development. We use spatial simulation methods to do so. The next section describes our method and reports the results of these policy simulations.

3.1. Policy simulations. We use the estimation results and a series of Monte Carlo simulations to analyze various policy scenarios in which we alter either the price per acre of land or the zoning density on parcels located in exurban and/or suburban areas and compare the effectiveness of each policy change in controlling leapfrog development patterns. Both of these policy levers – a change in the zoning density on a particular parcel or a development fee or tax on certain parcels – are policy tools that are available to regulators and that have been used in the past to control development (Brueckner, 2009). We investigate the potential implications of each of these policies by comparing predicted development outcomes under a baseline scenario, which is produced by running our simulations on the original data, versus a series of alternative policy scenarios in which we alter zoning density or price of a developable parcel[1].

To examine the efficiency of our model in matching in-sample development outcomes, we apply a similar simulation technique to Lewis, Provencher and Butsic (2009) and Wrenn (2012). We begin with the entire sample of developable parcels at the beginning of our study period. Then, we use the estimated parameters and the covariance matrix from our random effects logit model and a set random draws from a standard normal distribution to produce a random draw from our estimated parameter distribution in a method similar to Krinnsky and Robb (1986). Each simulated parameter is a combination of the original parameter, a Cholesky decomposition of the covariance matrix and

[1] Throughout this section, we take parcel to mean the original raw land parcel and lots to mean the number of buildable, subdivided lots created after development occurs.

a standard normal draw, *Theta hat* = $\theta + Cd_r$, where θ is the entire parameter vector from our model, C is the Cholesky decomposition of the variance-covariance matrix and d_r is a random draw from a standard normal distribution.

Table 4. Random effects logit model

		Timing decision
	Coeff.	Std. err.
Accessibility		
DisttoBalt	-0.033"	0.014
DisttoPrimeroads	0.171"	0.043
Development costs		
*Soil*1	0.006	0.004
*Soil*2	0.004	0.004
SteepSlp	-0.001	0.002
FrstPrcnt	-0.011"	0.003
FloodPlne	-0.266*	0.161
Land use regulation		
ZonedLots	0.007"	0.003
CnsvZone	-0.074	0.229
*R*40*Zone*	-0.166	0.269
*R*20*Zone*	-0.762*	0.393
*R*10*Zone*	-0.665*	0.398
EaseElig	-0.242	0.151
Approval	-0.094**	0.031
Land market		
Compete	-0.005*	0.003
PricePerAcre	-0.083*	0.050
Constant	-3.002**	0.731
Log likelihood	-2173.501	
a	1.248**	0.551
p	0.321**	0.046

Note: $^{*}p < 0.10$, $^{**}p < 0.05$. The standard errors for the panel data values were produced using the Delta method. A full set of time fixed effects was included in the model. The *PricePerAcre* and *Surprimerd* coefficients are multiplied by 1000.

For each random draw of the parameters, the predicted probability of development is calculated for each parcel in the first period using the coefficients from our logit model. Then, a random uniform draw, $U \sim [0,1]$, equal to the number of parcels in the dataset in the first period is taken. The random development probabilities on each parcel are compared to the random uniform draws and those parcels whose predicted probabilities are greater than or equal to this draw considered as developed. Once a parcel develops it is removed from the dataset and the process is repeated for each of our 13 time periods with the updated dataset used in each subsequent period. The time fixed effects from discrete-time duration the model account for changes in unobserved macro-level changes and the estimate of the panel-level random effect accounts for time-invariant individual heterogeneity. This simulation process is repeated 200 times for each exercise, and the predicted number of subdivision developments created both in total and divided out between exurban and suburban areas are averaged across all the simulations to produce our simulation results.

Using this method to simulate the policy impacts, we compare several different policy scenarios with a baseline scenario of no policy change. The hypothetical policy scenarios are designed with the goal of reducing the environmental impacts of land development by reducing the amount of land fragmentation in the more rural areas of our study region. We therefore choose policy scenarios that promote new development in higher-density suburban areas and discourage the amount of new development in lesser-developed exurban areas. First, we examine the predicted development outcomes for several different zoning changes that alter the allowable density of development. The first two policy alternatives correspond to a reduction in the allowable number of lots that can be developed in the exurban zone. To implement these scenarios, we reduce the value of *ZonedLots* for all parcels located in the exurban areas from the equivalent of one house per 15 acres to one house per 20 acres (scenario 1) and one house per 40 acres (scenario 2). We also consider a policy scenario in which the maximum allowable density in the exurban zone is reduced to one house per 20 acres and increased to one house per acre in the conservation zones and two houses per acre in the *R*40 zones (scenario 3). Next we consider several different fee-based policies. Scenarios 4 and 5 consider the implementation of a development fee in the exurban zones that raises the costs of development by 20% and 50% of the land price, respectively. Finally, we consider the combination of a fee and subsidy that imposes a development fee on all exurban parcels that increases their costs by 20% of their land price and a subsidy to all suburban parcels that decreases their costs by 20% of their land price.

The results from our series of simulation exercises are shown in Table 6. First, by comparing the baseline scenario to the actual outcome from the data, we can assess the validity of our model and approach. We note that the baseline comes very close to an exact prediction of the outcomes. It slightly overpredicts exurban development (by 2%) and underpredicts suburban development (by 5%), but overall provides a very good predictive fit to the data. Turning to the results of the policy scenarios, we find that the hypothetical zoning policy changes are predicted to generate substantial impacts on land development. Scenarios 1 and 2 impose a reduction in the current allowable density of development in exurban areas by 33% and 167%, respectively. These increased zoning constraints are predicted to decrease the amount of exurban development by 60% and 82%, respectively. Scenario 3 combines the first scenario, a reduction in the maximum allowable density in exurban areas to one house per 20 acres, with an increase in the allowable density of development in conservation and R40 zones.

Table 6. Policy simulation results

		Predicted subdivs	Exurban subdivs	Suburban subdivs
	True outcomes from the data	397	247	150
	Baseline scenario	395	253	142
Density scenarios				
1	1 house per 20 acres exurban	246	102	144
2	1 house per 40 acres exurban	191	46	145
3	1 house per 20 acres exurban; 1 house per acre conservation; 2 houses per acre R40	266	105	161
Price-change scenarios				
4	20% increase in price per acre exurban	391	248	143
5	50% increase in price per acre exurban	389	245	144
6	20% increase in price per acre exurban; 20% decrease in price per acre suburban	391	248	143

Note: The true values are the actual results from the original data.

These increases represent a 67% and 50% increase in allowable density in these two zones, respectively. The results show that this combination of policies generates a reduction in exurban development by 57%, which is about the same reduction as is achieved in scenario 1, and a 13% increase in the amount of new development in suburban areas. In contrast to the predicted impacts of these hypothetical zoning changes, development outcomes are very insensitive to price-based policies. Scenarios 4 and 5 posit an additional fee for development in exurban zones that is equivalent to 20% and 40% of the parcel's expected land price, respectively. In both cases, the development outcomes are changed only slightly: a development fee of 20% of the land price is predicted to reduce development in the exurban areas by only 2% and a fee of 40% of the land price is predicted to reduce development by only 3%. Scenario 6, which considers the combination of a 20% development fee in the exurban areas and a 20% subsidy in the suburban areas reduces exurban development by just 2% and increases suburban development by only 0.7%.

Our model is a partial equilibrium model and therefore we do not capture the price feedbacks or development spillovers to other locations that would likely occur if these policies were to actually be implemented. For example, a non-marginal reduction in the amount of developable land will bid up land prices that, in a competitive market and in the absence of zoning controls, would increase the density of land development. However, because the density controls imposed by the zoning constraint are binding, the higher land price will raise housing costs without increasing the supply of housing. To the extent that neighboring locations are substitutable, housing demand will spillover to neighboring jurisdictions. Since we only consider one jurisdiction in a partial equilibrium framework, our predicted development outcomes ignore such market feedbacks and, therefore, miss a potentially important source of additional land use fragmentation caused by policy spillovers. Nonetheless, our results are useful in terms of showing the relative responsiveness of development to these two different policies. The hypothetical changes in zoning in the exurban areas decreases the amount of new development simply because this policy imposes a strict reduction on the supply of developable parcels. Exurban parcels that are developable under the current zoning policy are no longer developable under the alternative policy scenarios that further constrict the allowable density. Given this, it is not surprising that the hypothetical zoning policy changes generate such a substantial change in development outcomes in these areas. More interesting are the results of the hypothetical economic-based incentives in which an additional fee is exacted for exurban development. Here we find very little responsiveness to cost increases imposed by the development fee. Interpreting the results of the policy simulation in terms of a land demand elasticity, we find that the predictions of scenario 4 and 5 correspond to demand elasticities of 0.1 and 0.06 respectively. The implication is that developers' demand for land as an input into housing production is extremely inelastic and that market-based incentives, such as a development fee or subsidy, are unlikely to generate sufficient changes in the amount of pattern of new land development that are needed to reduce land fragmentation. On the other hand, the highly inelastic demand for land by developers implies that any regulation that restrict the supply of developable land, such as the zoning controls considered here, imposes potentially large welfare losses. If the zoning constraint binds supply to a level below the competitive outcome, developers will be willing to pay more for an additional acre of developable land than the marginal costs of landowners to supply it. Given developers' highly inelastic demand for land, the forgone market benefits that are imposed by such a supply restriction are likely to be substantial. A full welfare analysis would consider the magnitude of these costs relative to the benefits from the reduction in land fragmentation that we show would also result from a reduction in the supply of developable parcels in the exurban areas.

Conclusion

Land fragmentation generates a host of environmental impacts, including habitat and biodiversity loss and a reduction in natural lands that control nutrient run-off and sedimentation that degrade water quality. The design of effective land use policies to control fragmentation relies on an understanding of how landowners, land developers and other actors in land and housing markets respond to market-based policies and land use regulations. Because land fragmentation is inherently a spatial phenomenon, effective policy design also relies on an understanding of how policy changes are likely to alter the spatial pattern of land use and the extent to which these changes can reduce land fragmentation by preserving larger areas of undeveloped land.

We investigate the predicted effects of a market-based versus regulatory policy instrument on land fragmentation by using spatial simulation methods and results from an econometric model of land development estimated with data on residential land development in a rapidly urbanizing county in Baltimore, Maryland region. Using a logit specification of a discrete-time duration model with random effects, we estimate the parameters of the developer's land development decision. Our dataset includes information on the location and price of land parcels and their physical characteristics as well as information on spatially heterogeneous zoning regulations that constrain a parcel's allowable density of development. The estimates from the land development model are then used to conduct a series of policy simulations in which we compare the development outcomes under a market-based policy that alters the relative economic incentives to develop land and with a land use zoning regulation that reduces the supply of developable land parcels. We find that the zoning policy changes are much more effective than the economic incentive policies in altering the predicted pattern of land fragmentation relative to the baseline case of no policy change. For example, a change in the allowable density of development from one house per 15 acres to one house per 20 acres is found to reduce development in the lesser-developed exurban areas of the county by 60%. On the other hand, a 50% increase in exurban development costs imposed by a hypothetical development fee is found to only decrease the amount of new exurban development by 3%. Thus we find that developers' demand for land is extremely inelastic and that market-based incentives, such as a development fee or subsidy, are unlikely to generate sufficient changes in the amount of pattern of new land development that are needed to reduce land fragmentation.

These results provide an initial evaluation for the land development case of the two most common policies considered in environmental economics: market-based policies, in which the net returns are altered by a tax or subsidy that seeks to internalize an externality, versus quantity-based policies that constrain the amount of an externality-producing good. We do not recover the underlying land supply function nor do we attempt to estimate the externality costs associated with land fragmentation and, therefore, we do not provide a formal welfare analysis of these policies. Instead, by accounting for the parcel-level variables that influence a developer's costs and returns from development and assuming profit-maximizing behavior, we are able to predict how a change in policy changes the likelihood that a parcel is developed. Thus, our results allow us to evaluate the relative effectiveness of these policies in altering development outcomes, which is a necessary first step towards assessing their relative efficiency.

References

1. Beck, N., J. Katz, and R. Tucker (1998). "Taking Time Seriously: Time-Series-Cross-Section Analysis with a Binary Dependent Variable", *American Journal of Political Science*, 42, pp. 1260-1288.
2. Brady, M., and E. Irwin (2011). "Accounting for spatial effects in economic models of land use: Recent developments and challenges ahead", *Environmental and Resource Economics*, 48, pp. 487-509.
3. Brueckner, J. (2009). *Government Land-Use Interventions: An Economic Analysis*, Springer. pp. 3-23.
4. Butsic, V., D. Lewis, and L. Ludwig (2011). "An Econometric Analysis ofLand Development with Endogenous Zoning Land Economics", *Land Economics*, 87, pp. 412-432.

5. Capozza, D., and R. Helsley (1989). "The Fundamentals of Land Prices and Urban Growth", *Journal of Urban Economics*, 26, pp. 295-306.
6. Carrion-Flores, C., and E. Irwin (2004). "The Determinants of Residential Land-Use Conversion", *American Journal of Agricultural Economics*, 86, pp. 889-904.
7. Duke, J., and J. Wu (2013). *Handbook of Land Economics*, Oxford University Press.
8. Hertel, T., S. Rose, and R. Tol (2009). "Land use in computable general equilibrium models: an overview", *Economic analysis of land use in global climate change policy*, Routledge.
9. Irwin, E., and N. Bockstael (2002). "Interacting Agents, Spatial Externalities and the Endogenous Evolution of Residential Land Use Patterns", *Journal of Economic Geography*, 2, pp. 31-54.
10. ___ (2004). "Land Use Externalities, Open Space Preservation, and Urban Sprawl", *Regional Science and Urban Economics*, 34, pp. 705-725.
11. Irwin, E.G. (2010). "New Directions for Urban Economic Models of Land Use Change: Incorporating Spatial Dynamics and Heterogeneity", *Journal of Regional Science*, 50, pp. 65-91.
12. Kalbfleisch, J., and R. Prentice (1980). *The Statistical Analysis of Failure Time Data,* New York: John Wiley & Sons.
13. Kalnay, E., and M. Cai (2003). "Impact of urbanization and land-use change on climate", *Nature*, 423, pp. 528-531.
14. Krinnsky, I., and L. Robb (1986). "On Approximating the Statistical Properties of Elasticities", *The Review of Economics and Statistics*, 68, pp. 715-719.
15. Lewis, D. (2010). "An Economic Framework for Forecasting Land-Use and Ecosystem Change", *Resource and Energy Economics*, 32, pp. 98-116.
16. Lewis, D., A. Plantinga, E. Nelson, and S. Polasky (2011). "The Efficiency of Voluntary Incentive Policies for Preventing Biodiversity Loss", *Resource and Energy Economics*, 33, pp. 192-211.
17. Lewis, D., B. Provencher, and V. Butsic (2009). "The Dynamic Effects of Open-Space Conservation Policies On Residential Development Density", *Journal of Environmental Economics and Management*, 57, pp. 239-252.
18. McConnell, V., M. Walls, and E. Kopits (2006). "Zoning, TDRs, and the Density of Development", *Journal of Urban Economics*, 59, pp. 440-457.
19. Nelson, E., S. Polasky, D. Lewis, A. Plantinga, E. Lonsdorf, D. White, D. Bael, and J. Lawler (2008). "Efficiency of Incentives to Jointly Increase Carbon Sequestration and Species Conservation on a Landscape", *Proceedings of the National Academy of Sciences*, 205, pp. 9471-9476.
20. Newburn, D., and P. Berck (2006). "Modeling Suburban and Rural-Residential Development Beyond the Urban Fringe", *Land Economics*, 82, pp. 481-499.
21. Postel, S., G. Daily, and P. Ehrlich (1996). "Human appropriation of renewable fresh water", *Science*, 271, pp. 785-788.
22. Sala, O., F.C. Ill, J. Armesto, E. Berlow, J. Bloomfield, and R. Dirzo (2000). "Global Biodiversity Senarios in the Year 2100", *Science*, 287, pp. 1770-1774.
23. Tilman, D., J. Fargione, and B. Wolff (2001). "Forecasting agriculturally driven global environmental change", *Science*, 292, pp. 281-284.
24. Towe, C., C. Nickerson, and N. Bockstael (2008). "An Empirical Examination of the Timing of Land Conversions in the Presence of Farmland Preservation Programs", *American Journal of Agricultural Economics*, 90, pp. 613-626.
25. Turner, B., E. Lambin, and A. Reenberg (2007). "The Emergence of Land Change Science for Global Environmental Change and Sustainability", *Proceedings of the National Academy of Sciences*, 104, pp. 20666-20671.
26. Wrenn, D. (2012). "Time Is Money: An Empirical Examination of the Dynamic Effects of Regulatory Uncertainty on Residential Subdivision Development", Unpublished.

Appendix. Study region

Fig. 1. Baltimore/Washington, D.C. metro area

1. Data construction. To estimate our panel data econometric model, we constructed several micro panel datasets. The first dataset we constructed was a panel of the historical subdivision development for the county. To construct these data, we joined the parcel boundary GIS shapefile of the county with the tax assessor's database using a tax assessment ID number. In addition to information on the attributes of the parcel, structure, purchase date and price, and information about the owner, the assessor's database contained information on the plat book and page number for the subdivision in which the parcel was located[1]. Using these numbers, we were able to locate the original plats at the Maryland historical archives. By matching the individual parcels in the parcel boundary shapefile with the plat maps, we could determine all of the parcels in each development, assign each development a unique ID number and provide a date when the subdivision first gained approval[2]. There were 1,910 subdivisions developed from 1924-2007. Of these, 1,098 were major developments and 812 were minor developments[3].

The second dataset we created was for the historical evolution of land preservation and protected open space in the county. Over the past several decades many state and local governments throughout the U.S. have developed and used voluntary incentive-based programs as a mechanism to prevent sprawl, limit growth and protect agriculture land. Within these programs landowners receive actual payment or equivalent tax deductions in exchange for voluntarily foregoing development on their property in perpetuity. In addition to the down zoning that took place in 1978, in 1980 Carroll began its own purchase of development rights (PDR) program as an additional measure to protect farmland. Using state and county funding sources, the county has preserved over 54,000 acres of land in four different programs since 1980. We created the data for the history of these programs by matching data received from the county officials with the parcel boundary file using names and tax ID numbers. While we do explicitly model this decision, these data give us the ability to control for this decision in our analysis by removing preserved parcels from the dataset in each time period that they are preserved as opposed to removing all of these parcels at the beginning of the study period. In theory, we could model this process simultaneously with the development decision, but that is outside of the scope of this paper.

The final dataset we created was a dataset of the historical subdivision approval process for county. As was noted in the paper, when landowners wish to subdivide a parcel they must follow the rules in the county subdivision development guide. One of the most uncertain aspects of the development process is the necessary time to gain final approval and the regulatory hurdles that delay the process. To reconstruct the history of this process for each of our subdivisions, we collected the official minutes from the planning commission's monthly meetings. Using these data and pattern matching algorithm written in Python, we matched subdivision names with the information from the commission's database to provide dates for the stages of the development process for each of the developments. Given that the county only had electronic data starting in 1989, we only have data on the process from 1989 through 2010.

Figure 2 shows an example plat map and Figure 3 shows the land-use pattern for the county at the end of 2007.

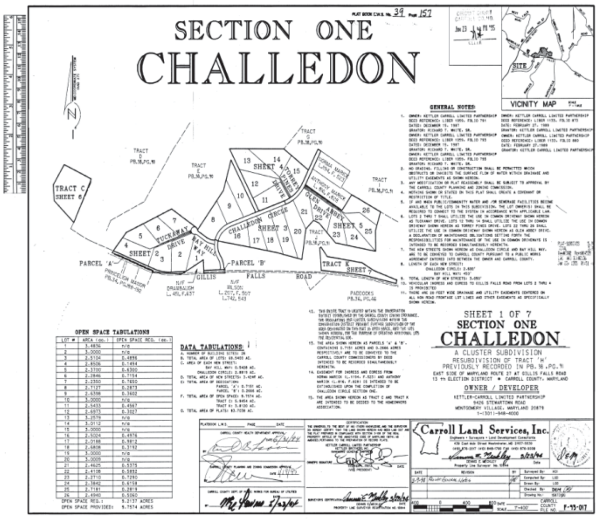

Fig. 2. Plat map example

---

[1] After a subdivision gains final approval from the county zoning commission, the plat of that development becomes public record, and is recorded and stored at the Maryland historical archives. These plats and the information contained on them are available to the public online at the following address: www.plats.net.

[2] In 12% of the cases the subdivision was completed in more than one phase. In the case of these multi-phase developments, we dated and assigned unique ID numbers to each section. We also gathered information about open space requirements, sewer, zoning, developer information and whether the development was a major or minor subdivision.

[3] In many ways the minor subdivision policy was internalizing a process that was already underway. Many small developments and single family homes were being built in the period preceding 1963. Part of the impetus for the plan was to help document and control the amount this type of development and protect vital farm land from develop-lead fragmentation. Thus, as is the case with many land-use policies, the subdivision policy for Carroll formalized an existing trend.

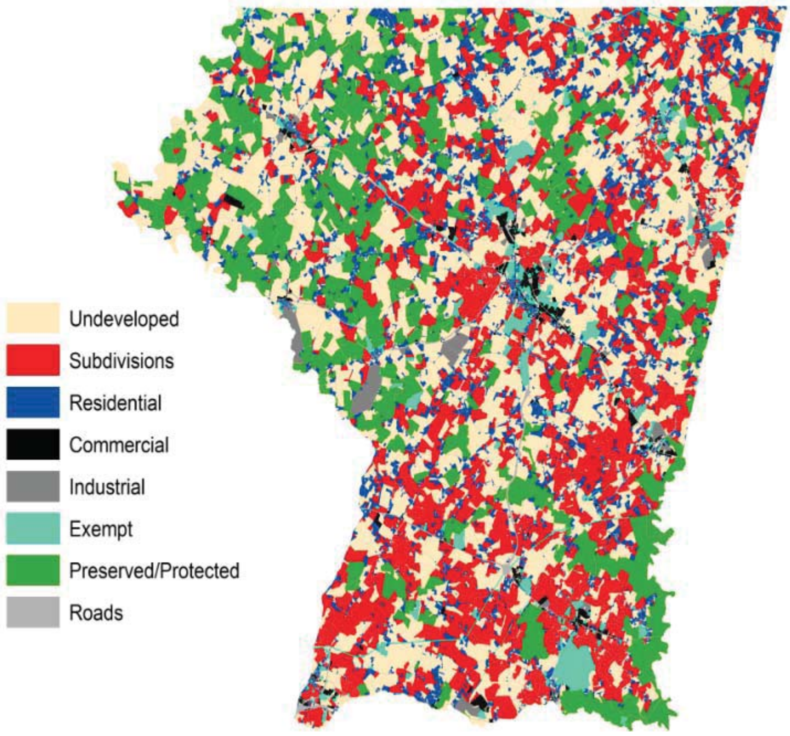

Fig. 3. Carroll county land use 2007