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Recent Advances in Empirical Land-Use Modeling

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Abstract

Data sets providing repeated observations of land use at fine spatial scales have enabled a new generation of land-use studies. In the past decade, these analyses have put increasing emphasis on empirical research designs that provide more convincing causal estimates. I review the use of instrumental variables, matching, difference-in-differences, regression discontinuity design, and randomized controlled trials in the recent land-use economics literature, exploring how new data have made possible the use of these research designs. I show that these estimators have produced different results than were obtained with traditional approaches and have provided new insights into important land-use policy issues such as additionality and spillover effects.

1. INTRODUCTION

The IPCC's *Climate Change and Land* special report (Shukla et al. 2019) presents a sobering assessment of human impacts on land ecosystems and biodiversity (see also Díaz et al. 2019). Approximately three-quarters of the ice-free land surface of the planet have been affected by human activities, which have resulted in significant losses of biodiversity. Climate change, driven in part by land clearing for agriculture, is affecting growing seasons, crop yields, and freshwater availability. The report calls for urgent action to reverse the negative effects on land ecosystems and the services they provide.

Resource economists have an important role to play in helping to meet this grand challenge. For state-controlled lands, resource economics provides a framework for evaluating the desirability of alternative strategies for managing public resources (Loomis 2002). For private lands, resource economics provides insights into three key questions: (*a*) How do land markets produce incentives for private land-use decisions? (*b*) How do land managers respond to these incentives? (*c*) How can land-use policies be designed to avoid undesired environmental effects? This review focuses on empirical studies of private land use and policies directed at these lands.[1]

Land economics has a long tradition dating to the early nineteenth century. David Ricardo formulated the concept of land rent, the surplus profits accruing to scarce features of land, and J.H. von Thünen showed how differences in rents give rise to spatial patterns of land use. In the modern era, theories of land use build on these early contributions to explain the spatial structure of cities and rural landscapes. Empirical analysis has focused on understanding the determinants of land prices and the response of land managers to market and policy incentives. Earlier reviews of the literature are found in publications by Anas et al. (1998) and Bell et al. (2006). Plantinga (2015) explores how economic land-use models have been integrated with biophysical models to analyze the environmental consequences of land-use decisions and policies.

Over the past 25 years, empirical analyses of land use have benefited tremendously from new data and increased computer power. The earliest economic studies relied on aggregate data, such as the area of land by use measured at the state (White & Fleming 1980) or county level (Stavins & Jaffe 1990). The availability of large numbers of land-use observations measured at the plot or parcel scale[2] has allowed researchers to measure land use and its determinants with much greater precision. In particular, parcel data have enabled the explicit modeling of spatial relationships, such as localized externalities (e.g., Irwin & Bockstael 2002), and the availability of repeated observations over time has allowed researchers to explicitly investigate the drivers of land-use change (e.g., Lubowski et al. 2008).

At the same time that land-use economists were taking advantage of better data and faster computers, the economics discipline was putting increasingly more emphasis on empirical research designs that can produce more convincing causal estimates (Angrist & Pischke 2010). Like all areas of applied microeconomics, land-use economics has been swept up in what Angrist & Pischke (2010) call the "credibility revolution." Over the past decade, empirical approaches such as difference-in-differences (DID) and regression discontinuity design (RDD) have been increasingly common in land-use analyses. In many cases, the use of these research designs has been

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[1]As such, I focus on the last two questions. The first question is addressed in hedonic property value model studies, which were surveyed recently by Bishop et al. (2020).

[2]A plot refers to a land unit that is part of an on-the-ground sample (e.g., the National Resources Inventory), and parcel refers to land units that are spatially contiguous. Parcel data are often collected through remote sensing (e.g., the National Land Cover Database) but can also be constructed from digitized maps (e.g., Lewis et al. 2009).

possible because of spatially explicit and time-series data. This article presents a survey of these recent advances in empirical land-use studies, emphasizing how land-use economists have harnessed new data in an effort to provide better information about the environmental impacts of private land markets and the effectiveness of land-use policies.

The next section discusses the new types of land-use data available to researchers. Section 3 covers the empirical research designs that have become increasingly common in land-use studies. Topics include instrumental variables, matching estimators, DID, RDD, and randomized controlled trials (RCTs). Section 4 provides discussion of what has been learned over the past decade from the use of new data and estimation approaches. A final section concludes.

2. NEW DATA ON LAND USE

Although satellite images of the Earth's land surface have been collected since the early 1970s, it took 25 years before applications by land-use economists began to appear. The reason for the delay is likely the need to process raw satellite data, interpret it, and manage large data sets, all of which benefit greatly from powerful computers. An early economics study to use satellite data to empirically model land use is by Nelson & Hellerstein (1997) (see also Pfaff 1999). The authors used a land cover map for Mexico to estimate a parcel-level, discrete-choice model of land allocation, with the goal of understanding the effects of roads on deforestation.[3] Another early study to use satellite data on forests is by Foster & Rosenzweig (2003), although the authors aggregate the data to match economic and demographic information at the village scale. Andam et al. (2008) combine aerial photography with satellite imagery for Costa Rica in an early study of the effectiveness of protected areas.

There are now a number of publicly available data sets derived from satellite imagery that provide repeated observations of parcel-scale land cover. These include Hansen et al.'s (2013) data, which map global forest loss and gain at 30-m resolution over the period 2000–2012; the Project for Monitoring Deforestation in the Legal Amazon (PRODES), which provides annual deforestation estimates for the region at 30-m resolution since 1988; and for the United States, the National Land Cover Database, Land Cover Trends, and the Cropland Data Layer, all of which provide high-resolution, parcel-scale observations over time. Empirical land-use analyses using these data include those by Saiz (2010), Dempsey & Plantinga (2013), Bigelow et al. (2017), Blackman et al. (2018), and Assunção et al. (2020). Economists have also developed their own land-use change data from satellite imagery. As an alternative to Hansen et al.'s (2013) data, which include all types of forests in a single category, Heilmayr & Lambin (2016) construct their own data set on forest cover change that distinguishes changes in natural forest and forest plantations (**Figure 1**). Jayachandran et al. (2017) develop a data set on tree cover change that provides observations at the beginning and end of a payment for ecosystems services (PES) program in Uganda. Donaldson & Storeygard (2016) review the use of satellite data in economics, and Jain (2020) takes a more focused look at studies in environmental economics.

In addition to data based on satellite imagery, researchers have also constructed land-use data sets using existing maps and geographic information system (GIS) software. Irwin & Bockstael (2007) construct land-use maps for Howard County, Maryland, starting with the county's tax map to delineate parcel boundaries and adding parcel attributes, such as number of dwellings, from a tax assessment database. The authors also make use of land-use maps from the Maryland Department

[3]As a sign of the times, the principal econometric issue that concerned the authors was the possibility of spatially correlated residuals.

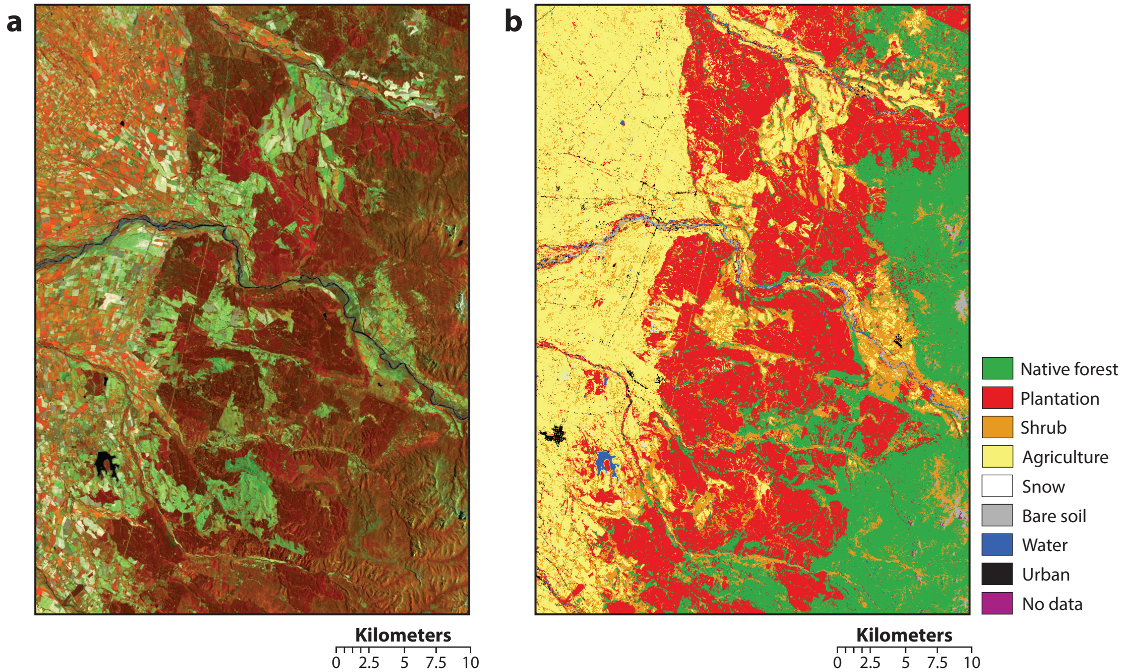

Figure 1

Remote sensing of land use. Heilmayr & Lambin (2016) classified Landsat imagery to distinguish natural forests from plantation forests in Chile. (*a*) The raw satellite image and (*b*) the classified image, where native forest is in green and plantation forest is in red. Images courtesy of Robert Heilmayr, University of California, Santa Barbara.

of Planning that are based on aerial photography and tax assessment data. Lewis et al. (2009) scan and digitize historical plat maps for Vilas County, Wisconsin, to create a spatially explicit database of subdivisions over time and then used GIS software to construct measures such as the length of lake frontage. Similarly, Wrenn et al. (2017) use digitized plat maps to create a subdivision database for three Maryland counties. Finally, Zipp et al. (2017) combine GIS layers on open space, parcel boundaries, and zoning to create a database of agricultural and developed land use over time for Door County, Wisconsin.

A number of RCTs have focused on discouraging deforestation or encouraging afforestation through incentive payments. In most studies, forest cover change is assessed from satellite imagery (Edwards et al. 2020, Jayachandran et al. 2017, Wren-Lewis et al. 2020), but two studies measure the outcome of interest through field surveys. In an afforestation study by Jack (2013), repeated field visits were made to monitor tree survival. A similar approach was used in the analysis of agroforestry incentives in Zambia by Oliva et al. (2020).

3. EMPIRICAL DESIGN

3.1. Instrumental Variables

In addition to having new sources of land-use data, researchers have been able to measure the determinants of land use in new and more accurate ways. This has strengthened the case for exogeneity of independent variables.[4] For example, in a study of urban housing supply, Saiz (2010) uses fine-scale data on coastlines, slopes, and water bodies to produce an exogenous measure of undevelopable land for 95 cities in the United States, an exercise that was possible only with satellite data and powerful computers. In a study of spillovers from protected areas in Costa Rica, Robalino et al. (2017) develop precise measures of the distances from unprotected forest plots to park entrances, roads, rivers, ports, and other features. Zipp et al. (2017) include parcel-level measures of slope and flood risk in an analysis of the effects of open space on land development. These are important factors to control for because they can explain both the value of developing a parcel and the likelihood that the parcel is located near open space.[5]

Wrenn et al. (2017) estimate a parcel-scale duration model of land development, including as an explanatory variable a quality-adjusted index of housing prices in the neighborhood where the land parcel is located. Although local housing prices are likely to be a good indicator of the profitability of development, they may be correlated with unobserved factors that affect the timing of development. As Wrenn et al. explain, unobserved changes in regulations affect the supply of housing, and hence housing prices, as well as the rate of land development. To address the potential for endogeneity bias, the authors implement a control function approach, which is an analog to two-stage least squares in nonlinear models (Blundell & Powell 2004). The authors follow Bayer & Timmins (2007) in using the characteristics of distant neighborhoods as an instrument for housing price in the focal neighborhood. The logic is that the focal price depends on attributes of distant neighborhoods in spatial market equilibrium but should be uncorrelated with errors in the profitability of developing the focal parcel. The authors find that the estimated coefficient on housing price is over three times larger when price endogeneity is addressed.

Robalino & Pfaff (2012) test for interactions among neighboring farmers in Costa Rica in land clearing decisions. For example, clearing many parcels in the same area may be advantageous if there are scale economies in transportation. The authors estimate a simultaneous equations model in which the probability that a given parcel is cleared depends on the probability that the neighboring parcel is cleared, and vice versa. They instrument for the neighbor's clearing decision using the slope of that parcel and that parcel's neighbor. The analysis makes use of satellite imagery to measure deforestation and topography at fine scales.

3.2. Matching

Matching estimators use observed data to pair treated units (e.g., land parcels) with untreated units, ideally finding matches that are identical except for treatment status. The difference in the outcome between treated and untreated units provides an estimate of the treatment effect.[6] In empirical land-use studies, matching has been used extensively in the evaluation of protected areas in tropical countries. There may be less deforestation in protected areas compared to unprotected areas, but the difference in deforestation rates indicates the effect of protection status only if protected and unprotected areas are otherwise identical. There are many reasons to doubt that this requirement will be met in a simple comparison of protected and unprotected lands, among them

[4] I do not distinguish here between right-hand-side variables in a least squares regression and instrumental variables used, for example, in two-stage least squares, because exogeneity is required for both.
[5] For example, if flood risk is high, the parcel may be closer to wetlands, which are often the target of conservation efforts.
[6] Compared to least squares, matching avoids the strong linearity assumption but also requires strong assumptions about the exogeneity of the treatment. See Black (2015) for a clear discussion of the differences between least squares and matching.

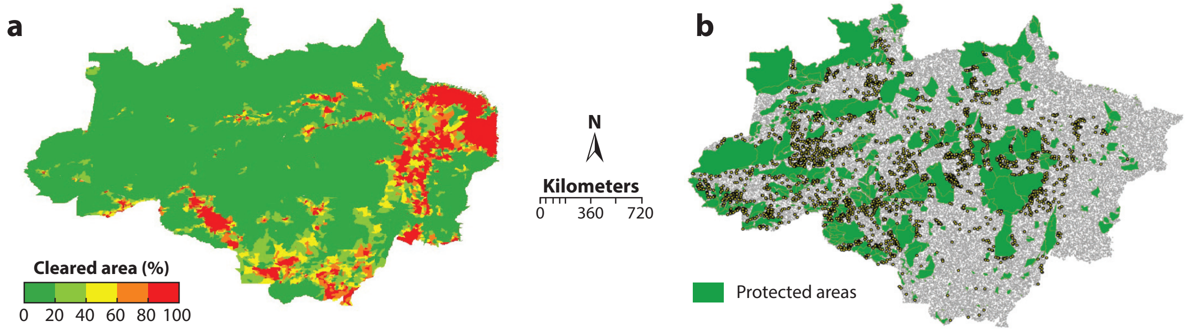

Figure 2

Protected areas in Amazonia tend to be located in places with less deforestation pressure. (*a*) The extent of deforestation up until 1991 and (*b*) the locations of protected areas. (The dots in panel *b* show two categories of unprotected parcels and can be disregarded.) Images courtesy of Alex Pfaff, Duke University.

the likelihood that protected areas will be located in relatively remote places that have not yet been subject to strong deforestation pressures. Matching pairs protected areas with otherwise similar unprotected areas, thus isolating the effect of protection status.

Andam et al.'s (2008) study is an early application of matching to protected areas. The authors examine deforestation in Costa Rica between 1960 and 1979 using a randomly drawn sample of parcels that were forested in 1960. Comparing parcels that were protected by 1979 to those that remained unprotected, they find that protected lands are less productive and farther from roads, two factors that can clearly affect rates of deforestation. Matching eliminates these differences and yields much smaller estimates of the effects of protection status compared to estimates that do not control for observable parcel characteristics. Robalino & Pfaff (2013) use matching to address nonrandom participation in a PES program in Costa Rica and Pfaff et al. (2017) use matching in a study of protected areas in Mexico, finding significant differences in the baseline characteristics of protected and unprotected forest parcels. **Figure 2** shows that protected areas in Amazonia tend not to be located in the region experiencing the most deforestation.

Matching has also been used in combination with regression (e.g., DID). As Ferraro & Miranda (2017) explain, by using matching to achieve balance between treated and control units, the assumptions of linear regression approaches (e.g., homogeneous treatment effects) are more plausible. The authors undertake a design replication that compares alternative estimators using observational data to experimental results, finding that DID replicates RCT estimates only when combined with matching. Examples of land-use studies that use matching with regression include those by Wendland et al. (2015), Heilmayr & Lambin (2016), Blackman et al. (2018), and Bigelow & Kuethe (2020). For example, Heilmayr & Lambin (2016) apply propensity score matching to a sample of timber industry properties in Chile using a large set of biophysical, geographic, and economic variables. Matching reduces the sample size by dropping untreated observations that are dissimilar to treated observations; however, the attendant loss of power is unlikely to matter in recent land-use applications using large data sets. For example, Wendland et al. (2015) have almost 200,000 observations left after matching.

3.3. Difference-in-Differences

DID has been applied extensively in the program evaluation literature and has been used in recent land-use applications to estimate effects of land-use policies. DID compares changes in the outcome variable for treated units (before and after treatment) to changes for untreated units,

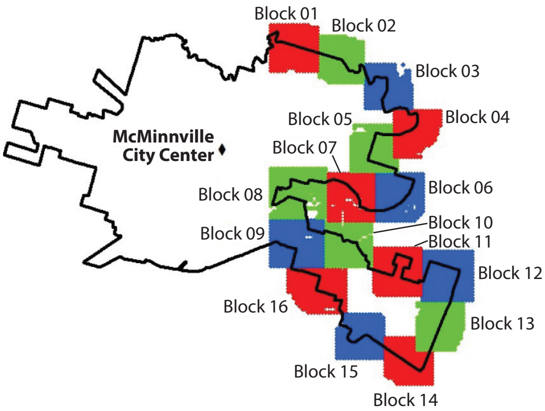

Figure 3

Dempsey & Plantinga (2013) use a difference-in-differences design to estimate the effect of urban growth boundaries (shown by the *black line* for McMinnville, Oregon) on urbanization rates. Urbanization is a binary variable (either urban or nonurban land use) measured at the scale of 60-m parcels. Parcels are collected into groups (shown as 1-km^2 blocks), and for each group, a fixed effect is estimated for the pre- and post-treatment periods. These fixed effects control for time-varying factors common to parcels within each block. Figure adapted with permission from Dempsey & Plantinga (2013).

thereby using the trend in the untreated units as the counterfactual. The appeal of DID is that differencing removes the influence of linearly additive time-invariant and common time factors, including any unobserved effects. Fienup & Plantinga (2020) use DID to estimate the effects of urban growth boundaries (UGBs) in Ventura County, California, on agricultural intensification (specifically, the change from grazing to irrigated agriculture) outside the boundaries. They measure intensification rates for agricultural parcels before and after the UGBs were adopted, comparing the changes in intensification rates to those in neighboring Santa Barbara County.[7] In another UGB application, Dempsey & Plantinga (2013) use a DID estimator to compare urbanization rates inside and outside of UGBs in Oregon, assessing the effectiveness of UGBs at containing development. In both studies, the authors make use of fine-scale spatial data to precisely locate land parcels with reference to growth boundaries. The abundance of data also allows Dempsey & Plantinga to control for time-varying effects for groups of parcels labeled as blocks in **Figure 3**.

Additional applications of DID to land use include the study by Heilmayr & Lambin (2016), who examine effects of nonstate-market-driven regimes on the conversion of natural forest in Chile; Panlasigui et al. (2018), who study the effects of certification on forest loss in Cameroon; and Bigelow & Kuethe (2020), who estimate the effects of use-value tax assessment on urbanization in the midwestern United States. BenYishay et al. (2017) investigate whether the formalization of indigenous land rights in Brazil affects deforestation rates. The authors develop a 29-year panel of annual observations of the normalized difference vegetation index (NDVI), a proxy for forest cover, for approximately 8,500 4-km cells within indigenous communities. They exploit variation in the timing of the formalization of rights, controlling for cell and common time-fixed effects. As such, outcomes for cells within the same community before formalization serve (in part) as the counterfactual. The authors find no effects of formalization on deforestation, as measured by changes in the NDVI.

[7]Fienup & Plantinga (2020) exploit a kind of natural experiment that makes the Santa Barbara County land parcels an appropriate control for Ventura County parcels.

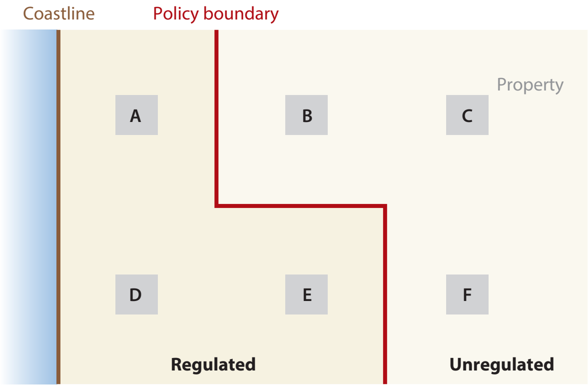

Figure 4

Severen & Plantinga (2018) use a spatial difference-in-differences (DID) estimator to remove confounding effects of the coastal amenity. With a standard DID design, the difference between the values of property A (in the regulated area) and property B (outside the regulated area) measures the effect of the regulation but also the amenity value of coastal proximity. A comparison of differences in parcel values at the same distance from the coast—for example, the difference between E and F minus the difference between B and C—removes the effect of coastal proximity and isolates the regulation's effect. Figure adapted with permission from Severen & Plantinga (2018).

Severen & Plantinga (2018) develop a spatial version of DID to estimate the effects of the California Coastal Act (CCA) on property values. A challenge in their study is that treatment is correlated with the coastal amenity. Namely, properties subject to CCA regulations are closer to the coastline, as shown in **Figure 4**. Thus, a comparison of properties A and B (or E and F) could be confounded by the change in the coastal amenity. Severen & Plantinga compare differences in the prices of properties at the same distance from the coast. For example, the difference between E and F, which span the policy boundary, is compared to the difference between B and C, which do not. Analogous to traditional DID, this spatial differencing removes the influence of changes in the coastal amenity.

A powerful use of empirical land-use models is the simulation of land-use policies (Plantinga 2015). For example, after estimating a nested logit model of land-use change, Lewis & Plantinga (2007) simulate payments for afforestation designed to reduce forest fragmentation. However, many of the recent panel data applications use the linear probability model (e.g., Dempsey & Plantinga 2013, Fienup & Plantinga 2020), which has appealing properties for identification but does not constrain land-use change probabilities to the unit interval. This is an obvious problem for simulations, as simulated probabilities can be negative or greater than one. An alternative used in recent land-use studies is correlated random effects (CRE) (Bigelow et al. 2017, Zipp et al. 2017). The basic idea behind CRE is to include in a logit or probit model the means of time-varying observables, referred to as the Mundlak device, as an approximation for parcel fixed effects. For example, in a binary model of land development, Bigelow et al. (2017) include the time averages of developed and undeveloped land values and show that the marginal effects of land values are similar to those obtained from a fixed effects linear probability model.

3.4. Regression Discontinuity Design

RDD exploits policy thresholds for random assignment to treatment and control groups. For example, in an early application to the economics of school quality, Black (1999) compares houses on either side of school attendance boundaries to estimate the marginal willingness to pay for higher test scores. By looking at houses within school districts and very close to attendance boundaries, the author controls for the effects of property taxes, school spending, and neighborhood quality, factors with clear effects on property values. An important assumption in RDDs is boundary exogeneity, namely, that the boundary placement not be correlated with the outcome of interest. For example, had the attendance boundaries in Black's (1999) study been set to partition districts according to income or race, this could confound the measurement of school quality effects. However, if a factor such as income varies continuously across the boundary, the RDD is still valid. This motivates covariate smoothness tests for observable variables.

In land-use studies, RDD has been used to evaluate effects of land-use policies, mostly on property values. These studies have been possible because of the availability of fine-scale data that allow properties to be precisely located with respect to policy boundaries. In an early study, Grout et al. (2011) estimate the effects of the Portland metropolitan statistical area (MSA) UGB on property values, comparing land prices for parcels just inside the boundary to those just outside. The authors examine how topography, soil quality, floodplains, and wetlands vary across the UGB, finding that the results are robust to dropping portions of the boundary where covariate smoothness does not appear to hold. Turner et al. (2014) use an RDD to measure the effects of regulatory stringency on land prices in US MSAs, comparing land parcels on either side of municipal boundaries. To bolster the case for boundary exogeneity, the authors limit their analysis to straight-line borders between municipalities, which are likely an artifact of the Land Ordinance of 1785 that divided the country into a regular grid. These arbitrary borders are unlikely to divide qualitatively different types of land. In addition to the spatial DID analysis discussed above, Severen & Plantinga (2018) use an RDD to estimate local effects of the CCA, comparing commercial property prices inside the coastal zone boundary to those outside (**Figure 5**). The authors document that the original boundary was set at a regular 1,000 yards from the mean high tide line, with provisions for deviating from this rule based on coastal geography. This reliance on physiographic features to determine the boundary location increases the likelihood that land parcels on either side are similar with respect to their value for commercial property development (i.e., that the boundary is exogenous). The authors also show that later adjustments to the boundary do not affect their estimates. Finally, Butsic et al. (2011) study the effects of tax incentives for agricultural land preservation in Wisconsin, exploiting a 35-acre threshold for program eligibility. Comparing parcels just below and above the threshold, the authors find little effect on the likelihood of subdivision.

3.5. Randomized Controlled Trials

RCTs use randomization to eliminate the influence of confounding factors on the outcome of interest. In a successful RCT, the only difference between the treatment and control groups is the group assignment; thus, the difference in the outcome for the two groups can be attributed to the intervention. Jayachandran et al. (2017) use an RCT to study the effects of conservation payments on deforestation in Uganda. The authors selected 121 villages for the study, randomly assigning 60 to the treatment, with the remaining 61 villages serving as a control. Within the treatment villages, two-year contracts were offered to 564 private forest owners that provided payments if forests were not cleared over this period. The authors find no differences in a large number of observable characteristics between the treatment and control villages and forest owners, suggesting the randomization was successful. Approximately 32% of owners in the treatment group enrolled in the program, and 88% of these complied with the terms of the contract. Using satellite imagery to measure changes in forest cover, the authors find that treated villages had a rate of tree loss of

Figure 5

Severen & Plantinga (2018) use the coastal zone boundary (*red line*) in a regression discontinuity design analysis of the California Coast Act. Prices for commercial properties (*blue dots*) on either side of the boundary are used to measure the local effect of the policy. The case for boundary exogeneity is supported by the reliance on physiographic features to determine the boundary's original location. Figure adapted with permission from Severen & Plantinga (2018).

4.2%, compared to 9.1% in the control villages. The effect of the payments on enrolled owners—the treatment on the treated estimate—is a reduction in forest loss of 0.88 ha per owner. Instead of providing payments to forest owners, Edwards et al. (2020) analyze effects of community-level fiscal incentives. They find no effect on land clearing in Indonesia, a result that could be due to collective action problems.

Jack (2013) studies whether auctions can improve the efficiency of afforestation programs by allocating contracts to lower-cost landowners. The author uses an RCT to compare tree survival rates under a uniform price, sealed bid procurement auction to a lottery mechanism that randomly assigns a fixed-price contract. In theory, the auction will achieve greater tree survival rates for a given budget if landowners have private information about their implementation costs. The auction and lottery mechanisms were randomly assigned to 433 landowning households in Malawi who agreed to participate in the study. The author finds that the cost per surviving tree is 30% lower under the auction, implying that self-selection can improve the efficiency of voluntary incentive programs. Oliva et al. (2020) use an RCT to study afforestation decisions by farmers in Zambia, finding evidence that uncertainty about profitability that is resolved after planting can explain why farmers do not follow through on cultivation.

4. DISCUSSION

Over the past decade, the availability of repeated observations of land use and its determinants at fine spatial scales has facilitated the use of more credible research designs. This is apparent in Robalino & Pfaff's (2012) study, which uses fine-scale measures of topography to instrument for the probability that a neighboring parcel is deforested. Dempsey & Plantinga (2013) control for unobserved factors using time-varying fixed effects for groups of parcels, a design that is possible only with panel data providing a large number of cross-sectional observations. New data have made possible spatial RDDs, which require precise measurement of property boundaries and policy thresholds at fine scales, as in Grout et al. (2011). Rich data sets have also allowed researchers to combine matching with DID to improve the balance between treatment and control observations (Wendland et al. 2015).

It is important to remember that bias is not a property of the estimator. Least squares on cross-sectional data will produce unbiased estimates if the error terms are uncorrelated with the regressors (and other assumptions hold). And, even if they are correlated, it is not clear that the bias is economically important. The famous study by Angrist (1990, p. 330) using the Vietnam War draft lottery to measure effects of veteran status on lifetime earnings concludes: "In light of the results reported here, some more conventional estimates of the effect of Vietnam era veteran status do not appear to be too far off the mark." Because the exogeneity assumption is untestable, we cannot know if new empirical designs have produced better estimates in land-use studies. The best we may be able to do is to see if estimates change when we adopt assumptions that we think are more plausible.

A number of land-use studies provide comparisons of estimates produced with the same data set but with different estimators. Wrenn et al. (2017) compare results for a duration model of land development with and without instrumenting for housing price. The instrumental variable model produces a much larger (almost four times) estimate of the price elasticity of land conversion. Butsic et al. (2011) estimate the effect of agricultural zoning on subdivision decisions, recognizing the potential for zoning and subdivision to depend on the same unobserved factors. The authors produce a variety of estimates with regression and matching techniques, finding weak evidence that failure to account for endogenous zoning affects parameter estimates. In contrast, Andam et al. (2008) find that conventional approaches to measuring the effectiveness of protected areas (e.g., difference in means) overstate their impact by three or more times relative to matching estimators. The study by Dempsey & Plantinga (2013) reveals that in 2000, 43.1% of land parcels inside the UGB in McMinnville, Oregon, were developed, compared to 8.4% outside the UGB. If the difference (34.7%) were taken to be the effect of the UGB, it would ignore the pre-existing difference in the development rate of 22%, which is removed by the DID estimator. When the results of an observational design are compared to those from an experimental design, such as an RCT, it is called a design replication (Ferraro & Miranda 2017). To my knowledge, this comparison has not been done in the context of land-use studies.

Policies targeting ecosystem services from land often involve voluntary incentives (Salzman et al. 2018). The opt-in feature of these programs raises the possibility that landowners would have provided these services in the absence of the incentive—that is, the services are not additional. Mason & Plantinga (2013) simulate a national (United States) subsidy policy for carbon sequestration in forests and find that payments for nonadditional afforestation add considerably to program costs. Recent empirical studies have been able to provide direct evidence on additionality. By pairing untreated land parcels with otherwise similar treated parcels, matching studies identify the additional effects of voluntary incentive programs. For example, Alix-Garcia et al. (2012) conclude that a PES program in Mexico has little effect on deforestation because clearing rates on enrolled and control parcels are similar. In an RCT, the actions of treated and untreated groups are directly observed. Jayachandran et al. (2017) find that in control villages, the deforestation rate is 9.1%, compared to 3.6% in villages receiving payments. Thus, the 5.5-percentage-point reduction in deforestation is additional.

Another concern with voluntary incentives is negative spillovers (also called leakage or slippage). In the land-use context, spillovers occur when a policy creates countervailing incentives on unenrolled lands.[8] Fine-scale data have also allowed researchers to measure some types of spillover effects of conservation programs. Alix-Garcia et al. (2012) assess whether landowners enrolled in a PES program in Mexico shift deforestation to unenrolled portions of their property. Using satellite imagery, together with matching to construct the counterfactual, the authors find that within-landowner spillovers reduce the program's impact by about 4%. Robalino et al. (2017) examine deforestation spillovers from national parks in Costa Rica, finding no effect on average. However, using high-resolution data to measure distances to road and park entrances, the authors find that this estimate masks significant heterogeneity in spillover effects.

Finally, the public availability of spatially explicit data sets, together with increased computing power, have enabled researchers to develop their own land-use measures and probe new research questions. Using satellite data on land use and topography, Saiz (2010) develops a new measure of undevelopable land within US cities. Heilmayr & Lambin (2016) develop their own data set from satellite imagery that distinguishes natural forest and forest plantations. MacDonald et al. (2019) use the National Land Cover Database to develop measures of forest fragmentation and investigate its effects on Lyme disease incidence in human populations. Irwin & Bockstael (2007) develop similar measures for developed land in an analysis of urban sprawl. These new data sources may also provide more objective measures of land use. Burgess et al. (2012) use satellite imagery to measure deforestation in Indonesia, noting that official government estimates fail to detect significant amounts of illegal logging.

5. CONCLUSIONS

Humans are having unprecedented effects on land ecosystems and biodiversity. Resource economists can contribute to the effective management of these impacts by quantifying the drivers of public and private land-use decisions and the response of managers to land-use policies. Over the past decade, new data sources, especially repeated observations of land use and its determinants at fine spatial scales, have given rise to a new generation of land-use analyses. These studies use empirical designs, including DID, RDD, and RCTs, that require weaker assumptions for causal identification. In many cases, these methods are found to produce different estimates than would be obtained with conventional approaches. More studies are needed comparing results across different estimation approaches. In particular, design replications that compare observational to experimental designs have not been done for land-use studies. The potential for combining research designs, especially matching with DID, also merits further investigation.

[8]For a complete discussion and review, see Pfaff & Robalino (2017).

Recent analyses have provided new insights into the drivers of land use and the performance of land-use policies. Spatially explicit data have allowed researchers to measure how proximity to cities, roads, coastlines, and other landscape features affects land-use decisions. These data have also enabled analyses of spatially delineated policies, including zoning, growth controls, and conservation lands. One of the most important results from the last decade of studies is the finding that land preservation is often applied to land parcels that would not otherwise change use. Thus, Andam et al. (2008) estimate that of the 900,000 ha of Costa Rican forest protected between 1960 and 1996, only 65–82,000 ha would have been deforested in the absence of protection. Finally, spillovers from land-use policies can happen in a variety of ways that either enhance or diminish the effectiveness of the policy (Pfaff & Robalino 2017). Land-use researchers have made progress in quantifying these effects, especially in the case of localized effects, but more research on spillovers is needed to give us a complete picture of the effectiveness of land-use policies.

Impact evaluations using quasi-experimental estimators are by their nature retrospective. Thus, they provide insights into how existing land-use policies have performed and potentially identify features that make policies more or less effective. It is difficult to know whether, in practice, insights from land-use studies have had an influence on the design of actual policies. West & Fearnside (2021) evaluate the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon, noting that protected areas designated during the second phase of the policy (2009–2011) were targeted to regions most threatened by deforestation. Carbon offset certifiers, such as Gold Standard (**https://www.goldstandard.org/**), attempt to account for additionality and spillovers when evaluating projects. These examples are, at least, consistent with results of empirical land-use studies having an impact on real-world policy making.

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