For. Sci. 60(2):298–307
http://dx.doi.org/10.5849/forsci.12-107

economics

Conservation Easements and Management by Family Forest Owners: A Propensity Score Matching Approach with Multi-Imputations of Survey Data

Nianfu Song, Francisco X. Aguilar, and Brett J. Butler

Increasingly, private landowners are participating in conservation easement programs, but their effects on land management remain to be addressed. Data from the USDA Forest Service National Woodland Owner Survey for the US Northern Region were used to investigate how conservation easement participation is associated with selected past and future forest management practices. Multiple data imputation was used to correct for missing data bias, and propensity score matching was applied to correct for selection bias. Results show that only the adoption of forest management plans, among 17 forest management practices, was significantly and positively correlated with easement participation. Conservation easements legally bind participants to maintain land forested, but there was no evidence of greater association between easement participation and active forest management practices, including timber harvesting. These findings suggest that adoption of conservation easements is a policy tool that can preserve forestland from changing to other uses but may not necessarily be conducive to wider implementation of land practices necessary for long-term protection of forests.

Keywords: selection bias, conservation easement, propensity score matching, multiple imputation, missing data

A conservation easement may be defined as a voluntary legally binding agreement between a landowner and a government agency or land protection organization (e.g., land trust) that limits certain land uses in an effort to attain land preservation and protection objectives (Merenlender et al. 2004). To attain these objectives, housing, commercial, or industrial uses are commonly banned from lands enrolled in a conservation easement. Landowners may sell or donate easements on their lands but retain ownership. Landowners may also benefit from tax deductions or credits for conservation easements on their lands (US Internal Revenue Service 2012).

There have been numerous studies evaluating the association between easements and land management (e.g., Liu and Lynch 2011, Pocewicz et al. 2011), public opinion (e.g., Cho et al. 2005, 2008), costs of conservation easements (e.g., Geoghegan et al. 2003), and landowner participation (e.g., D'Amato et al. 2010, Ma and Kittredge 2011). The analysis conducted by Liu and Lynch (2011) suggested that nondevelopment easements have reduced the rate of farmland loss by 40−55% in the US Mid-Atlantic region and, on average, slowed farmland loss per county by 375−550 acres/year. Pocewicz et al. (2011) using analysis of variance (ANOVA) suggested that easements in Wyoming had no significant impact on land management practices, but landowners who signed up for conservation easements exhibited a tendency to seek management assistance more often than others. Cho et al. (2005) showed that an average homeowner in the Blue Ridge Mountains of North Carolina was willing to pay $10−22 per year for easement programs. A spatial model for three Maryland counties suggested that having land under conservation easements increased the values of surrounding properties and, in turn, increased tax revenues to a level that was sufficient to finance these easements (Geoghegan et al. 2003). Ma and Kittredge (2011) found that the major factors driving Massachusetts family forest owners' decisions to participate in conservation easements included forest acreage owners' age, attitude toward the environment, existence of trails in the forest, and cooperation with neighbors. By comparing the net present value of tax payments, D'Amato et al. (2010) showed that easement participation in the Massachusetts section of the Deerfield River Watershed

Manuscript received August 29, 2012; accepted May 8, 2013; published online August 8, 2013.

Affiliations: *Nianfu Song (songn@missouri.edu), University of Missouri, Department of Forestry, University of Missouri, Columbia, MO. Francisco X. Aguilar (aguilarf@missouri.edu), University of Missouri. Brett J. Butler (bbutler01@fs.fed.us), USDA Forest Service.*

Acknowledgments: *This research was supported in part by the USDA Forest Service through agreement number 09-JV-11242311-008.*

may be motivated by a reduction in local property taxes. Despite existing studies, there is ample consent that potential effects of conservation easements need to be further investigated, given the substantial increase in the number of easements and land trusts instituted in recent years in the United States (Ferraro and Pattanayak 2006, Rissman and Merenlender 2008, Land Trust Alliance 2011, Liu and Lynch 2011).

This research was motivated by a lack of studies investigating the correlation between enrollment in conservation easements and management practices aimed to preserve and protect private forestlands and the treatment of potential participation bias. The literature, to our knowledge, seems to focus primarily on agricultural lands and relatively little has been done to study the association of conservation easements and management of privately owned forestlands at a regional scale. In one of the few exceptions, Hagan et al. (2005) concluded that timberland under a no-development easement had a higher level of adoption of management practices to promote biodiversity only when specific biodiversity stipulations were included in the agreement, but failed to provide statistical significance of the reported differences. The ANOVA of Pocewicz et al. (2011) ignored the fact that easement participation was not a random process, and their findings may be affected by selection bias (Heckman 1979). This study focused on family forest owners, defined as families, individuals, trusts, estates, family partnerships, and other unincorporated groups of individuals that own forestland (Butler 2008). Families own 35% of US forests, the most of any other public or private groups, and play an instrumental role in achieving forest preservation and protection objectives.

The aim of this research was to determine whether conservation easements are correlated with past and stated future land management practices by family forest landowners. We addressed this research query by using a comprehensive data set of family forest owners and analytical tools not previously reported in the forest management literature to estimate easement participation effects with missing values and binary response variables. Empirically, this question was answered using data from the USDA Forest Service National Woodland Owner Survey (NWOS) specific to the US Northern Region (20-state quadrant bounded by Maine, Maryland, Missouri, and Minnesota) where family forests comprise 55% of all forestlands (Smith et al. 2009, US Natural Resources Conservation Service 2011). Econometrically, this study faced the challenge of a large number of missing observations in the surveys gathered from the NWOS and potential selection bias, a type of endogeneity bias stemming from landowners' nonrandom decisions to enroll in a conservation easement program (Heckman 1979). In this study, the missing data issue was addressed using the multiple imputation (MI) method, and the selection bias was treated with propensity score matching (PSM). This study is, as far as we know, the first application of PSM in the study of public forest programs. It enriches the forest literature by demonstrating the application of PSM with MI and advances the understanding of the effectiveness of conservation easement programs. Our findings have important implications because the adoption of forest management practices on family-owned forestlands can support preservation and protection objectives including avoidance of forest land-use changes, healthier forests, and reduction of fire hazards and also increase the supply of forest products.

Conservation Easements and the US Northern Region

About 52,835 easements, 65% of the total number of easements in the United States, are found in the US Northern Region. This region currently has approximately 6 million acres of lands under conservation easements. The average area of each easement in the US Northern Region is 117 acres, barely half of the average acreage of forest under conservation easements in the rest of the country (Conservation Registry 2012). Easement payments landowners receive per acre of forest in the US Northern Region vary from zero (i.e., donation) to several thousand dollars (Kline et al. 2004). About 98% of the land area protected by conservation easements in the US Northern Region and 95% nationwide are under private ownership (Conservation Registry 2012). In the US Northern Region, 42% conservation easement contracts were held by state governments, 9% by federal government, 4% by other local governments, and 45% by land trusts and nongovernment organizations. Nationwide, the US federal, state, and local governments hold 59% of conservation easement contracts and nongovernment organizations hold the remaining 41% (Conservation Registry 2012).

The US Northern Region is unique for its high proportion of land under conservation easements and the small average area covered under each contract. The US Northern Region also differs from other regions because of its high population density and a large number of small family forests. This region accounts for 18% of the US land but has 41% of its population. Furthermore, 44% of US private forest owners are found in this region (Shifley et al. 2012). The vast majority (94%) of forest owners in the US Northern Region are families who own most private forests (62%) and a large proportion have less than 100 acres of forested land (Butler 2008).

Methods

Past studies have estimated the effect of public program participation (such as conservation easements) using an independent binary variable (Geoghegan et al. 2003) or ANOVA (Pocewicz et al. 2011). However, such approaches to modeling the effects of conversation programs have been argued to be biased (Rubin 1974, Heckman 1990, Heckman et al. 1998a). An individual's decision to sign up for a conservation easement is not a random event but a function of variables describing the characteristics of an individual landowner and economic and biophysical conditions relevant to forest management decisions. Hence, impacts of participation in a conservation easement program cannot be consistently estimated using a binary explanatory variable because of selection bias (Heckman 1990).

There are several methods to correct the selection bias. The Heckman model can be estimated consistently by either maximum likelihood or a two-stage process with the inverse of Mill's ratio included in the regression model (Heckman 1979, Miranda and Rabe-Hesketh 2006). Nickerson and Lynch (2001) provide an example for the application of this method in evaluating conservation easements, but this approach is limited to continuous and normally distributed dependent variables. In the case of binary dependent variables, the Heckman method has no appropriate distribution, and inferences based on such procedures may yield misleading conclusions (Heckman 1979, deVen and Praag 1981). In the particular case of our study, all variables capturing forest management practices were binary, hence, the Heckman model was not a suitable

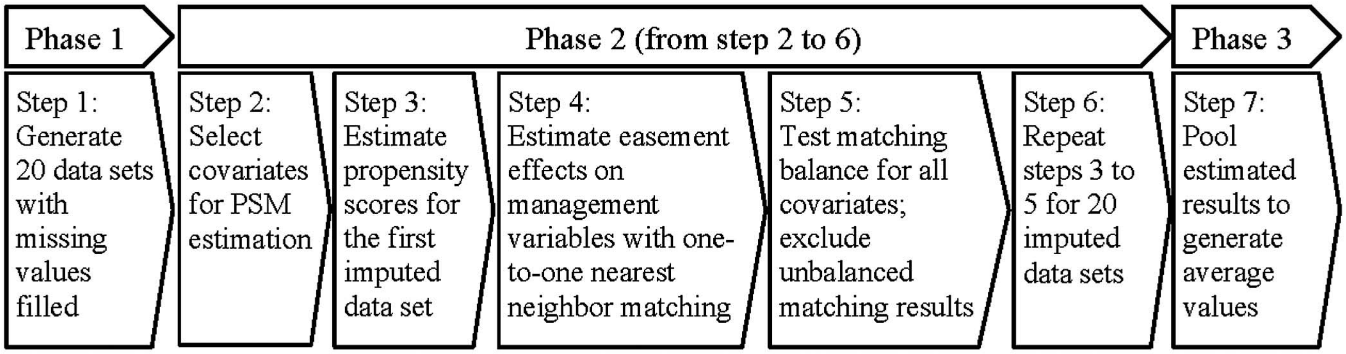

Figure 1. Three multiple-imputation phases incorporating propensity score matching to analyze the association of participation in conservation easements and stated past and future forest management practices.

estimation method. The two-step probit or logit models with corrected variance have also been suggested to estimate the effects of participation on binary outcomes (Ovaskainen et al. 2006). These methods treat the binary variable for participation in a program as being endogenous along with a binary response variable. However, preliminary analyses conducted by the authors (not presented in this article because of space limitations but available on request) showed that the estimation routine for this approach was too computationally demanding when combined with MI and a sample as large as the NWOS data set for the US Northern Region. A method recommended by Liu and Lynch (2011) to estimate the impact of easement participation on forest management is PSM. The PSM method was developed to correct for selection bias in estimating the treatment effects (Heckman et al. 1997) and suggested to be used with binary response variables (Austin 2011).

In addition to concerns about selection bias, the study encountered the challenge of a substantial number of missing values. Each record in the NWOS data set corresponds to a landowner who provided answers to multiple survey questions (Butler et al. 2007, Butler 2008). About 10% of the values for the variables used in this study were missing in the NWOS data set for the US Northern Region (i.e., questions lacked a response), but these were scattered across 83% of landowners. The MI method was chosen in this study as a tool to replace the missing values and obtain unbiased estimates (Rubin 1996, Schafer and Olsen1998, Royston 2004, 2005). PSM was applied to each of the MI-generated data sets, and the results were combined following Rubin (1996). The challenges of missing data and selection bias were dealt with simultaneously using a three-phase MI method combined with PSM as outlined in Figure 1 and described in the following subsections.

MI Method for Missing Data

MI generates more than one data set, each with different values for the same missing observations under the assumption that data are missed at random. The MI process mimics the inherent uncertainty of missing values; hence, the data sets generated are slightly different as a result of random data imputation. Analyses with MI were performed in three phases (Schafer and Olsen 1998). First (phase 1), missing data were imputed and *m* complete data sets were generated. Second (phase 2), each of the *m* generated complete data sets was analyzed following specified study methods (e.g., PSM). Last (phase 3), results from phase 2 were pooled into final results. This study used 20 (m=20) imputations.[1]

We used a procedure suggested by van Buuren et al. (1999) to generate data sets with replaced missing data. This MI procedure is commonly used in standard software packages (e.g., STATA, R, and SAS) to fill missing data by chain equations. The imputation in this study was performed with command ICE in STATA (version 10). Explanatory variables used in the imputation were selected using a forward stepwise model. The model selection procedure used a 5% *P* value criterion to determine variables to be retained during imputation. Missing values for binary variables were filled with binary values generated with logit models, but those for other variables were imputed using ordinary least squares following van Buuren et al. (1999). The parameters of these imputation models were drawn from random numbers created with the Bayesian method described in van Buuren et al. (1999) and the empirical computation procedure in White et al. (2010) and Royston and White (2011).

PSM Method

The PSM is a tool used to resample a data set by matching treated with nontreated units and discarding unmatched ones (Apel and Sweeten 2009). This method has been shown to be more robust for estimating treatment effects than others (LaLonde 1986, Dehejia and Wahba 1999, 2002) and was incorporated into phase 2 of the MI method. In our study, treated units represented family forest owners who reported participation in a conservation easement. The probability for a unit (e.g., family forest owner) to have a treatment (e.g., easement program participation) was first estimated with a logistic regression. The estimated probability for an individual was also the propensity for the landowner to be in the treatment group (i.e., to participate in an easement program). Let D be a binary variable capturing participation in a conservation easement program (D = 1 for participants, 0 for nonparticipants).

$$D^* = X'\beta + \varepsilon \tag{1}$$

$$D = 1 \ \text{ if } \ D^* > 0, \ \text{ otherwise } \ D = 0$$

where D^* is a latent variable in a logistic model, X is an matrix of covariates relevant to the values for D (i.e., program participation) and response variables (i.e., forest management variables), β is a vector of corresponding coefficients, and ε is a random error with a logistic distribution and mean zero (Rosenbaum and Rubin 1983, 1985, Heckman et al. 1998b). The propensity score is $p(D = 1) = p(D^* > 0) = p(X'\beta + \varepsilon > 0)$, or $p(D = 1) = p(\varepsilon > -X'\beta) = p(\varepsilon < X'\beta)$. Thus, the propensity score is a logistic function of X with parameter vector β, and $p(D = 1) = p(X)$ (Greene 2002). Covariates

Table 1. Definitions, types, and units of variables for estimating easement effects on forest management.

Variable	Definitions	Types and Units
EASEMENT	Have an easement on forestland 1, otherwise 0	Treatment (0 or 1)
AGE	Age, numbers for every 10 yr from 20 to 80	Demographic (yr)
DGR_BACH	Bachelor's degree is the highest degree 1, otherwise 0[a]	Demographic (0 or 1)
DGR_ADV	Master or PhD is the highest degree 1, otherwise 0[a]	Demographic (0 or 1)
INCOME	Annual household income in US thousand dollars, stepwise values	Demographic ($1000)
MALE	Owner is male 1, otherwise 0	Demographic (0 or 1)
NONWHITE	Owner is not white 1, white 0	Demographic (0 or 1)
LFOREST_ACRE	Logarithm of total forestland (acres) in a state	Size (acres)
LAKESTATES	US states of Michigan, Minnesota, and Wisconsin 1; otherwise 0[b]	Location (0 or 1)
MIDATLANT	US states of Delaware, Maryland, New Jersey, New York, Pennsylvania, and West Virginia 1; otherwise 0[b]	Location (0 or 1)
NORTHEAST	US states of Connecticut, Massachusetts, Maine, New Hampshire, Vermont, and Rhode Island 1; otherwise 0[b]	Location (0 or 1)
PRIM_HOME	Forest is less than 1 mile from the primary home 1, otherwise 0	Location (0 or 1)
SECOND_HOME	Forest is less than 1 mile from the secondary home 1, otherwise 0	Location (0 or 1)
BOUGHT	Forest was bought 1, otherwise 0	Acquisition (0 or 1)
GIFTED	Forest was a gift 1, otherwise 0	Acquisition (0 or 1)
INHERITED	Forest was inherited 1, otherwise 0	Acquisition (0 or 1)
OBJ_AESTH	Importance of aesthetics, ordinal scales 1 to 7[c]	Motivation (0 or 1)
OBJ_BIODIV	Importance of biodiversity, ordinal scales 1 to 7[c]	Motivation (0 or 1)
OBJ_FIREWD	Importance of firewood, ordinal scales 1 to 7[c]	Motivation (0 or 1)
OBJ_HUNT	Importance of hunting, ordinal scales 1 to 7[c]	Motivation (0 or 1)
OBJ_INVEST	Importance investment, ordinal scales 1 to 7[c]	Motivation (0 or 1)
OBJ_LEGACY	Importance of legacy, ordinal scales 1 to 7[c]	Motivation (0 or 1)
OBJ_PRIVA	Importance of privacy, ordinal scales 1 to 7[c]	Motivation (0 or 1)
OBJ_RECR	Importance of recreation, ordinal scales 1 to 7[c]	Motivation (0 or 1)
OBJ_TIMB	Importance of timber production, ordinal scales 1 to 7[c]	Motivation (0 or 1)
N_YR	The number of years of ownership	Years of ownership
F_AFFO	Will convert non-forestland into forestland 1, otherwise 0	Management (0 or 1)
F_BUY	Will buy forestland 1, otherwise 0	Management (0 or 1)
F_DEFFO	Will convert forestland in other uses 1, otherwise 0	Management (0 or 1)
F_FIREWOOD	Will produce firewood 1, otherwise 0	Management (0 or 1)
F_HEIR	Will have land inherited 1, otherwise 0	Management (0 or 1)
F_NTFP	Will produce nontimber product, otherwise 0	Management (0 or 1)
F_SAWLOG	Will produce sawlogs 1, otherwise 0	Management (0 or 1)
F_SELL	Will sell forestland 1, otherwise 0	Management (0 or 1)
F_SUBDIV	Will subdivide forestland into small tracts 1, otherwise 0 (subdivision results in parcellization)	Management (0 or 1)
CHM_APPL	Applied chemical 1, otherwise 0	Management (0 or 1)
FIRE_REDU	Practiced fire hazard reduction 1, otherwise 0	Management (0 or 1)
MANAG_PLAN	Made forest plan on paper 1, otherwise 0	Management (0 or 1)
ROAD_MAINT	Did road maintenance 1, otherwise 0	Management (0 or 1)
SITE_PREP	Did site preparation 1, otherwise 0	Management (0 or 1)
TIMB_HVST	Harvested timber 1, otherwise 0	Management (0 or 1)
TREE_PLANT	Planted trees 1, otherwise 0	Management (0 or 1)
WILDLIFE_HAB	Improved wildlife habitat 1, otherwise 0	Management (0 or 1)

[a] Nondegree is the baseline for educational degree variables.
[b] Midwest (US states of Iowa, Illinois, Indiana, Missouri, and Ohio) is the baseline for subregional variables.
[c] Ordinal scales from 1 for "very important" to 6 "some importance" to 7 "not important."

in X were selected from a pool of a total of 25 variables (see Table 1 and description in Empirical Model, Sensitivity Analysis, and Data) by minimizing the Akaike information criterion to reduce noise from redundant variables in the estimation of propensity scores (step 2 in Figure 1) (Caliendo and Kopeinig 2008).

The estimated propensity score $p(X)$ was used to match conservation easement participants with nonparticipants (Dehejia and Wahba 1999). One-to-one nearest neighboring matching has been suggested for large sample sizes (Heckman et al. 1998b, Dehejia and Wahba 2002, Austin 2007) and was our matching method of choice because the US Northern Region data set had more than 9,000 observations. A matching is valid only if treated and untreated groups have a common support and covariates of two groups of matched landowners have equivalent distributions to ensure compatible participants and nonparticipants. A common support requires each participant to have a positive probability to be a nonparticipant. In this study, common support was obtained by removing observations with extreme propensity scores using the minima and maxima method (Caliendo and Kopeinig 2008). A two-sample t-test was used to check the matching balance and ensure the equivalent distributions of individual covariates of the two landowner groups, and a likelihood ratio test was used to examine the overall equivalence of the two groups of matched landowners (Caliendo and Kopeinig 2008). When any of these tests (step 5) rejected the null hypotheses of equivalent distributions, matching results for the corresponding imputation were excluded from the final pooling in step 7 (Figure 1).

A measurement of relative risk for binary variables was used to compute the association of easement participation with forest management practices (Austin 2007, 2011). Following Dodge (2008), the relative risk RR was defined as

$$RR = \frac{a/b}{c/d} \tag{2}$$

where a is the number of landowners adopting a particular forest management practice in the participant group, b is the total number of landowners in the participant group, c is the number of landowners practicing the same forest management in the matched nonparticipant group, and d is the total number of landowners in the matched nonparticipant group. With one-to-one matching in our study, $b = d$; hence, $RR = a/c$. Relative risk RR in this study represented the ratio of the proportion of owners who adopt forest management practices in the participant group and the proportion of such owners in the nonparticipant group. The probability for an easement program participant to practice a certain management (e.g., timber harvest) on his or her forestland is RR times that for a similar nonparticipant to perform the same management. The estimated change in the proportion of adopting a management practice as a result of easement participation is $RR - 1$ times the proportion of nonparticipants who did perform the management activity. $T = \ln(RR)$, was used as the treatment effect in PSM estimation, and its variance was estimated with $SE^2_{RR} = (1/a) - (1/b) + (1/c) - (1/d)$ (Katz et al. 1978, Dodge 2008). $T > 0$ ($T < 0$) implies a positive (negative) treatment effect, and $T = 0$ indicates no effect.

Another computationally feasible method used as an alternative for one-to-one nearest neighbor matching is local linear regression matching. The difference of the means of management variables was estimated to measure the effect of easement participation when local linear regression matching was used. However, reliable variances of estimates cannot be obtained, and there is no test method for local linear regression matching (Leuven 2013). The description of this method can be found in Caliendo and Kopeinig (2008).

Combination of PSM Results for Multiple Imputations

Theoretically, MI can be combined with any other statistical method (Rubin 1996, Schafer and Olsen 1998). In this study, the PSM method was applied to each of the m data sets in phase 2 of the MI analysis. A sample was sorted randomly before PSM matching to reduce possible order bias (Austin 2007).

The pooled estimator for a parameter is the average of the estimated values over m imputations (Rubin 1996, Schafer and Olsen 1998). In this study the pooled estimator for a parameter is the average of T denoted by $\bar{T}$

$$\bar{T} = \Sigma \frac{T}{m} \tag{3}$$

The variance of $\bar{T}$ is

$$V_{\bar{T}} = \bar{U} + \left(1 + \frac{1}{m}\right) B, \tag{4}$$

where $\bar{U} = \Sigma(SE^2_T/m)$ is the within imputation variance, and SE^2_T/m is the estimated variance from a standard method such as SE^2_{RR}/m for an imputed data set (Rubin 1996). $B = [(1/m - 1)\Sigma(T - \bar{T})^2]$ is the between-imputation variance. The estimated $\bar{T}$ has a Student t distribution with $t = \bar{T}/V_T$ and an adjusted degree of freedom (df)

$$df = (m - 1)\left(1 + \frac{m\bar{U}}{(m+1)B}\right)^2 \tag{5}$$

The t-test with a hypothesis $\bar{T} = 0$ was used to test the statistical significance of the effect of easement participation (Rubin 1996, Schafer and Olsen 1998).

Empirical Model, Sensitivity Analysis, and Data

Our empirical analysis was founded on the assumption that a landowner's derived utility from owning forestland is a function of variables describing the landowner and his or her land, management and participation in public programs (Pocewicz et al. 2011). In Table 1, 25 variables for demographic information (e.g., age, education, income, gender, and race), forest size, location of land (e.g., subregion within the US Northern Region and adjacency to primary home), acquisition type (e.g., bought, gifted, inherited, or other), ownership motivation (e.g., timber, recreation, and/or privacy), and years of ownership were included in the covariate matrix X. Forest size was originally measured in acres, but the natural logarithm was used instead because it has been reported that the log-transformed value of forest acres is linearly associated with forest management variables (Butler 2008). Variables capturing information about subregions, the survey divisions defined by the US Census Bureau (2012), and indicators for forests less than 1 mile away from primary or secondary homes were among the variables controlling for location effects relative to residence. Types of acquisition of an owner's forest and ownership motivations were variables capturing forest ownership information. The variable for easement participation (*EASEMENT*) in Table 1 corresponded to the treatment variable D in the PSM (Equation 1).

The 17 forest management variables listed in the bottom half of Table 1 include timber harvesting, forest regeneration activities (e.g., treeplanting and site preparation), road maintenance, chemical application to improve forest health, wildlife habitat improvement, the adoption of a forest management plan, and future forest management activities. They were outcome variables (i.e., response variables) for the PSM, describing how the forests were managed and would be managed in the future. Values of RR, combined mean values of $\bar{T}$, and the variance V_T were computed for each of these 17 individual forest management variables.

To investigate the sensitivity of PSM estimates to the MI process, the estimation was repeated for data sets including landowners without missing information on conservation easement participation, landowners without missing information about forest management practices, and landowners without missing values for easement participation and management. The use of different data sets to explore the sensitivity of our findings resulted, as expected, in different sample sizes. Thus, to implement this sensitivity analysis steps 3–7 (Figure 1) were conducted for each of the 17 forest management variables separately.

The NWOS data used in this study corresponded to a random sample of forest owners in the US Northern Region collected over a 5-year period from 2002 to 2006 (Butler et al. 2005, Butler 2008). The cooperation rate for this cycle of the NWOS was 51%. The data set for the US Northern Region included 9,318 family forest landowners (Butler 2008). About 5% of forestland owners were enrolled in easement programs.

Interpretation of data from the NWOS required a thorough understanding of the meaning of their numerical value, and some had to be transformed before econometric estimation. For instance, demographic information (e.g., owner's age and income) was gathered using ordinal intervals in the original NWOS. Age values in our data set corresponded to mid-values of the age intervals (e.g., 20 for "under 25," 30 for "25–34," 40 for "35–44," 50 for "45–54," 60 for "55–64," 70 for "65–74," and 80 for "75 or older"). Household income values represented the lower bound of annual gross income intervals in thousand dollars (e.g., 20 for "<$25,000," 25 for

Table 2. Descriptive information, number, and percentage of missing values in the original NWOS data set for the US Northern Region and model forms used for multiple imputation (n = 9,318 family forest landowners).

Variable	Mean	Minimum	Maximum	No. of missing values	Percentage of missing data	Imputation model form
EASEMENT	0.05	0	1	809	8.68	Logit
AGE	60.90	20	80	1,844	19.79	OLS
DGR_BACH	0.14	0	1	0	0	Logit
DGR_ADV	0.17	0	1	0	0	Logit
INCOME	54.52	20	200	2,741	29.42	OLS
MALE	0.87	0	1	1,189	12.76	Logit
NONWHITE	0.02	0	1	0	0	Logit
LFOREST_ACRE	4.15	0	12.85	0	0	OLS
LAKESTATES	0.45	0	1	0	0	Logit
MIDATLANT	0.22	0	1	0	0	Logit
NORTHEAST	0.09	0	1	0	0	Logit
PRIM_HOME	0.64	0	1	760	8.16	Logit
SECOND_HOME	0.24	0	1	1,098	11.78	Logit
BOUGHT	0.85	0	1	1,682	18.05	Logit
GIFTED	0.04	0	1	1,682	18.05	Logit
INHERITED	0.23	0	1	1,682	18.05	Logit
OBJ_AESTH	2.07	1	7	1,907	20.47	OLS
OBJ_BIODIV	2.56	1	7	2,143	23	OLS
OBJ_FIREWD	4.70	1	7	1,482	15.9	OLS
OBJ_HUNT	3.19	1	7	1,727	18.53	OLS
OBJ_INVEST	3.67	1	7	1,765	18.94	OLS
OBJ_LEGACY	2.93	1	7	1,701	18.25	OLS
OBJ_PRIVA	2.55	1	7	2,029	21.78	OLS
OBJ_RECR	3.50	1	7	2,099	22.53	OLS
OBJ_TIMB	4.80	1	7	1,497	16.07	OLS
N_YR	25.70	0	246	2,691	28.88	OLS
F_AFFO	0.03	0	1	412	4.42	Logit
F_BUY	0.12	0	1	412	4.42	Logit
F_DEFFO	0.03	0	1	412	4.42	Logit
F_FIREWOOD	0.40	0	1	412	4.42	Logit
F_HEIR	0.14	0	1	412	4.42	Logit
F_NTFP	0.11	0	1	1,690	18.14	Logit
F_SAWLOG	0.23	0	1	412	4.42	Logit
F_SELL	0.07	0	1	412	4.42	Logit
F_SUBDIV	0.02	0	1	412	4.42	Logit
CHM_APPL	0.10	0	1	0	0	Logit
FIRE_REDU	0.10	0	1	0	0	Logit
MANAG_PLAN	0.15	0	1	609	6.54	Logit
ROAD_MAINT	0.34	0	1	0	0	Logit
SITE_PREP	0.10	0	1	0	0	Logit
TIMB_HVST	0.66	0	1	379	4.07	Logit
TREE_PLANT	0.25	0	1	0	0	Logit
WILDLIFE_HAB	0.17	0	1	0	0	Logit
Total				38,702	9.59	

OLS, ordinary least squares.

"\$25,000–49,999," 50 for "\$50,000–99,999," 100 for "\$100,000–199,999," and 200 for "≥\$200,000"). The importance of objectives for forest ownership was evaluated by landowners using a 7-point ordinal scale ranging from 1 = "very important" to 7 = "not important" in the NWOS. The numbers 1−7 were used as the values of these variables. The number of years of ownership (*YR_OWN*) was calculated by subtracting the survey year from the year when a forest was acquired.

Results and Discussion

There were 38,502 missing values (out of 400,674) for all 43 variables in the original data set. A total of 7,727 landowners in the data set had missing data for at least one of the variables used in this study. The numbers and percentages of missing values for each variable along means in the original data set are in Table 2.

In step 2 of the estimation, 15 of the 25 candidate explanatory variables were selected as covariates in X using forward stepwise selection for Equation 1. These variables were *DEG_BACH*, *DEG_ADV*, *INCOME*, *LFOREST_ACRE*, *LAKESTATES, MIDATLANT*, *NORTHEAST*, *SECOND_HOME*, *INHERITED*, *OBJ_BIODIV*, *OBJ_HUNT*, *OBJ_INVEST*, *OBJ_LEGACY*, *OBJ_RECR*, and *OBJ_TIMB* that described landowner's socioeconomic and forest characteristics. Ma and Kittredge (2011) and Pocewicz et al. (2011), among others, have identified education, income, forest area, secondary home location, forest acquisition through inheritance, and forest ownership objectives as important factors behind conservation easement participation.

Examples of values for T estimated in steps 3 and 4 are included in Table 3 to illustrate variation across the 20 MI-generated data sets. The distributions of propensity scores of participants and nonparticipants for the first imputed data set are shown in Figure 2. Most of the participants had propensity scores overlapping with those of nonparticipants. The shapes observed in the frequency charts for the two groups show skewedness to the same side, and the frequencies of most nonparticipants were several times larger than

Table 3. Estimated $T = \ln(RR)$ values for selected imputations using one-to-one nearest neighbor matching.

Management variables	Imputation 1	Imputation 2	Imputation 3	...	Imputation 20
F_AFFO	−0.0572	−0.1823	−0.2513	...	0.0690
F_BUY	−0.0136	0.0142	0.0896	...	0.1796
F_DEFFO	−0.6131	0.1671	−0.0690	...	−0.5261
F_FIREWOOD	−0.0476	0.0000	0.0242	...	0.0000
F_HEIR	−0.1178	−0.0267	0.0870	...	−0.2147
F_NTFP	−0.0480	−0.0165	0.1591	...	0.1596
F_SAWLOG	−0.0650	−0.1372	−0.0353	...	0.0150
F_SELL	−0.2029	−0.1823	−0.2451	...	0.0572
F_SUBDIV	−1.5041	−0.4520	−0.3365	...	−1.3863
CHM_APPL	−0.0157	0.3087	0.0323	...	0.3205
FIRE_REDU	−0.5905	−0.1417	−0.1252	...	−0.2136
MANAG_PLAN	0.4658	0.6248	0.6783	...	0.6617
ROAD_MAINT	−0.0339	−0.0664	0.0557	...	0.0100
SITE_PREP	0.2007	0.3983	0.2776	...	0.3129
TIMB_HVST	−0.0162	0.0110	0.0112	...	0.0702
TREE_PLANT	0.0073	0.1518	0.0674	...	0.1368
WILDLIFE_HAB	−0.2583	−0.0196	0.0321	...	0.0335

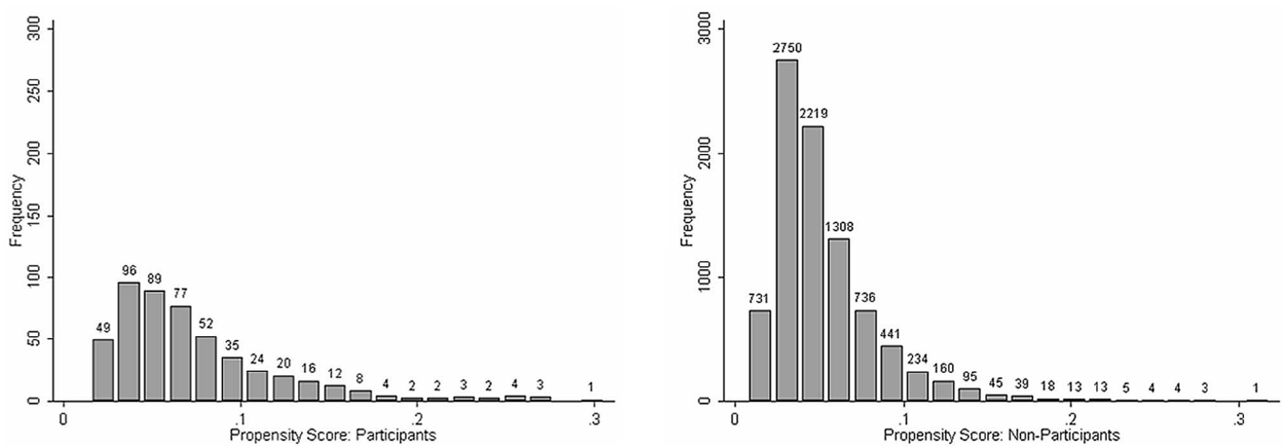

Figure 2. Distribution of propensity scores for conservation easement participants (left) and nonparticipants (right).

those of participants in their corresponding propensity score categories. Thus, there was a large pool of nonparticipants for one-to-one nearest neighbor matching.

The results of step 5 produced $P > 0.05$ for all two-sample t-tests and likelihood ratio balance tests. Because there were 20 likelihood ratio tests and a total of 300 t-tests (15 tests for each of the 20 imputations), these results are not reported in this article. These results suggested that the two groups of landowners in each matching were equivalent with a balanced distribution of covariates. Consequently, matching was deemed to be statistically valid, and all of the 20 estimated values of T for each management variables were used in step 7 to compute pooled results included in Table 4. Test results in Table 4 suggest that only one management practice (adoption of forest management plan) was significantly associated with conservation easement participation with $P < 0.01$. Effects of easement programs on all other management practices of forest landowners were found to be not statistically significant with all $P > 0.05$.

The estimated *RR* for the adoption of a forest management plan was as large as 1.93, suggesting that the adoption rate of forest management plans increased by 0.93 times as a result of conservation easement participation. The easement participation increased forest management plan adoption rate by 0.19 (last column of Table 4) from 0.21 for matched easement nonparticipants to 0.40 for easement participants. The statistically nonsignificant effects of easements on other variables implies a weak association of conservation easements with forest harvest, treeplanting, forest fire reduction, and habitat improvement and other conservation management practices. Differences in stated future land management practices between conservation easement participants and nonparticipants were not statistically significant either.

Results from estimations using data sets excluding landowners with missing values of management variables, the easement indicator, or both showed similar results (Table 5). Some of the PSM estimated values were invalid and were excluded from step 7 of the estimation because of poor balance test results, but there were at least 17 valid values of T used in the estimation for each management variable. Similar to results in Table 4, only the effect on the adoption of a forest management plan was statistically significant at the 0.05 type I error level (Table 5). The estimated values of *RR* for the forest management plan with data sets with different combinations of missing values ranged from 1.79 to 1.89, slightly smaller than but close to the corresponding 1.93 in Table 4, suggesting that the filled missing values for *EASEMENT* and management variables had no substantial effect on final results.

Easement effects on forest management practices estimated with local linear regression matching (as an alternative for one-to-one nearest neighbor matching) are almost the same as those in Table 4. Results for the three selected variables that have small P values in Table 4 are presented as Table 6. The estimated changes in means of

Table 4. Effects of conservation easements on 17 forestland management activities estimated with a combination of MI and PSM methods ($n = 9{,}318$, $m = 20$).

Management variable	$\bar{T}$[a] mean of ln(*RR*)	t^b	Adjusted *df*	*P* value for $\bar{T}$ (one-tailed *t*-test)	*RR*	Mean of matched nonparticipants	Estimated change of means as results of easement participation
F_AFFO	0.102	0.22	182	0.41	1.11	0.03	<0.01
F_BUY	0.062	0.32	142	0.38	1.06	0.14	0.01
F_DEFFO	−0.107	−0.25	212	0.40	0.90	0.03	<0, >−0.01
F_FIREWOOD	0.008	0.08	90	0.47	1.01	0.42	<0.01
F_HEIR	0.035	0.18	156	0.43	1.04	0.14	0.01
F_NTFP	0.051	0.25	229	0.40	1.05	0.12	0.01
F_SAWLOG	−0.069	−0.53	128	0.30	0.93	0.29	−0.02
F_SELL	−0.058	−0.21	123	0.42	0.94	0.08	<0, >−0.01
F_SUBDIV	−0.930	−1.36	168	0.09	0.39	0.02	−0.01
CHM_APPL	0.180	0.86	206	0.20	1.20	0.11	0.02
FIRE_REDU	−0.201	−0.79	111	0.22	0.82	0.11	−0.02
MANAG_PLAN	0.655	4.96	132	<0.01	1.93	0.21	0.19
ROAD_MAINT	0.032	0.33	130	0.37	1.03	0.40	0.01
SITE_PREP	0.268	1.22	156	0.11	1.31	0.10	0.03
TIMB_HVST	0.032	0.62	136	0.27	1.03	0.70	0.02
TREE_PLANT	0.075	0.53	94	0.30	1.08	0.26	0.02
WILDLIFE_HAB	−0.018	−0.10	92	0.46	0.98	0.20	<0, >−0.01

[a] Twenty values of $\bar{T}$ were used to estimate means.
[b] t statistics for $\bar{T}$ were computed with $t = \bar{T}/SE_{\bar{T}}$.

Table 5. *RR* results using observations with different combinations of missing values and one-to-one nearest neighbor matching method.

Management variable	Observations without missing values for treatment variable *EASEMENT*: *RR*	No. of estimated values of *T* included	Observations without missing values for management variables: *RR*	No. of estimated values of *T* included	Observations without missing values for treatment and management variables: *RR*	No. of estimated values of *T* included
F_AFFO	1.05	17	0.97	20	1.03	19
F_BUY	1.04	17	1.05	20	1.04	19
F_DEFFO	0.86	17	1.07	20	0.86	19
F_FIREWOOD	1.01	17	1.02	20	1.01	19
F_HEIR	1.01	17	1.00	20	0.98	19
F_NTFP	0.99	17	1.05	18	1.03	18
F_SAWLOG	0.96	17	0.93	20	0.92	19
F_SELL	0.97	17	0.98	20	0.97	19
F_SUBDIV	0.41	17	0.33	20	0.43	19
CHM_APPL	1.20	17	1.20	20	1.20	17
FIRE_REDU	0.82	17	0.85	20	0.85	17
MANAG_PLAN	1.83*	17	1.89*	20	1.79*	19
ROAD_MAINT	1.03	17	1.01	20	1.01	17
SITE_PREP	1.31	17	1.26	20	1.26	17
TIMB_HVST	1.05	17	1.05	18	1.04	20
TREE_PLANT	1.08	17	1.06	20	1.06	17
WILDLIFE_HAB	0.98	17	0.97	20	0.97	17
No. of landowners in each data set	8,829		7,628–9,318		7,255–8,829	

*Estimates are significant at 0.05 type I error level.

Table 6. Easement effects on selected forest management practices estimated by local linear regression matching using Tricube kernel in step 4 with all observations in each of the 20 imputations.

Selected management variables	Mean of participants	Mean of nonparticipants	Effect (change of mean)
F_SUBDIV	0.01	0.02	−0.01
MANAG_PLAN	0.40	0.21	0.19
SITE_PREP	0.13	0.10	0.03

these selected variables were the same as their corresponding values in Table 4, suggesting that this alternative local linear regression matching produced results similar to those estimated with one-to-one nearest neighbor matching.

The significance of the effect of estimated conservation easements on the adoption of forest management plans suggests that forest landowners have met the obligations of some of the easement programs such as the federal Forest Legacy Program that requires landowners to have one. Forest management plans help forest landowners integrate conservation principles into their forest management, facilitate the supervision of easement programs, and ensure forestlands to be used with the restrictions set by these programs. In most cases, forestlands with easements were required to be managed as forestland permanently (Kiesecker et al. 2007).

The statistically nonsignificant association found between conservation easements on the other 16 stated forestland management activities suggests that the existing management on family forests has not been significantly changed by easement contracts. Thus, timber and nontimber production has not been significantly affected by conservation easements. Our findings of easements on forest management in the US Northern Region are in line with those of Pocewicz et al. (2011) for Wyoming. Our conclusion on the nonsignificant difference in biodiversity practices as a result of easements for the US Northern Region is in agreement with Hagan et al. (2005) for timberland in four US States.

Although our results suggest that no significant differences in stated forest management practices have been made by conservation easements on forestland in general, ecological benefits of easements could be significant. For instance, according to Kiesecker et al. (2007) most conservation easements are located in high-conservation properties critical to regional ecosystems. This condition would in turn suggest that management practices conducted on easement-enrolled lands would be ecologically or socially more important than the same practices adopted on other lands. Arguably, greater importance should be given to forest management practices on lands under easements in an evaluation of their ecological or social benefits. However, an evaluation of ecological impacts of conservation easements using the NWOS is restricted by the anonymous nature of the data that has no explicit information about the location of the land. Conceptually, a multidisciplinary effort that allocates weights according to the ecological importance of different forestlands might be an option to evaluate environmental benefits of conservation easements. The actual ecological and conservation benefits of conservation easements, beyond an increment in the adoption of forest management plans, could be better assessed if appropriate importance weights were assigned to those lands.

There is an important limitation inherent to the data used in this analysis. All forest management variables in this study were binary, i.e., whether they have been adopted in a practice or not. Such a type of data ignores the difference in the intensity or quality of management practices. Hence, we were not able to quantify how much a management practice has contributed to forest conservation. Future studies should attempt to use data that better capture quality and intensity of management for an improved estimation of the relationship between conservation easements and their conservation benefits.

Conclusions

Analysis of the relationship between land management and conservation easements needs to reflect the fact that landowner participation is not a random process. PSM was combined with MI to obtain unbiased estimates for differences in forest management activities associated with conservation easements. NWOS data with information on thousands of individual family forest owners in the US Northern Region were used in the estimation. The MI method was used to fill missing values that affected 83% of all observations in the original data set.

The results showed that only the adoption of forest management plans were significantly associated with conservation easements. No statistically significant difference in timber harvest and other production activities was detected between easement participants and matched nonparticipants. These results suggest that conservation easements can preserve forestland by legally preventing land-use change without significantly affecting timber production. However, the association between easements and conservation activities such as fire prevention and habitat protection were found to be nonsignificant statistically. Consequently, these results suggest that easements have not resulted in greater implementation of forest management practices on forestland in general, beyond adoption of written management plans.

This study confirmed that conservation easement programs are effective policy tools to protect forest from development and ensure that forestlands are managed following specific plans with conservation objectives. By showing that easement programs can help restrain the conversion of forest to nonforest, the results of this study justify support from the public and government agencies. However, if conservation easement objectives include wider adoption of management practices that can support forest conservation, our findings showed no statistical evidence to that effect. This study was limited to the determination of differences in the adoption of management practices among family owners participating in conservation easements (compared to nonparticipants) and it did not assess easements potential subsequent environmental benefits because of the nature of the NWOS data. Future analyses on the relationship between easements and forestlands should incorporate spatially explicit societal and ecological benefits. A multidisciplinary effort to define weights for the social and/or ecological importance of forest management on easement-enrolled versus nonenrolled lands might result in different findings.

Endnote

1. There is no agreement on the optimal numbers of imputations with suggestions ranging from 5 (Schafer and Olsen 1998, Royston and White 2011) to 20 or more (Graham et al. 2007). Exploratory estimations conducted by the authors showed that final results changed little when the number of imputations was greater than 10 and were stable at $m = 20$.

Literature Cited

Apel, R.J., and G. Sweeten. 2009. Propensity score matching in criminology and criminal justice. P. 543–562 in *Handbook of quantitative criminology*, Piquero, A., and D. Weisburd (eds.). Springer, New York.

Austin, P.C. 2007. Propensity-score matching in the cardiovascular surgery literature from 2004 to 2006: A systematic review and suggestions for improvement. *J. Thorac. Cardiovasc. Surg.* 134:1128–1135.

Austin, P.C. 2011. An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multi. Behav. Res.* 46:399–424.

Butler, B.J. 2008. *Family forest owners of the United States, 2006.* USDA For. Serv., Gen. Tech. Rep. NRS-27, Northern Research Station, Newtown Square, PA. 72 p.

Butler, B.J., E.C. Leatherberry, and M.S. Williams. 2005. *Design, implementation, and analysis methods for the National Woodland Owner Survey.* USDA For. Serv., Gen. Tech. Rep. NE-336, Northeastern Research Station, Newtown Square, PA. 43 p.

Butler, B.J., M. Tyrrell, G. Feinberg, S. VanManen, L. Wiseman, and S. Wallinger. 2007. Understanding and reaching family forest owners: Lessons from social marketing research. *J. For.* 105(7):348–357.

Caliendo, M., and S. Kopeinig. 2008. Some practical guidance for the implementation of propensity score matching. *J. Econ. Surv.* 22(1):31–72.

Cho, S.H., D.H. Newman, and J.M. Bowker. 2005. Measuring rural homeowners' willingness to pay for land conservation easements. *For. Pol. Econ.* 7:757–770.

Cho, S.H., S.T. Yen, J.M. Bowker, and D.H. Newman. 2008. Modeling willingness to pay for land conversation easements: Treatment of zero and protest bids and application and policy implications. *J. Agr. Appl. Econ.* 40(1):267–285.

Conservation Registry. 2012. *National conservation database.* Updated in August 2011. Available online at app.databasin.org/app/pages/datasetPage.jsp?id=d85fb27b3b8f440ca2aeee2fc6f930bd; last accessed June 1, 2012.

D'Amato, A.W., P.F. Catanzaro, D.T. Damery, D.B. Kittredge, and K.A. Ferrare. 2010. Are family forest owners facing a future in which forest management is not enough? *J. For.* 108:32–38.

Dehejia, R.H., and S. Wahba. 1999. Causal effects in non-experimental studies: Re-evaluating the evaluation of training programmes. *J. Am. Stat. Assoc.* 94:1053–1062.

Dehejia, R.H., and S. Wahba. 2002. Propensity score-matching methods for nonexperimental casual studies. *Rev. Econ. Stat.* 84(1):151–161.

deVen, W.V., and B.V. Praag. 1981. The demand for deductibles in private health insurance: A probit model with sample selection. *J. Econ.* 17:229–252.

Dodge, Y. 2008. Risk P. 461–463 in *The concise encyclopedia of statistics.* Springer, New York. 616 p.

Ferraro, P.J., and S.K. Pattanayak. 2006. Money for Nothing? A call for empirical evaluation of biodiversity conservation investments. *PLoS Biol.* 4(4):e105.

Graham, J.W., A.E. Olchowski, and T.D. Gilreath. 2007. How many imputations are really needed? Some practical clarifications of multiple imputation theory. *Prev. Sci.* 8:206–213.

Geoghegan, J., L. Lynch, and S. Bucholtz. 2003. Capitalization of open spaces into housing values and the residential property tax revenue impacts of agricultural easement programs. *Agr. Resour. Econ. Rev.* 23:251–264.

Greene, W.H. 2002. *Econometric analysis*, 5th ed. Prentice Hall, Upper Saddle River, NJ. 92 p.

Hagan, J.M., L.C. Irland, and A.A. Whitman. 2005. *Changing timberland ownership in the northern forest and implications for biodiversity.* Manomet Center for Conservation Sciences, Rep. MCCS-FCP-2005-1, Brunswick, ME. 25 p.

Heckman, J.J. 1979. Sample selection bias as a specification error. *Econometrica* 47(1):153–161.

Heckman, J.J. 1990. Varieties of selection bias. *Am. Econ. Rev.* 80:313–318.

Heckman, J.J., H. Ichimura, J.A. Smith, and P. Todd. 1998a. Characterizing selection bias using experimental data. *Econometrica* 66(5): 1017–1098.

Heckman, J.J., H. Ichimura, and P.E. Todd. 1997. Matching as an econometric evaluation estimator: Evidence from evaluating a job training program. *Rev. Econ. Stud.* 64:605–654.

Heckman, J.J., H. Ichimura, and P.E. Todd. 1998b. Matching as an econometric evaluation estimator. *Rev. Econ. Stud.* 65(2):261–294.

Katz, D., J. Baptista, S.P. Azen, and M.C. Pike. 1978. Obtaining confidence intervals for the risk ratio in cohort studies. *Biometrics* 34: 469–474.

Kiesecker, J.M., G. Amaon, T. Comendant, T. Grandmason, E. Gray, C. Hall, R. Hilsenbeck, et al. 2007. Conservation easements in context: A quantitative analysis of their use by the nature conservancy. *Front. Ecol. Environ.* 3(5):125–130.

Kline, J.D., R.J. Alig, and B. Garber-Yonts. 2004. Forestland social values and open space preservation. *J. For.* 102:39–45.

LaLonde, R. 1986. Evaluating the econometric evaluations of training programs. *Am. Econ. Rev.* 76(4):604–620.

Land Trust Alliance. 2011. *2010 National Land Trust census report: A look at voluntary land conservation in America.* Land Trust Alliance, Washington, DC. 20 p.

Leuven, E. 2013. *Help for pstest.* Available online at fmwww.bc.edu/repec/bocode/p/pstest.html; last accessed Jan. 15, 2013.

Liu, X., and L. Lynch. 2011. Do agricultural land preservation programs reduce farmland loss? evidence from a propensity score matching estimator. *Land Econ.* 87(2):183–201.

Ma, Z., and D.B. Kittredge. 2011. How family forest owners consider timber harvesting, land sale, and conservation easement decisions: Insights from Massachusetts, USA. *Int. J. For. Res.* doi:10.1155/2011/290353.

Merenlender, A.M., L. Huntsinger, G. Guthey, and S.K. Fairfax. 2004. Land trusts and conservation easements: Who is conserving what for whom? *Conserv. Biol.* 18:65–75.

Miranda, A., and S. Rabe-Hesketh. 2006. Maximum likelihood estimation of endogenous switching and sample selection models for binary, count, and ordinal variables. *Stata J.* 6(3):285–308.

Nickerson, C.J., and L. Lynch. 2001. The effect of farmland preservation programs on farmland prices. *Am. J. Agr. Econ.* 83(2):341–351.

Ovaskainen, V., H. Hänninen, J. Mikkola, and E. Lehtonen. 2006. Cost-sharing and private timber stand improvements: A two-step estimation approach. *For. Sci.* 52(1):44–54.

Pocewicz, A., J.M. Kiesecker, G.P. Jones, H.E. Copeland, J. Daline, and B.A. Mealor. 2011. Effectiveness of conservation easements for reducing development and maintaining biodiversity in sagebrush ecosystems. *Biol. Conserv.* 144(1):567–574.

Rissman, A.R., and A.M. Merenlender. 2008. The conservation contributions of conservation easements: Analysis of the San Francisco Bay Area protected lands spatial database. *Ecol. Soc.* 13(1):40.

Rosenbaum, P.R., and D.B. Rubin. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70(1):41–55.

Rosenbaum, P.R., and D.B. Rubin. 1985. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *Am. Statistician* 39(1):33–38.

Royston, P. 2004. Multiple imputation of missing values. *Stata J.* 4(3):227–241.

Royston, P. 2005. Multiple imputation of missing values: Update of ice. *Stata J.* 5:527–536.

Royston, P., and I.R. White. 2011. Multiple imputation by chained equations (MICE): Implementation in Stata. *J. Stat. Softw.* 45(4):1–20.

Rubin, D.B. 1974. Estimating causal effects of treatments in randomized and non-randomized studies. *J. Educ. Psychol.* 66:688–701.

Rubin, D.B. 1996. Multiple imputation after 18+ years. *J. Am. Stat. Assoc.* 91:473–489.

Schafer, J.L., and M.K. Olsen. 1998. Multiple imputation for multivariate missing-data problems: Data analyst's perspective. *Multivariate Behav. Res.* 33(4):545–571.

Shifley, S.R., F.X. Aguilar, N. Song, S.I. Stewart, D.J. Nowak, D.D. Gormanson, W.K. Moser, S. Wormstead, and E.J. Greenfield. 2012. Introduction. P. 1–8 in *Forests of the Northern United States*. USDA For. Serv., Gen. Tech. Rep. NRS-90, Northern Research Station, Newtown Square, PA. 202 p.

Smith, W.B., P.D. Miles, C.H. Perry, and S.A. Pugh. 2009. Table 10. P. 182–191, in *Forest resources of the United States, 2007.* USDA For. Serv., Gen. Tech. Rep. WO-78, Washington Office, Washington, DC. 336 p.

US Census Bureau. 2012. *Census regions and divisions of the United States.* Available online at www.census.gov/geo/www/us_regdiv.pdf; last accessed June 28, 2012.

US Internal Revenue Service. 2012. *Conservation easement audit techniques guide.* Available online at www.irs.gov/businesses/small/article/0,id=249135,00.html; last accessed June 28, 2012.

US Natural Resource Conservation Service. 2011. *Easements.* Available online at www.nrcs.usda.gov/wps/portal/nrcs/main/national/programs/easements; last accessed Feb. 20, 2012.

van Buuren, S., H.C. Boshuizen, and D.L. Knook. 1999. Multiple imputation of missing blood pressure covariates in survival analysis. *Stat. Med.* 18:681–694.

White, I.R., R. Daniel, and P. Royston. 2010. Avoiding bias due to perfect prediction in multiple imputation of incomplete categorical variables. *Comput. Stat. Data Anal.* 54:2267–2275.