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Factors associated with family forest landowner enrollment in state preferential forest property tax programs in the United States

Gregory E. Frey[a,*], Justin T. Meier[b], Michael A. Kilgore[b], Stephanie A. Snyder[c], Charles R. Blinn[b]

[a] USDA Forest Service, Southern Research Station, Research Triangle Park, NC, United States
[b] University of Minnesota, Department of Forest Resources, St. Paul, MN, United States
[c] USDA Forest Service, Northern Research Station, St. Paul, MN, United States

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ABSTRACT

All fifty states in the United States offer preferential forest property tax programs (PFPTPs) that defer, reduce, or eliminate property taxes on enrolled private forest lands, to foster ecosystem services. Among individual programs, there is wide variability in enrollment levels, as well as program structure and administration. Past research has explored patterns of enrollment in individual states, but to our knowledge has never been conducted at the national level. We used binary logistic regression with multiple imputation for missing data to explore the landowner, land, and program characteristics that correlate with likelihood of enrollment in a PFPTP. We found that most landowner objectives and concerns, including those that would appear to be linked to program enrollment, such as concern about the level of taxes, were generally not correlated with likelihood of enrollment. Owning more forest area was correlated with higher likelihood of enrollment. The link of enrollment to population density suggested that enrollment is higher in moderate densities, with higher and lower densities having lower enrollment, possibly due to conflicting incentives for enrollment as land values increase. Program characteristics were negatively correlated with likelihood of enrollment, especially those that restrict uses or management. The owner's desire for wooded land to stay wooded and higher levels of penalty for program withdrawal were positively correlated with likelihood of enrollment and average rates of tax reductions were not significantly correlated, suggesting that landowners may see programs as a method of conserving and protecting their forestland in the future more than as simply a way to save money.

1. Introduction

Family forest owners (FFOs)[1] own 290 million acres (117 million hectares) of forest in the United States, about 35% of the country's total (Butler et al., 2016c; Oswalt et al., 2018). Private (including family and other private) forest lands account for 89% of U.S. timber harvests (Oswalt et al., 2018) as well as numerous other ecosystem services such as wildlife habitat and carbon sequestration (Millenium Ecosystem Assessment, 2005). Although total forest area in the United States has been expanding (Oswalt et al., 2018), existing privately owned tracts are threatened by urbanization and parcelization (Riitters and Costanza, 2019).

All fifty states have some type of preferential forest property tax program (PFPTP) that lowers property taxes on participating forest land in order to incentivize sustainable production of ecosystem services[2] by preventing land use change and forest fragmentation and encouraging (or requiring) the application of certain forest management actions (Kilgore et al., 2018a,b). Property taxes can be a significant annual cost of family forest ownership and can have a substantial effect on the financial returns derived from managing family forest lands (Cushing and Newman, 2018; Greene, 1995; Stier et al., 1988). Many FFOs are concerned about high property taxes, often suggesting that high tax costs could cause them or their heirs to sell or parcelize their land (Butler et al., 2012; Gruver et al., 2017; Stone and Tyrrell, 2012; Williams et al., 2004). PFPTPs attempt to promote ecosystem services (Kilgore et al., 2018a). Administered by state and/or local governments, PFPTPs are highly variable in their structure, administration, and performance (Kilgore et al., 2018b).

Many FFOs are motivated by the nonmonetary benefits associated with owning forests (Butler et al., 2016b), but those whose forest-

* Corresponding author.
E-mail address: gregory.e.frey@usda.gov (G.E. Frey).

[1] Following Butler et al. (2016a), we use the term "family forest owners" to include individual and joint ownerships, trusts, partnerships, and estates, but exclude corporations, non-governmental organizations, unincorporated partnerships/associations/clubs, or Native American reservations.

[2] Following Kilgore et al. (2018a), we use an inclusive definition of "ecosystem services" that includes goods such as timber and non-timber forest products.

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derived income makes up a relatively larger share of their total income are often swayed by financial incentives available to FFOs (Koontz, 2001). Financial incentives have been shown to increase management activities such as tree planting (Royer, 1987; Royer and Moulton, 1987; Ruseva et al., 2015; Zhang and Flick, 2001), but perhaps it is not surprising that property tax rates affect private forest land uses and management only inelastically (Polyakov and Zhang, 2008; Poudyal and Hodges, 2009).

Regardless of their efficiency at changing FFO behavior, if PFPTPs are to achieve their goal of maintaining ecosystem services, they must first attract substantial enrollment by FFOs. Past research has explored factors that are correlated with higher PFPTP enrollment in individual state programs (Brockett and Gebhard, 1999; Dennis and Sendak, 1992; Fortney et al., 2011; Kauneckis and York, 2009; Stevens et al., 2002; Williams et al., 2004; Wolde et al., 2016). However, to our knowledge none have undertaken the analysis at a national level. A national-level analysis allows us to explore how state-by-state differences in PFPTP structure, administration, and incentives (Kilgore et al., 2018b), as well as landowner and land characteristics, may affect enrollment. Specifically, the objective of this study was to develop a national model of FFO enrollment in PFPTPs to quantify how landowner, parcel, and program characteristics are linked to participation.

2. Background

Property taxes and PFPTPs are one part of a broad and complex policy environment affecting private forests (Amacher, 1997; Kilgore and Blinn, 2004; Wagner et al., 2002). PFPTPs are voluntary and intended to influence FFO behavior by providing a financial incentive in the form of reduced property taxes, thereby falling under the broader policy category which we will call “voluntary forest incentive programs” (VFIPs). Other types of VFIPs include income tax incentives (Greene et al., 2004), cost-share programs (Kilgore et al., 2007), and other direct payments (Kilgore et al., 2008a). While this research focuses on PFPTPs specifically, these other VFIPs for conservation and management are similar and can inform our research.

Table 1 compares seven studies that have explored explanatory covariates of enrollment in PFPTPs alone or in combination with other VFIPs. The factors identified in Table 1 are those that appeared in multiple studies. In general, the factors that were commonly utilized can be grouped into three broad categories: landowner characteristics, land characteristics, and program characteristics. Many explanatory variables are not statistically significant consistently across studies in different regions or across different programs. Similar research on other VFIPs that do not include PFPTPs are not included in Table 1, but inform the discussion below.

2.1. Landowner characteristics

A wide variety of landowner characteristics have been empirically shown to be correlated with FFOs’ decisions to enroll in PFPTPs and other VFIPs. These include landowner demographics, objectives and concerns, and other actions and characteristics. In terms of demographics, greater likelihood of participation in VFIPs has been found to correlate with higher levels of education (Dennis and Sendak, 1992; Ma et al., 2012; Song et al., 2014b; Wolde et al., 2016), higher income, and younger age (Fortney et al., 2011).

Landowner objectives and stated concerns for their property have been included in studies of willingness to enroll in VFIPs. FFOs have been consistently found to express a preference for amenity and aesthetic benefits over strictly economic incentives such as timber production (Koontz, 2001; Ryan et al., 2003). Stewardship and a conservation ethic are also motivations for some FFOs (Daniels et al., 2010; Erickson et al., 2002; Fortney et al., 2011). Still, ownership objectives/reasons are largely not correlated with VFIP enrollment (Ma et al., 2012). Plans to harvest timber or objectives of managing for timber income have been inconsistently related to enrollment in VFIPs (Brockett and Gebhard, 1999; Fortney et al., 2011; Ma et al., 2012; Song et al., 2014b; Wolde et al., 2016). Many FFOs express an intent or desire that their land remain forested in the future, and this desire may be correlated with higher enrollment (Fortney et al., 2011). Concerns about land development and taxes have been found to have a positive association with enrollment in PFPTPs (Fortney et al., 2011), although not consistently (Brockett and Gebhard, 1999).

Other landowner actions and characteristics are potentially linked to enrollment. One factor consistently shown to be positively correlated with VFIP enrollment is if the landowner has a written forest management plan (Brockett and Gebhard, 1999; Ma et al., 2012; Wolde et al., 2016). However, the causality of this variable is questionable, as many VFIPs, including some PFPTPs, require a forest management plan as an eligibility requirement for enrollment (Kilgore et al., 2018b). Landowners who do not reside near their forested land are commonly referred to as absentee landowners. Absenteeism is hypothesized to reduce forest management overall, because it is more costly and time-consuming for the landowner to participate frequently in the management of their land. Similarly, it might be expected that absentee landowners are less likely to enroll in VFIPs because they spend less time overall thinking about or visiting their forest land. However, most past research has shown no statistically significant effect associated with absentee status on VFIP enrollment (Ma et al., 2012; Song et al., 2014b; Stevens et al., 2002; Williams et al., 2004; Wolde et al., 2016).

2.2. Land characteristics

Land characteristics, including individual parcel characteristics, land and ownership history, and land context are often included in empirical studies of VFIP enrollment behavior (Kauneckis and York, 2009). Area of forest owned is generally positively correlated with enrollment (Dennis and Sendak, 1992; Ma et al., 2012; Song et al., 2014b; Wolde et al., 2016), possibly because larger areas generally command a larger absolute financial benefit, or that it represents a larger proportion of the landowner’s total income (Koontz, 2001).

Land and ownership history may be correlated with enrollment. Acquisition of land by purchase (as opposed to inherited or received as a gift) has been shown to typically be negatively correlated with enrollment in VFIPs, although the reason for this is not clear (Fortney et al., 2011; Stevens et al., 2002; Wolde et al., 2016) and some contradictory findings exist (Song et al., 2014b). The number of years of forestland ownership is generally positively correlated with enrollment (Ma et al., 2012; Song et al., 2014b; Wolde et al., 2016), possibly because landowners have had more time to become aware of and enroll in various programs.

Land context, such as characteristics of the surrounding land, are often included as explanatory variables in VFIP enrollment models. Development pressure may affect enrollment; therefore, several measures such as population density, population growth, and distance to population centers have been tested in the past. However, the effect of development pressure on enrollment in VFIPs has been inconsistent (Bagdon and Kilgore, 2013; Dennis and Sendak, 1992; Kauneckis and York, 2009; Udayanganie, 2012, 2013). This inconsistency in results related to development pressure may be due to conflicting incentives. For instance, higher financial benefits in the form of larger tax reductions are often derived from higher market land values, but this benefit may be offset by potentially high opportunity costs of capitalizing on development of high value lands. Proximity to other natural amenities (e.g., water features) or infrastructure (e.g., roads) may play a role in enrollment as well (Bagdon and Kilgore, 2013).

2.3. Program characteristics

Past literature has recognized the importance of VFIP program characteristics in inducing enrollment and land-use changes by FFOs;

Table 1
Past research on family forest owners (FFOs) in the United States measuring correlation between enrollment in preferential forest property tax programs (PFPTPs) and explanatory factors.

	Brockett and Gebhard (1999)	Dennis and Sendak (1992)	Fortney et al. (2011)	Kauneckis and York (2009)	Stevens et al. (2002)	Williams et al. (2004)	Wolde et al. (2016)
Program(s) analyzed [1]	P	P	P	P, C, T, E	P, I, C	P	P, C, T
State(s) [2]	TN	VT	WV	IN	MA	TN	VA, TX
n	188	338 / 252	330	226	209	117 / 52	229
Model [3]	S	P	L	L	C	P	L
Landowner characteristics							
Education		+	n.s.	n.s.	n.s.	n.s.	+
Income			+		n.s.	n.s.	n.s.
Age			–		n.s.		
Timber objective [4]	n.s.		n.s.				+
Investment objective [4]	n.s.					–	
Wildlife objective [4]	n.s.						
Intent or desire to preserve forest [5]			+		n.s.	n.s.	
Development concern [6]	n.s.						
Tax concern [6]	n.s.		+				
Management plan [7]	+						+
Absentee [8]			+		n.s.	n.s.	n.s.
Land characteristics							
Forested area		+	n.s.	n.s.	n.s.		+
Purchased [9]			–		–		–
Years owned			n.s.				+
Agricultural use [10]			n.s.	n.s.			
Population [11]		n.s.		n.s.			
Population growth		–					
Program characteristics							
Tax reduction amount		n.s.			+		
Use restrictions or requirements					–	–	

+ or – = positively or negatively correlated and statistically significant (alpha = 0.05).
n.s. = not statistically significant.
[1] P = preferential property tax; C = cost-sharing; T = technical assistance; I = incentive payment; E = easement.
[2] IN = Indiana; MA = Massachusetts; TN = Tennessee; TX = Texas; VA = Virginia; VT = Vermont; WV = West Virginia.
[3] S = simple correlation; L = logistic regression model (logit); P = probit model; C = conjoint analysis.
[4] There are various formulations of the variables related to the landowner's objective for owning forestland, but generally refer to the landowner viewing this as an important objective, purpose, or motivation for owning or managing the land.
[5] Some studies code intent or desire to preserve forest as forest as 1 and intent to develop as 0, others code in the opposite manner. In this table, we have corrected the sign so that the result indicate the effect of intent to preserve forest (coded as 1).
[6] There are various formulations of the variables related to the landowner's concerns about their forestland, but generally refer to the landowner viewing this as something about which they are concerned for the future, or a threat.
[7] Landowner has a written management plan.
[8] Some studies code absentee owner as 1 and those living nearby their forestland as 0, others code in the opposite manner. In this table, we have corrected the sign so that the results indicate the effect of absenteeism (coded as 1).
[9] Land was purchased by the current owner, rather than inherited or received as a gift.
[10] Land is used partially for agriculture (in addition to forested land use).
[11] As measured by population density or distance to population center.

however, a consistent understanding has been elusive. For instance, Ma et al. (2014) found no link between property tax program attributes considered important and either self-assessed (i.e., by program administrators) or actual program effectiveness. Partially, the lack of results related to VFIP program characteristics is because most previous studies have focused on a single VFIP, or compared relatively few programs.

Financial incentive levels appear to affect landowner decisions and program enrollment inelastically, that is, large changes in the financial incentives induce only small landowner changes (Kilgore et al., 2008a, b; Polyakov and Zhang, 2008; Poudyal and Hodges, 2009), and financial incentives may be secondary in consideration to other program requirements and benefits (Bagdon and Kilgore, 2013). PFPTPs create financial incentives by reducing the property taxes owed each year. All else equal, higher regular (non-enrolled) tax rates and lower current use (enrolled) tax rates generate higher PFPTP enrollment (Stevens et al., 2002; Udayanganie, 2012, 2013), and may have an effect on delaying conversion of forest land to developed uses (Anderson et al., 2000). Taken in full context of the forest policy environment, tax reductions may not create substantial additional changes in landowner behavior (Kilgore, 2014; Wagner et al., 2002; Williams et al., 2004).

Transaction costs associated with VFIP enrollment, such as requiring forest management plans may reduce enrollment (Ma et al., 2014). Opportunity costs related to deed restrictions and restrictions on management autonomy negatively impact enrollment in PFPTPs (Butler et al., 2012; Fortney et al., 2011; Kilgore et al., 2008b). In particular, deed restrictions that limit property rights have been found to reduce enrollment significantly (Bagdon and Kilgore, 2013; Stevens et al., 2002). Additionally, a general aversion to government control and management authority may play a role in limiting program enrollment (Daniels et al., 2010; Fortney et al., 2011; Mehmood and Zhang, 2005).

3. Methods

3.1. Data

Data for this project came from three general sources: the National

Woodland Owner Survey (NWOS) version 5 provided information on individual landholdings (Butler et al., 2016a), geospatial data from the National Land Cover Database and U.S. Census gave the landholdings context, and a 2014 review of PFPTPs in all 50 states provided information on characteristics of PFPTPs by state (Kilgore et al., 2018a, b). The variables used in our analysis are described in Table 2.

The NWOS, administered by the USDA Forest Service, is a national-level, repeated survey conducted of private forest landowners in the United States. Data contained in version 5 were collected in all states from 2011 to 2013. The NWOS includes questions regarding landowner familiarity with and enrollment in state-specific PFPTPs,[3] and the extent of the landowner's concerns for their land, including high property taxes.[4] Other relevant data collected through the NWOS include characteristics of landowners and their forest land, reasons for ownership, past and intended future land management practices and uses, and other attitudes and concerns (Butler et al., 2016a Appendix 1). Data from corporate, non-governmental organization, unincorporated partnerships/associations/clubs, and Native American land on reservations were screened out to focus on FFOs only.

The NWOS sample frame utilizes the plots sampled by the USDA Forest Service's Forest Inventory and Analysis (FIA) program[5] (Butler et al., 2016a). Based on these FIA sample plots, georeferenced land use and socio/economic characteristics of the area surrounding each NWOS respondent's plot were compiled (Butler et al., 2016a). Two variables indicative of the land surrounding each FIA plot were used: the proportion of the surrounding land base with a 0.6 mile (1 km) radius classified as agricultural use extracted from the 2011 National Land Cover Database (Homer et al., 2015), and census block population density per square mile (2.6 square km) obtained from the 2010 U.S. Census as a proxy for fair market value since greater population pressure increases land value (Heimlich and Anderson, 2001). We also included the square of population density because of conflicting incentives for enrollment under development pressure (described in more detail in separate section below on "Conflicting incentives for enrollment under development pressure").

State PFPTP programmatic administrative and structural characteristics that could affect enrollment were identified from Kilgore et al. (2018a, 2018b). The first programmatic variable included was the average annual tax reduction per acre (0.4 ha) for enrollees in a state.[6] Second was maximum number of years of back taxes that could be used to assess a penalty for early program withdrawal, which is related to the cost of withdrawal from enrollment. Third was whether the natural resource agency reviewed the landowner's enrollment application, which could cause delays or stricter enforcement of requirements, thus restricting enrollment. Fourth were whether the program imposed restriction on commercial uses and buildings or other development on enrolled lands, which would be associated with the stringency of preservation and indicative of limitations to management autonomy (e.g., restrictions on commercial operations associated with enrolled lands). Fifth was whether the program required a forest management plan for enrollment. Sixth was PFPTP emphasis on timber production, which may not align with woodland management objectives of many FFOs. A final programmatic variable used was whether or not the program has a minimum commitment period for enrollment.

Finally, there may be a variety of potential state-specific factors that affect enrollment, such as the legal, policy, and cultural context of a state. To control for this would require adding 44 dummy variables (45 states in the filtered dataset, minus one excluded), essentially tripling the number of independent variables. Also, some of the states have only a limited number of respondents in the filtered dataset (10 or fewer). Taken together, including state-specific fixed effects would risk overfitting the model. Our approach was to compromise by including dummy variables for each of four regions in the United States: North, South, Rocky Mountain, and Pacific Coast (excluding the dummy for the North Region for regression purposes). This is appropriate under the assumption that states within a region are more similar than they are to states in other regions with respect to the legal, policy, and cultural context, and other possible factors. The regional definitions are the same as those utilized in the USDA Forest Service's Resources Planning Act (RPA) Assessment[7] and Kilgore et al. (2017).

3.2. Data filters

The NWOS and associated data described above contained 10,109 observations. However, the NWOS includes responses from landowners which would not provide meaningful information for our purposes. It was necessary to filter out some of the observations to obtain consistent and meaningful responses for the current analysis. First, questions in the NWOS are not parcel-specific, so there is no way of attributing a specific action (e.g., conducted a timber harvest) to a specific parcel in cases where the landowner owns multiple parcels, so we applied a single-parcel filter. Second, PFPTPs often have eligibility criteria, the most basic of which typically is a forest area requirement, so we applied forest area filter(s) by state. A total of 3,850 respondents met these two data requirements; in addition, Arizona and Delaware had no information regarding average statewide PFPTP tax reduction (Kilgore et al., 2018a), so respondents from those two states were eliminated, leaving $n = 3,751$.

3.2.1. Single-parcel filter

Thirty percent of the NWOS respondents in the data set owned multiple parcels in the same state. Landowners owning multiple parcels in the state for which they answered the NWOS questionnaire were filtered out. Owners of multiple parcels are different than single-parcel owners in some respects (Kilgore et al., 2015), so the results of our research should only be considered valid for single-parcel owners.

3.2.2. Forest area filter

We filtered out records with forestland area too small or too large to be eligible in their state's PFPTP, using area eligibility criteria from Kilgore et al. (2017) (Table A1 [Appendix]). When states had multiple PFPTPs with different forest area requirements, the program with the highest enrollment in the state was used to set the data filter.

[3] NWOS Question 19 states, "Some state and local governments have programs that defer, reduce, or eliminate property taxes for wooded land. In [STATE], there is the [PROGRAM NAME] program. "How familiar are you with this program? ANSWERS: 5 – Extremely familiar; 4 – Moderately familiar; 3 – Somewhat familiar; 2 – Slightly familiar; 1 – Not at all familiar "Is any of your wooded land in [STATE] currently enrolled in this program or a similar one? ANSWERS: 1 – Yes; 0 – No; 9 – Don't know"

[4] NWOS Question 26 states, "Please indicate your level of concern about each of the following topics for your wooded land in [STATE]. TOPICS: Air pollution; Damage or noise from off-road vehicles; Damage from animals; Development of nearby lands; Drought or lack of water; Global climate change; High property taxes; Invasive plant species; Keeping land intact for future generations; Misuse of wooded land, such as vandalism or dumping; Trespassing or poaching; Unwanted insects or diseases; Water pollution; Wildfire; Wind or ice storms; Other. "ANSWERS: 5 – Great concern; 4 – Concern; 3 – Moderate concern; 2 – Of little concern; 1 – No concern; 8 – Not applicable"

[5] That is, the FIA program measures forest characteristics in sampled forest plots, and the NWOS asks questions of the owners of those plots, if determined to be privately owned.

[6] The average annual tax reduction per acre is calculated by subtracting the annual per acre tax liability for forest land enrolled in a PFPTP from the annual per acre tax liability in a nonpreferential tax program for such property (such as an agricultural cropland property tax program) (Kilgore et al., 2018a)

[7] See RPA regional definitions at https://www.fs.fed.us/research/rpa/regions.php. [Date accessed 7 May 2019]. See Table 2 for list of states in each region.

Table 2
Summary of variables used in the analysis.

Variable	Description	Source [1]	Hypothesized Effect
Dependent variable			
Enrollment	Parcel is enrolled in a PFPTP program that defers, reduces, or eliminates property taxes for wooded land. Binary: yes = 1, no = 0.	NWOS	N/A
Landowner characteristics			
Familiar	Level of familiarity with the state program that defers, reduces, or eliminates property taxes for wooded land. Categorical from 'Not at all familiar' = 1 to 'Extremely familiar' = 5.	NWOS	Positive
Familiar binary	Level of familiarity with the state program that defers, reduces, or eliminates property taxes for wooded land. Binary: 'Not at all familiar' = 0, 'Slightly familiar' or greater = 1.	NWOS	Positive
Education	Highest degree or level of school completed of primary owner. Categorical from 'Less than high school' = 1 to 'Advanced degree' = 6.	NWOS	Positive
Income	Household annual income. Categorical from 'Less than $25,000' = 1 to '$200,000 or more' = 5.	NWOS	Positive
Income from Woods	Average percentage of household annual income derived from wooded land. Continuous.	NWOS	Positive
Age	Age of primary owner in years. Continuous.	NWOS	Ambiguous
Timber Objective	Importance of timber products, such as logs or pulpwood, as a reason for owning wooded land. Categorical from 'Not important' = 1 to 'Very important' = 5.	NWOS	Positive
Investment Objective	Importance of land investment as a reason for owning wooded land. Categorical from 'Not important' = 1 to 'Very important' = 5.	NWOS	Positive
Wildlife Objective	Importance of protecting or improving wildlife habitat as a reason for owning wooded land. Categorical from 'Not important' = 1 to 'Very important' = 5.	NWOS	Positive
Want Stay Wooded	Landowner wants his/her wooded land to stay wooded. Categorical from 'Strongly disagree' = 1 to 'Strongly agree' = 5.	NWOS	Positive
Development Concern	Level of concern about development of nearby lands. Categorical from 'No concern' = 1 to 'Great concern' = 5.	NWOS	Positive
Tax Concern	Level of concern about high property taxes. Categorical from 'No concern' = 1 to 'Great concern' = 5.	NWOS	Positive
Heirs Concern	Level of concern about keeping land intact for future generations Categorical from 'No concern' = 1 to 'Great concern' = 5.	NWOS	Positive
Absentee	Absentee landowner. Binary: Primary residence not within one mile (1.6 km) of any of the owner's wooded land in the state = 1, Otherwise = 0. [2]	NWOS	Negative
Land characteristics			
ln(Area)	Natural logarithm of the total acres (1 acre = 0.4 ha) of wooded land owned in the state. Continuous.	NWOS	Positive
Purchased	Wooded land was acquired by purchasing (rather than inherited or received as gift) Binary: yes = 1, no = 0.	NWOS	Positive
Years Owned	Number of years landowner has owned wooded land. Continuous.	NWOS	Positive
Surrounding Agriculture Land	Proportion of land that is agricultural crop or pasture land within a 0.6 mile (1 km) radius of respondent's wooded land. Continuous.	NLCD	Negative
Population Density	Number of people per square mile (2.6 square km) within census block group. Continuous.	Census	Positive
Population Density Squared	Square of Population Density. Continuous.	Census	Negative
Program characteristics			
Average Tax Reduction	Average annual statewide PFPTP tax reduction, $ per acre (1 acre = 0.4 ha). Continuous. State-level variable.	Kilgore et al. (2017)	Positive
Withdrawal Penalty Years	Maximum number of years a retroactive monetary penalty could be assessed for early program withdrawal. Continuous. State-level variable.	Kilgore et al. (2017)	Negative
Application Review	Natural resource agency reviews enrollment application. Binary: yes = 1, no = 0. State-level variable.	Kilgore et al. (2017)	Negative
Commercial Use Restricted	Restrictions of some commercial use (e.g., ag, mining, or commercial development) on enrolled property. Binary: yes = 1, no = 0. State-level variable.	Kilgore et al. (2017)	Negative
Building Restricted	Restrictions on residence/ buildings on enrolled property. Binary: yes = 1, no = 0. State-level variable.	Kilgore et al. (2017)	Negative
Management Plan Required	Forest management plan required for enrollment. Binary: yes = 1, no = 0. State-level variable.	Kilgore et al. (2017)	Negative
Program Timber Emphasis	Emphasized justification for program existence, as described in state law, is timber production. Binary: yes = 1, no = 0. State-level variable.	Kilgore et al. (2017)	Negative
Minimum Commitment Period	Program imposes a minimum commitment period. Binary: yes = 1, no = 0. State-level variable.	Kilgore et al. (2017)	Negative
Region [3]			
South Region	States of: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia		Ambiguous
Rocky Mountain Region	States of: Arizona [4], Colorado, Idaho, Kansas, Montana, Nebraska, Nevada [4], New Mexico, North Dakota, South Dakota, Utah, Wyoming		Ambiguous
Pacific Coast Region	States of: Alaska [4], California, Hawaii [4], Oregon, Washington		Ambiguous

[1] NWOS = National Woodland Owner Survey version 5 (2011–2013) (see: Butler et al., 2016a); NLCD = 2011 National Land Cover Database (see: Homer et al., 2015; Xian et al., 2011); Census = 2010 U.S. Census.

[2] Note that we reverse the NWOS structure here, for which presence of the home is coded as yes = 1, because we chose to use absence, rather than presence, of the home as the indicator, consistent with past literature that discusses absenteeism.

[3] North Region omitted for estimation purposes. States of: Connecticut, Delaware, Illinois, Indiana, Iowa, Maine, Maryland, Massachusetts, Michigan, Minnesota, Missouri, New Hampshire, New Jersey, New York, Ohio, Pennsylvania, Rhode Island, Vermont, West Virginia, Wisconsin.

[4] The following states either had no respondents in the filtered sample, or had insufficient information about the state property tax program to include in the regression: Alaska, Arizona, Delaware, Hawaii, Nevada.

3.3. Multiple imputation for missing values

As is common in surveys, some NWOS respondents did not respond to one or more questions, leaving missing data for some variables. Of the 3,751 respondents after data filtering, 1,838 (49%) were missing data for one or more variables used in our analysis. Standard regression procedures would simply delete those respondents from the sample. To avoid potential bias due to differences in respondents who answer all questions and those who do not, we used a multiple imputation procedure to fill missing values with statistically-unbiased values (Rubin, 1987, 1996). Such procedures have been used successfully in the past with NWOS data (e.g., Song et al., 2014a). By imputing multiple random values from a distribution for each missing value, this approach imitates the uncertainty inherent in the unobserved information.

Because the missing data involved numerous variables and was non-monotonic in nature, we utilized a multivariate normal Markov-Chain Monte Carlo data augmentation approach (Li, 1988; Schafer and Olsen, 1998). Five imputed values were generated for each of the missing observations. These imputations were then combined for the final logistic regression, adjusting coefficients and standard errors based on the variability between the imputations, using rules described in Rubin (1987, p. 77). A robustness check was performed by estimating the logistic regression models described below without multiple imputation and discarding respondents with missing data.

3.4. Endogeneity of variables

One of the variables considered to be a potentially important predictor of enrollment in PFPTPs was level of familiarity with the program. Understanding the effect of level of familiarity on enrollment could have policy implications, as it might indicate whether outreach/educational programs could be effective at drawing more enrollment. However, this variable likely is endogenous. That is, landowners are more likely to enroll when they are familiar with a program, and are more likely to be familiar with a program if they enroll. This would be a case of simultaneity, with each variable (familiarity and enrollment) affecting the other. This endogeneity of the level of familiarity with the program could cause biased results (Wooldridge, 2006), invalidating its use to understand cause-and-effect with enrollment.

The standard method to deal with endogenous variables in cross-sectional data is to utilize an instrumental variable that is correlated with the endogenous explanatory variable, but not otherwise related to the dependent variable (Wooldridge, 2006). After reviewing various potential variables in the NWOS and other sources, none were found to serve as instruments. That is, all variables that could be correlated with level of familiarity were also thought potentially to be correlated with enrollment through other pathways.

Simply omitting the potentially endogenous variable could cause bias as well. To the extent that other explanatory variables are correlated with the omitted variable, and thus potentially correlated with the error term, those other explanatory variables would be biased (omitted variable bias). It is therefore necessary to control for the endogenous term in the equation, even if the coefficient for that single variable is biased (in order to avoid bias on other coefficients). Williams et al. (2004) describes how creating a model of enrollment and ignoring the effect of familiarity with the program can confound the enrollment decision with the revelation of information to the individual.

We used two alternative approaches to deal with this endogenous variable. The first is simply to include all five levels of familiarity with the PFPTP, but not ascribe any particular meaning to the (potentially biased) coefficient of that variable. The reason for including the variable in this case is simply to control for its effects on other variables. The purpose of this model is to understand how the other variables are related to the likelihood to enroll, while holding familiarity with the program constant.

The second approach is to include the familiarity variable only as a 0/1 binary explanatory variable with 'not at all familiar' coded as 0 and anything greater (at least 'slightly familiar') as 1. This is done under the assumption that the initial step in gaining familiarity (from 'not at all familiar' to 'slightly familiar') represents an exogenous shock, rather than endogenous. This assumption would hold true if the first step in familiarity from not at all to slightly familiar represents simply knowing that such a program exists, which is caused by randomly becoming aware of the program from some external source without seeking out the information. However, this would not be true if the likelihood of hearing about the program is not random, but somehow caused by other unmeasured factors related to likelihood of enrollment. One potential example would be if unlikely enrollers and likely enrollers tend to receive information from different sources, which have different probabilities of informing the landowner about the program. Additionally, a weakness of this model is that it could be partially susceptible to the omitted variable bias because not all the levels of familiarity are included in the model.

Because virtually no landowners stated that they were enrolled in the program and also had no familiarity with the program, this approach is consistent with treating it like a program eligibility requirement, rather than as an explanatory variable. This is essentially saying that in order to enroll in a PFPTP, you have to at least know it exists first (at least 'slightly familiar').This is consistent with approaches such as Williams et al. (2004), which first filter out respondents based on whether or not they are at least slightly familiar with the program, before employing the enrollment model.

To be clear, we believe that the first model (with the full familiarity variable) will be more likely to have unbiased estimates for the remaining (exogenous) explanatory variables, whereas the second model will be more likely to have an unbiased (or less biased) estimate for the familiarity (endogenous) explanatory variable.

Other independent variables in our model are potentially endogenous, as well. Most notably, one could imagine a scenario in which enrollment in a program, over time, affects a respondent's objectives and concerns for the property. If this were true, these objectives and concerns for the property would be more strongly correlated with enrollment than their true causative effect.

3.5. Conflicting incentives for enrollment under development pressure

By their nature, PFPTPs only are available to benefit landowners as long as their land remains forested. In most cases, since the property tax on non-enrolled land is related to its highest and best use fair market value, and the tax on enrolled land is related to its value as forest land, the largest tax reductions are given to those lands where development pressure, and thus fair market land values, are the highest. On the other hand, many PFPTPs impose penalties for withdrawal from the program (e.g., to convert the land to developed uses) (Kilgore et al., 2018b). Often, these penalties are correlated with the cumulative tax savings provided to the landowner while enrolled (Kilgore et al., 2018b). If development of the land is foreseen (or kept as an option) in the relatively near future, the present value of potential future costs of withdrawal could be high relative to the benefits of enrollment. However, if withdrawal is seen in the more distant future, the present value of those future costs would be relatively small.

This creates conflicting incentives for forestland where development is a real potential possibility in the near future – those landowners have the most tax reduction to gain, but also the highest present value of the costs of withdrawal. We hypothesize these conflicting incentives could cause a non-linear response in enrollment to development pressure. Enrollment may be low for land where there are few alternative higher-value land uses to forestry and therefore receive a modest tax reduction, thereby providing little incentive to enroll. Enrollment may also be low for forest land where development pressure is high and landowners anticipate capitalizing on high land prices in the near future. Enrollment may be highest on forest lands somewhere in the middle where the tax reduction is moderate, but development is not anticipated in the near future. For this reason, we constructed the regression model using both population data and its square term to accommodate a non-linear response. We anticipate that the coefficient on population density will be positive, but the coefficient on population density squared will be negative.

3.6. Logistic regression analysis

Binomial logistic regression using maximum likelihood estimation (MLE) procedures in SAS 9.4 was used to identify statistically significant factors that are associated with a landowner's decision to participate in a PFPTP. Significance was identified at $\alpha = 0.1$, 0.05, and 0.01 levels. Binomial logistic regression assigns probabilities to each of the two possible outcomes. For a binary response variable Y and a vector of explanatory variables X, these probabilities are (Cox and Snell, 1989; Mehmood and Zhang, 2005):

$$prob(Y_i = 1 | X_i) = \theta_i = \frac{e^{X_i B}}{1 + e^{X_i B}} \tag{1}$$

$$prob(Y_i = 0 | X_i) = 1 - \theta_i = 1 - \frac{e^{X_i B}}{1 + e^{X_i B}} = \frac{1}{1 + e^{X_i B}} \tag{2}$$

where θ_i represents the probability of a landowner, i, from the set of eligible landowners, having participated in a PFPTP given the values of the explanatory variables X_i; B is a vector of regression coefficients, and e is the exponential function.

Logistic regression utilizes maximum likelihood estimation. The coefficient estimates in a logistic regression do not carry the implication of per unit impact typically ascribed in ordinary least squares regression. The odds ratio, however, is constant across values of the explanatory variables, and allows for comparison between variables. The odds ratio, OR_j, is the relative change in the relative probability of success to failure (the "odds") for a one unit change in one of the explanatory variables, x_j, holding other variables constant (Peng et al., 2002):

$$Odds = \frac{\theta}{1 - \theta} = e^{XB} \tag{3}$$

$$OR_j = \frac{Odds(x_j = x_{ij})}{Odds(x_j = (x_{ij} - 1))} = e^{\beta_j} \tag{4}$$

4. Results

Tables 3–5 report results indicating statistical significance alternately at the 0.1, 0.05, and 0.01 alpha-levels. In these results and discussion, however, we generally consider statistical significance to be evaluated at the 0.05 alpha-level.

4.1. Data, data filters, and level of familiarity with PFPTP

After filtering the data for ownership of a single parcel and eligibility for the PFPTP based on size of the landholding, 1,752 (46%) of 3,850 respondents were at least slightly familiar with the PFPTP in their state, and 1,088 (28%) were enrolled in the PFPTP in their state. Of those who were at least slightly familiar, 62% were enrolled.

Table 3 presents mean values of the respondent-level (i.e., not state-level) explanatory variables for PFPTP enrollment comparing landowners who were at least 'slightly familiar' with 'not at all familiar', and comparing those enrolled with not enrolled. There were statistical differences in the mean values of those familiar/not familiar for variables within the landowner and land characteristic variable categories. This finding demonstrates correlation between level of familiarity and several other variables and, thus, the importance of including the level of familiarity variable in the logistic regression model in order to avoid omitted variable bias with the coefficients of the other explanatory variables. The results for enrollees versus non-enrollees demonstrates the need for regression to understand the effects of individual variables on enrollment.

Landowners who were at least slightly familiar with their PFPTP on average had higher education and income levels, were younger, were more concerned about taxes and development of the surrounding land, and ranked timber production higher as a woodland management objective than owners who were not at all familiar. Owners who were familiar, on average, more strongly agreed that they want their wooded land to stay wooded. Similarly, enrollees on average had higher levels of education and income; concern about development and taxes; and objectives of timber, wildlife, and their wooded land staying wooded than non-enrollees.

Characteristics of the land differed significantly between owners who were familiar and not familiar. Familiar landowners, on average, had larger forest area, were more likely to have purchased the land, had owned the land longer, and had less agricultural land around their forest land. Enrollees on average had larger land area, less agricultural land nearby, and were located near higher population densities than non-enrollees.

Pearson's correlation coefficients were calculated for the explanatory variables of the logistic regression to check for potential issues arising from multicollinearity. With a few exceptions, none of the absolute values of the correlation coefficients were greater than 0.5. The exceptions were age with years owned (0.54), years of penalty for withdrawal with agency review of application (0.56), and population density with population density squared (0.88).

4.2. Logistic regression analysis

The first regression analysis (Table 4) was conducted using all five levels of PFPTP familiarity as one of the explanatory variables. As noted earlier, causal meaning cannot be ascribed to the familiarity coefficient, but its inclusion eliminates a potential source of (omitted variable) bias for the coefficients of the other variables.

From a general standpoint, we note that relatively few of the landowner-related variables had statistically significant effects, whereas several of the land- and program-related variables did. Utilizing a 0.05 alpha-level, desire for wooded land to stay wooded was the only landowner characteristic that was statistically significant, being related to higher likelihood of enrollment. However, we remind the reader that there is a possibility of endogeneity with this variable as well, so this correlation should not be interpreted as causation. Level of landowner education, income, age, concern about taxes or development, and various landholding objectives were not statistically significant at the 0.05 alpha-level. Because endogeneity would have the effect of making the correlation stronger, this lack of statistical significance would stand even if those variables were endogenous.

Forested area, number of years owned, and population density and its square term were correlated with likelihood of enrollment. Landholding size (natural logarithm of wooded acres [1 acre = 0.4 ha]) was positively related to likelihood of enrollment. Years of ownership was negatively correlated to likelihood of enrollment, with an additional year of ownership decreasing the relative odds of enrollment by over 1%. Population density was positively correlated with likelihood of enrollment while the square term was negatively correlated. Having purchased the land (versus inheriting or receiving as a gift), and proportion of surrounding land that is agricultural, were not linked to likelihood of enrollment.

Several PFPTP characteristics examined in our analysis were found to be associated with likelihood of enrollment. However, the variable related to the average financial benefit (statewide average annual PFPTP tax reduction) was not among them. Restrictions on commercial use of the land and the existence of a minimum commitment period were also not correlated with likelihood of enrollment. By contrast, other program characteristics had significant effects. Review of the

Table 3
T-test for statistical differences of mean values of variables hypothesized to be predictors of preferential forest property tax program (PFPTP) enrollment for landowners who were at least 'slightly familiar' versus 'not at all familiar'; and for those enrolled versus not enrolled. Respondents have been screened to remove those with multiple parcels and those who do not meet minimum PFPTP forest area requirements in their state. n = 3,850.

Category/Variable	At Least Slightly Familiar	Not At All Familiar	Pr > |t|	Enrolled	Not Enrolled	Pr > |t|
Landowner characteristics						
Education	4.09	3.58	< .001***	4.23	3.65	< .001***
Income	3.01	2.83	< .001***	3.07	2.85	< .001***
Income from Woods	3.28	2.64	.092*	3.39	2.75	.136
Age	63.2	64.2	.019**	63.7	63.8	.866
Timber Objective	3.13	2.65	< .001***	3.25	2.72	< .001***
Investment Objective	3.32	3.36	.362	3.33	3.34	.848
Wildlife Objective	4.19	4.18	.609	4.25	4.16	.016**
Stay wooded	4.52	4.43	< .001***	4.58	4.43	< .001***
Development Concern	3.27	3.10	< .001***	3.29	3.13	.002***
Tax Concern	4.24	4.15	.009***	4.26	4.16	.021**
Absentee	0.39	0.42	.055*	0.41	0.41	.923
Land characteristics						
ln(Area)	4.52	4.16	< .001***	4.68	4.18	< .001***
Purchased	0.75	0.72	.025**	0.73	0.73	.830
Years Owned	26.0	24.7	.026**	25.8	25.1	.270
Surrounding Agriculture Land	0.17	0.23	< .001***	0.15	0.22	< .001***
Population Density	74.5	66.6	.086*	86.2	63.9	< .001***

*, **, *** represent statistically different mean values at the 0.1, 0.05, and 0.01 alpha-levels, respectively.

Table 4
Logistic regression model, including the full variable for familiarity with state property tax program. The dependent variable is enrollment in the state property tax program. n = 3,751.

	Coefficient	Odds Ratio	t	p-value
Landowner characteristics				
Familiar	1.761***	5.819	29.058	0.000
Education	0.021	1.021	0.428	0.669
Income	−0.044	0.957	−0.604	0.546
Income from Woods	−0.010	0.990	−1.510	0.133
Age	0.015*	1.015	1.917	0.059
Timber Objective	0.060	1.062	0.982	0.329
Investment Objective	−0.034	0.966	−0.592	0.554
Wildlife Objective	−0.081	0.922	−1.065	0.287
Want Stay Wooded	0.198**	1.219	2.000	0.046
Development Concern	−0.023	0.977	−0.409	0.683
Tax Concern	−0.039	0.962	−0.575	0.565
Heirs Concern	0.055	1.056	0.762	0.446
Absentee	0.169	1.184	1.175	0.240
Land characteristics				
ln(Area)	0.158***	1.172	2.794	0.005
Purchased	−0.104	0.901	−0.644	0.520
Years Owned	−0.015**	0.985	−2.589	0.011
Surrounding Agriculture Land	−0.420	0.657	−1.118	0.264
Population Density	0.006***	1.006	5.222	0.000
Population Density Squared	-3.2×10^{-6}***	1.000	−3.280	0.001
Program characteristics				
Average Tax Reduction	−0.001	0.999	−0.177	0.860
Withdrawal Penalty Years	0.024***	1.024	3.034	0.002
Application Review	−1.025***	0.359	−4.905	0.000
Commercial Use Restricted	−0.201	0.818	−1.100	0.272
Building Restricted	−0.307**	0.736	−2.041	0.041
Management Plan Required	−0.369**	0.692	−2.180	0.029
Program Timber Emphasis	−0.705***	0.494	−4.449	0.000
Minimum Commitment Period	−0.070	0.933	−0.356	0.722
Region				
South Region	−0.383	0.682	−1.578	0.115
Rocky Mountain Region	−1.168***	0.311	−2.635	0.008
Pacific Coast Region	0.003	1.003	0.008	0.993
Constant	−6.613***	0.001	−8.546	0.000
F-statistic	30.98***			0.000

*, **, *** represent statistical significance at the 0.1, 0.05, and 0.01 alpha-levels, respectively.

Table 5
Logistic regression model, including the binary variable for familiarity with state property tax program (1 = at least 'slightly familiar'; 0 = 'not at all familiar'). The dependent variable is enrollment in the state property tax program. n = 3,751.

	Coefficient	Odds Ratio	t	p-value
Landowner characteristics				
Familiar Binary	6.014***	409.186	15.430	0.000
Education	0.059	1.061	1.460	0.146
Income	0.048	1.049	0.736	0.464
Income from Woods	−0.005	0.995	−0.773	0.443
Age	0.008	1.008	1.222	0.229
Timber Objective	0.155***	1.167	3.237	0.001
Investment Objective	−0.003	0.997	−0.071	0.943
Wildlife Objective	0.054	1.055	0.842	0.400
Want Stay Wooded	0.325***	1.384	3.850	0.000
Development Concern	−0.026	0.974	−0.552	0.581
Tax Concern	−0.017	0.983	−0.292	0.771
Heirs Concern	0.069	1.071	1.163	0.245
Absentee	0.129	1.138	1.080	0.280
Land characteristics				
ln(Area)	0.221***	1.248	4.496	0.000
Purchased	−0.105	0.900	−0.773	0.440
Years Owned	−0.009*	0.991	−1.911	0.059
Surrounding Agriculture Land	−0.192	0.825	−0.628	0.530
Population Density	0.005***	1.005	5.061	0.000
Population Density Squared	−2.10E-06**	1.000	−2.318	0.020
Program characteristics				
Average Tax Reduction	0.002	1.002	0.379	0.705
Withdrawal Penalty Years	0.031***	1.032	4.899	0.000
Application Review	−0.890***	0.411	−5.289	0.000
Commercial Use Restricted	−0.328**	0.720	−2.168	0.030
Building Restricted	−0.181	0.834	−1.454	0.146
Management Plan Required	−0.437***	0.646	−3.181	0.001
Program Timber Emphasis	−0.666***	0.514	−5.069	0.000
Minimum Commitment Period	−0.066	0.936	−0.420	0.674
Region				
South Region	−0.708***	0.493	−3.508	0.000
Rocky Mountain Region	−1.574***	0.207	−4.022	0.000
Pacific Coast Region	−0.430	0.651	−1.412	0.158
Constant	−8.563***	0.000	−11.040	0.000
F-statistic	13.95***			0.000

*, **, *** represent statistical significance at the 0.1, 0.05, and 0.01 alpha-levels, respectively.

application by a state natural resource agency, restrictions on buildings on the property, requiring a forest management plan, legal emphasis on commercial timber production all were associated with lower likelihood of enrollment. The characteristic with the largest magnitude effect on likelihood of enrollment was review of application. The odds of enrollment in a state with application review was about 36% the odds of enrolling in a state with no application review, all else equal. Similarly, the odds ratios for building restrictions and timber programmatic emphasis were 69% and 49%, respectively. By contrast, increasing penalty for withdrawal actually had the effect of increasing likelihood of enrollment, all else equal. Increasing the penalty by one year's worth of tax reduction has the effect of increasing the odds of enrollment by 3%.

Among regions, respondents in the Rocky Mountain Region had lower likelihood of enrolling in a state PFPTP than those in the North Region. The South and Pacific Coast Regions were not statistically different than the North Region.

The second model (Table 5) includes familiarity with the PFPTP as a binary variable, with not at all familiar coded as 0, and at least slightly familiar as 1. In this model the assumption would be that the transition from not at all to at least slightly familiar with the state's PFPTP represents some type of random, exogenous shock. While the coefficient on the familiarity binary variable is significant and its odds ratio extremely large (i.e., the odds of landowners with at least some familiarity enrolling is 536 times the odds of enrollment among landowners with no familiarity), some caution about inferring causality is due.

The coefficients for the other explanatory variables in Table 5 may be considered to be more likely to be biased than those from the model presented in Table 4 because of potential omitted variable bias; however, we present the full results for completeness. In general the results of the model with the binary familiarity variable (Table 5) were consistent with the model with the full familiarity variable (Table 4); however, a few different variables were statistically significant. The differences in the second model are principally the following: Among landowner characteristics, timber objective was correlated with higher likelihood of enrollment, while age was not correlated with enrollment. Among program characteristics, restrictions on commercial use was correlated with lower likelihood of enrollment, but restrictions on building were not correlated.

Among regions, respondents in the Rocky Mountain and South Regions had lower likelihood of enrolling in a state PFPTP than those in the North Region. The Pacific Coast Region was not statistically different than the North Region.

A robustness check was performed on the multiple imputations by estimating the logistic regression without multiple imputation and discarding respondents with missing data (Tables A2 and A3 [Appendix]). These models without imputation show relatively minor differences from Tables 4 and 5, and do not change the general conclusions. Of the statistically-significant variables, none changed sign in either model. In model with the full familiarity variable (Tables 4 and A2), only one variable that was statistically significant in the model with imputations became insignificant (withdrawal penalty years) without imputations. In the model with the binary familiarity variable (Tables 5 and A3), two significant variables became insignificant (timber objective and commercial use restricted), and one insignificant became significant (building restricted).

5. Discussion and conclusions

To our knowledge, this research is the first to model factors associated with enrollment in preferential forest property tax programs (PFPTPs) at the national level. Past research has been conducted at the state level, but with often inconsistent results (Table 1). Our research broadens the understanding of these factors and, importantly, allows for comparisons of program characteristics across states, which had been relatively unexplored to date.

Past research in individual states has found some landowner characteristics to be statistically correlated with enrollment, even though consistent relationships across studies have been elusive (Table 1). We found few of the characteristics related to landowner demographics, objectives, and concerns were linked to likelihood of enrollment (Tables 4 and 5), which was unexpected (Table 2). For example, we hypothesized that more concern about the levels of development or taxes in particular would be more common among those enrolled in a program designed to reduce development pressure and high taxes (Fortney et al., 2011), but apparently is not. Of these, concern about taxes is perhaps the most surprising. One explanation for this might be related to the opportunity cost associated with enrolling in a PFPTP. With the level of taxation derived from the land's market value, one would expect the forest land owned by those most concerned about property taxes to have high development value. For these landowners, enrolling in a PFPTP that requires the land to be kept in a forested condition means forgoing the opportunity to capture this development potential.

Further, investment and timber forest ownership objectives, which were hypothesized to be related to enrollment since those landowners presumably place value on monetary outcomes and would want to lower costs, were also insignificant. One possible explanation is that some states have programs that encourage enrollment of landowners with those characteristics, while other PFPTPs do not – such a situation could make the overall signal statistically insignificant. This, along with the fact that the desire for wooded land to stay wooded was positively correlated and that programs with a timber emphasis were negatively correlated with likelihood of enrollment, suggests that enrollees who are interested in non-financial amenities of forests may be more likely to enroll. FFOs tend to value and own their forest land for multiple reasons, with non-timber production reasons usually rating higher in importance than timber production goals (Butler et al., 2016b, c). Thus, our findings suggest that PFPTPs which are designed to be more in alignment with FFO goals for amenity attributes and uses of their land might see greater enrollment. In addition, more information that illustrates how active timber management and production, which are common requirements of timber-focused PFPTPs, could be implemented to support amenity aspects of ownership (potentially including forest health) might also be a way to facilitate greater enrollment in PFPTPs.

If concern for forest land taxes truly has no association with PFPTP participation, then a reduction in taxes as an incentive to participate in a PFPTP may not be effective. Alternative incentive vehicles such as direct financial payment for participation, or free or cost shared services aimed at addressing FFO objectives such as wildlife habitat might be viewed more favorably.

On the other hand, some land characteristic variables seemingly linked to financial outcomes are linked to enrollment. Consistent with past empirical studies (Kilgore et al., 2008b; Ma et al., 2012; Wolde et al., 2016), forested area was positively related to enrollment, even when controlling for level of familiarity with the program, which is consistent with past research (Table 1) and our hypothesis that a larger landholding will see a larger total financial benefit from enrollment and thus more likely to be enrolled. It could also be a function of larger ownerships having a greater propensity to undertake land management activities and participate in conservation and assistance programs in general (Beach et al., 2005), and perhaps greater attention from forestry professionals and program managers.

A few variables that could be related to financial benefit of participation were significant predictors, including population density around the landholding and size of the landholding. Higher population density would increase the financial benefit of enrolling, but also the penalties for withdrawal; size of landholding would increase the absolute amount of the financial benefit of enrolling. Despite being consistently negatively correlated with enrollment in past state-level studies, acquisition of forest land through purchase was not statistically correlated with enrollment in our study.

Population density and its square term had the hypothesized effects on enrollment (Table 2; see also section on "Conflicting incentives for enrollment under development pressure") – density had a positive effect while the square term had a negative effect. This indicates a nonlinear response, with those landholdings surrounded by high and low population densities having the lowest likelihood of enrollment, while those in the middle with moderate population density the most likely to be enrolled. Conceptually, those owning forest land in areas with very low population densities have the least to gain from enrollment (since highest and best use values would be close to forest land values), and those whose land is in high population density areas have the most to lose from enrollment if they foresee development in the near future – thereby triggering penalties. Those owners of forest land in the middle may not see development as a likelihood in the near future, but still some reasonable financial benefit from enrolling. Past research has explored the effect of incentive values on FFO enrollment (Table 1), but never used a quadratic term to explore potential nonlinearity from conflicting financial incentives.

Among the PFPTP characteristics that we tested, the variable related to the average financial benefits of enrollment and costs (penalties) of withdrawal had unexpected findings. We expected that states with higher average tax reductions due to enrollment and lower penalties for withdrawal to have higher rates of enrollment overall (Table 2), but this was not the case. Average tax reduction was not linked to likelihood of enrollment, and withdrawal penalties were actually linked to higher likelihood of enrollment. It may be that any potential effects of average tax reduction are masked by the specific effects based on the value of individual properties. The counter-intuitive result that programs with larger penalties for withdrawal tend to be associated with greater likelihood of enrollment implies that some FFOs are actually attracted to programs that make it more difficult to change land uses in the future. This finding, coupled with the insignificance of the average program tax reduction and positive effect on enrollment of the desire for wooded land to stay wooded, may be an indication that some FFOs are using enrollment in PFPTPs as a means to help keep their forests as forests into the future rather than strictly as a way to lower tax rates. This finding is consistent with the idea that FFOs who value non-financial amenities and wish to protect forestland for the future are more likely to enroll. This is similar to findings by Fortney et al. (2011) that West Virginia forest owners identified a longer commitment period as a favorable change to their state's Managed Timberland program, and Miller et al. (2014) that FFOs wanted long-term restrictions on their land so that heirs or buyers would not develop the property in the future. Additional research that focuses on commitment periods and the associated financial costs of the withdrawal penalty for PFPTPs is needed to better understand how this may influence enrollment, as well as research on relationships between PFPTP participation and succession planning.

Variables related to the restrictiveness of the program (e.g., requirement of application review, building restrictions, forest management plan restrictions, timber emphasis) were negatively related to enrollment. For some FFOs, any reduction in management autonomy or flexibility of how their forestlands can be utilized may supersede the benefits of PFPTP participation. Moreover, previous research has found that some FFOs do not want the added oversight and/or administrative burden associated with enrolling in government-sponsored assistance programs (Daniels et al., 2010; Leahy et al., 2008). However, existence of a minimum commitment period was not linked to likelihood of enrollment.

Among regions, respondents in the Rocky Mountain and South Regions tended to be correlated with lower likelihood of enrollment across models, whereas Pacific Coast and North Regions had somewhat higher likelihood.

While this is the first national analysis of its type to model enrollment in PFPTPs, it does suffer from some inherent limitations. First, we did not have data on an individual landowner's financial benefit of PFPTP participation, so we had to utilize proxies including the average statewide financial tax reduction per unit of land area, and the population density around the tract. Population density may undervalue the tax reduction awarded to highly-valued lands in low population areas. One potential example of a misevaluation is in agrarian regions, where farmable land values may be high but populations may be low. Second, the NWOS provided data per landowner and not per parcel, so landowners with multiple parcels posed a particular problem because we could not attribute parcel characteristics. Therefore, we had to limit the analysis to FFOs with a single parcel. Third, an exogenous instrumental variable to control for the endogeneity of the level of familiarity with the tax program eluded us. Indeed it is difficult to conceive of a consistent instrument that is correlated with the level of familiarity but not potentially correlated with enrollment in some other way. One option might be distance from the landowner's home to a cooperative extension office or extension workshop. Distance to access various amenities has been used as an instrument for use of those amenities in past work (e.g., Card, 1993; Newhouse and McClellan, 1998). Finally, state-specific effects not included in our model might affect enrollment. We partially controlled for this by including regional-level dummies, under the assumption that states within a region are more similar than they are to states in other regions with respect to the legal, policy, and cultural context, and other possible factors. If this assumption does not hold, or if states vary significantly within region, our model may not effectively control state-level effects.

Future research might use an experimental or quasi-experimental design to explore a causal relationship between level of familiarity with a landowner program and enrollment in that program. For example, in a hypothetical experiment, participants of a landowner extension program could be randomly subdivided into two groups. The treatment group is taught about the PFPTP as well as other forestry topics, and the control group is taught about the other forestry topics but not the PFPTP. After a given period of time, the groups are surveyed to see if the treatment group has increased enrollment in the PFPTP relative to the control. In a hypothetical quasi-experiment two neighboring counties might be otherwise similar, but have different levels of forestry extension/education.

Another valuable research question to explore in the future is the extent to which PFPTPs affect actual FFO behavior. Do those who enroll make the same forest management and land use decisions that they would have anyway, or are the programs effective at stemming land use change, fostering good management, or generating economic or environmental benefits? For example, do programs with an emphasis on timber production generate more or higher quality timber, or additional logging or milling jobs?

Overall, landowner characteristics, including their concerns and objectives, were less frequently correlated with likelihood of enrollment than land and PFPTP characteristics. Furthermore, objectives and concerns that are most related to financial outcomes were typically not correlated with likelihood of enrollment. We believe that the overall outcomes of the regression models are suggestive of the idea that landowners with non-financial amenity reasons for owning forestland are those who are the most inclined to enroll.

Disclaimer

The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy.

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Appendix A

Table A1
Minimum and maximum area requirements for participation in preferential forest property tax programs (PFPTPs) by state, used to filter National Woodland Owner Survey (NWOS) responses. When states had multiple PFPTPs with different forest area requirements, the program with the highest enrollment in the state was used to set the data filter. Source: Kilgore et al. (2017).

State	PFPTP Program Name	Minimum Area Requirement (Acres)	Maximum Area Requirement (Acres)
Alabama	General Property Tax law	5	—
Alaska	General Revenue and Tax Laws (natural resource exemption)	—	—
Arizona	General State Property Tax law	—	—
Arkansas	General Property Tax Law(Assessment of Timberland	—	—
California	California Timberland Productivity Act	—	160
Colorado	General State Property Tax Law: Forest Land	40	—
Connecticut	Current Use Value Assessment (Public Act 490)	25	—
Delaware	Current Use Valuation and Commercial Forest Plantation Exemption	10	—
Florida	Agricultural Lands (Greenbelt Program)	—	—
Georgia	Conservation Use Valuation (CUVA)	—	—
Hawaii	General State Property Law (Agricultural Districts, Conservation Districts) Native Forest Dedication (County of Hawaii)	10	—
Idaho	General Property Tax Law: Forest Land	—	—
Illinois	Conservation Stewardship Act	5	—
Indiana	Classified Forest and Wildlands Program	10	—
Iowa	Forest and Fruit Tree Reservation Act	2	—
Kansas	Agricultural Property Tax Classification	—	—
Kentucky	General Property Tax Law: Timber	10	—
Louisiana	General Property Tax Law: Timberland	3	—
Maine	Tree Growth Tax Law	10	—
Maryland	Forest Conservation and Management Program	5	—
Massachusetts	Recreation Land Classification (61B)	5	—
Michigan	Commercial Forest Program	40	—
Minnesota	Managed Forest Land (Class 2c)	20	1920
Mississippi	General Property Tax Law	—	—
Missouri	State Forestry Law (Forest Cropland)	20	—
Montana	Forest Land Tax Act	15	—
Nebraska	General Property Tax Law: Agriculture and Horticulture Land (trees, timber)	—	—
Nevada	General Property Tax Law: Agriculture and Open Space Program	7	—
New Hampshire	Current Use Tax Law	10	—
New Jersey	Farmland Assessment Act	5	—
New Mexico	Agricultural Use Property Tax Law	1	—
New York	Real Property Tax Law	50	—
North Carolina	General Property Tax Law: Forest land	20	—
North Dakota	Forest Stewardship Tax Program	10	—
Ohio	Current Agricultural Use Value (CAUV)	10	—
Oklahoma	General Property Tax Law: Real Property (trees, timberland)	—	—
Oregon	Forestland Program	2	—
Pennsylvania	Farmland and Forest Land Assessment Act (Clean and Green Program)	10	—
Rhode Island	Farm, Forest and Open Space Act	10	—
South Carolina	Agricultural Real Property (trees, forestry)	5	—
South Dakota	General Property Tax Law: Agricultural Land (timber, woodland)	20	160
Tennessee	Forest land and Open Space	15	1500
Texas	Open Space Timberland	—	—
Utah	Farmland Assessment Act (Greenbelt Act)	5	—
Vermont	Managed Forest Land Use Value Appraisal Program	25	—
Virginia	General Property Tax Law: Forest Real Estate	20	—
Washington	Classified Timber and Forest Lands (Designated Forestland)	20	—
West Virginia	Timberland and Managed Timberland Program	10	—
Wisconsin	Managed Forest Law	10	—
Wyoming	Agricultural Use-Rangeland (timber)	—	—

— No known forest area requirement.

Table A2
Logistic regression model, including the full variable for familiarity with state property tax program, with no imputations (cf. Table 4). The dependent variable is enrollment in the state property tax program. n = 1,905.

	Coefficient	Odds Ratio	t	p-value
Landowner characteristics				
Familiar	1.891***	6.624	20.161	0.000
Education	0.011	1.011	0.165	0.869
Income	−0.120	0.887	−1.205	0.228
Income from Woods	−0.012	0.988	−1.256	0.209
Age	0.027***	1.028	2.728	0.006
Timber Objective	−0.054	0.947	−0.667	0.505
Investment Objective	−0.020	0.980	−0.258	0.796
Wildlife Objective	−0.016	0.984	−0.153	0.878
Want Stay Wooded	0.312**	1.367	2.180	0.029
Development Concern	−0.117	0.890	−1.462	0.144
Tax Concern	0.020	1.020	0.201	0.841
Heirs Concern	−0.076	0.926	−0.772	0.440
Absentee	0.416	1.517	2.063	0.039
Land characteristics				
ln(Area)	0.194**	1.215	2.290	0.022
Purchased	−0.268	0.765	−1.160	0.246
Years Owned	−0.021***	0.979	−2.715	0.007
Surrounding Agriculture Land	0.225	1.252	0.430	0.667
Population Density	0.006***	1.006	3.791	0.000
Population Density Squared	−3.39E-06**	1.000	−2.307	0.021
Program characteristics				
Average Tax Reduction	0.004	1.004	0.400	0.689
Withdrawal Penalty Years	0.011	1.011	0.940	0.347
Application Review	−1.417***	0.242	−4.849	0.000
Commercial Use Restricted	−0.065	0.937	−0.251	0.801
Building Restricted	−0.401*	0.670	−1.894	0.058
Management Plan Required	−0.499**	0.607	−2.065	0.039
Program Timber Emphasis	−0.726***	0.484	−3.230	0.001
Minimum Commitment Period	−0.020	0.980	−0.074	0.941
Region				
South Region	−0.538	0.584	−1.652	0.099
Rocky Mountain Region	−1.227*	0.293	−1.950	0.051
Pacific Coast Region	−0.102	0.903	−0.218	0.828
Constant	−7.130***	0.001	−6.514	0.000
F-statistic				

*, **, *** represent statistical significance at the 0.1, 0.05, and 0.01 alpha-levels, respectively.

Table A3
Logistic regression model, including the binary variable for familiarity with state property tax program (1 = at least 'slightly familiar'; 0 = 'not at all familiar'), with no imputations (cf. Table 5). The dependent variable is enrollment in the state property tax program. n = 1,905.

	Coefficient	Odds Ratio	t	p-value
Landowner characteristics				
Familiar Binary	6.216***	500.605	10.446	0.000
Education	0.074	1.077	1.423	0.155
Income	0.013	1.013	0.160	0.873
Income from Woods	−0.002	0.998	−0.307	0.759
Age	0.010	1.010	1.267	0.205
Timber Objective	0.101	1.106	1.576	0.115
Investment Objective	0.023	1.023	0.372	0.710
Wildlife Objective	0.117	1.124	1.370	0.171
Want Stay Wooded	0.533***	1.704	4.398	0.000
Development Concern	−0.104	0.901	−1.598	0.110
Tax Concern	0.020	1.020	0.250	0.802
Heirs Concern	−0.007	0.993	−0.088	0.930
Absentee	0.211	1.235	1.284	0.199
Land characteristics				
ln(Area)	0.252***	1.287	3.602	0.000
Purchased	−0.100	0.904	−0.531	0.596
Years Owned	−0.011*	0.989	−1.791	0.073
Surrounding Agriculture Land	0.079	1.083	0.187	0.852
Population Density	0.006***	1.006	4.054	0.000
Population Density Squared	−2.39E-06*	1.000	−1.867	0.062

(*continued on next page*)

Table A3 (*continued*)

	Coefficient	Odds Ratio	t	p-value
Program characteristics				
Average Tax Reduction	0.009	1.009	0.978	0.328
Withdrawal Penalty Years	0.031***	1.032	3.388	0.001
Application Review	−1.380***	0.252	−5.783	0.000
Commercial Use Restricted	−0.043	0.958	−0.194	0.846
Building Restricted	−0.315*	0.730	−1.773	0.076
Management Plan Required	−0.592***	0.553	−2.961	0.003
Program Timber Emphasis	−0.874***	0.417	−4.717	0.000
Minimum Commitment Period	−0.086	0.917	−0.413	0.680
Region				
South Region	−0.895***	0.409	−3.240	0.001
Rocky Mountain Region	−1.761***	0.172	−2.959	0.003
Pacific Coast Region	−0.270	0.763	−0.694	0.488
Constant	−9.448***	0.000	−8.654	0.000
F-statistic				

*, **, *** represent statistical significance at the 0.1, 0.05, and 0.01 alpha-levels, respectively.

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