# Factors that affect the management of common property resources: the case of community forest management in Michoacán, Mexico

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***Selected Paper prepared for presentation at the 2018 Agricultural & Applied Economics Association Annual Meeting, Washington, D.C., August 5-August 7***

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**Abstract**

The purpose of this study is to evaluate the factors that lead to the adoption of forest management plans by the communities in the state of Michoacán in Mexico. We construct a theoretical model, where the adoption decision is based on the expected benefits and costs of adoption versus the net benefit of expanding the agricultural frontier or of not controlling access to the forest and allow for it to be harvested illegally. Using a panel data set of 1785 communities from 1993 to 2013, we estimate a probit model, where we control for the unobserved time-invariant heterogeneity by using Mundlak's device. We find that the relative distribution of land use between forest and agriculture as well as the elevation of the forestland, have a significant effect, together with a positive effect of the price of pinewood. Furthermore, we find evidence of spatial spillovers for the adoption decision, as a community whose neighbors have previously adopted a forest management plan, is also more likely to adopt.



JEL Codes: Q23, Q28, C33

# 1 Introduction

The importance of forests has been widely recognized, both for the environmental services they provide, and for the welfare of the communities that derive their livelihood from them. As such, their loss is seen as having negative socioeconomic and environmental effects. Deforestation contributes to 11% of global greenhouse gas emissions (IPCC, 2014), and it has a negative effect on various species' habitats and on biodiversity (Sánchez-Cordero et al., 2009). Poor communities in developing countries tend to be located near dense forest areas (Sunderlin et al., 2008) and a significant number of poor people depend on the resources provided by forests (Bowler, Buyung-Ali, Jones, & Pullin, 2010). This paper examines the factors that determine the adoption of community forestry management plans for communities in the state of Michoacán in Mexico, between 1993 and 2013.

Given the importance of forests, their protection has been a significant part of policy agenda in the last decades. As such, when thinking about forest conservation policies, it is necessary to consider who owns and manages these forests. Agrawal, Chhatre & Hardin (2008) estimate that governments own 86% of the world's forestlands. Since the 1980s, more communities have been in charge of managing state-owned forests, due to a growing trend in decentralization. As a result, community managed forests have become more important for conservation policy.

Community forestry is particularly important in Mexico given its communal land tenure structure. Over half (52%) of the total land in the country is owned under a communal-based ejido system, and ejidos and indigenous communities hold 80% of its forestlands[1]. This makes Mexico the second largest holder of communal forests in the world, after Papua New Guinea (Barnes, 2009). In this context, any conservation initiative aimed at reducing deforestation must take into account the communities in charge of the forests. Thus, community forest management (CFM) has become an important policy alternative in the prevention of deforestation in Mexico.

Due to this reality, there have been two important policy changes in the regulatory framework governing forestry in Mexico. The first one was the change of the forestry law

[1] Both 'ejidos' and 'comunidades indigenas' (indigenous communities) are a form of communal based land tenure system. Therefore, throughout the paper we will refer to these communities either by calling them ejidos or communities, and the term would refer to both land tenure systems, unless it is specified otherwise.

in 1986, which ended the government's leasing system for private firms, and allowed communities to harvest their forests (Merino, Alatorre, Cabarle, Chapela, & Madrid, 1997). In 1992, the law changed and liberalized the sector by eliminating what was, at the time, considered as excessive regulation. Since then, a community can only harvest their forest if they have a forest management plan drawn up by a certified forester and designed specifically for their forest. The change to the law in 1992 also privatized the technical services provided by foresters, and in 1993 the law was loosened further to allow communities to hire any certified forester they choose. The management plans drawn up by foresters must establish the amount to be harvested every year, where the harvesting should take place, and what trees can be felled. The plans are integrated management plans, and as such they focus on both the commercial production of the forest and on the ecological services that the forest provides (Antinori, 2000). Each plan varies in both duration and the size of the area covered. In the state of Michoacán, the duration of each plan is on average 10 years.

Therefore, a community with a forest on its land has a set of choices regarding the management of that forest. It can decide to coordinate its members to enforce control over that common property resource and adopt a forest management plan to sustainably harvest the forest. Or, it can decide to maintain the status quo, where no control is enforced and the harvest of the forest can only be done illegally, predominantly by individual members of the community. This paper aims to answer what factors influence the decision of a community to adopt a forest management plan by examining the adoption by communities in the state of Michoacán in Mexico.

Understanding the determinants of CFM adoption is important for three main reasons. The first one is that deforestation is an important problem in Mexico, and studies have established a link between deforestation and land tenure. Deforestation in Mexico has been estimated to be around 0.43% per year, which is equivalent to a loss of 545,000 ha/year between 1976 and 2000 (Velázquez, Mas, & Palacio-Prieto, 2002). After a 1992 reform that aimed to liberalize the land market in Mexico, DiGiano, Ellis, & Keys (2013) found that for a sample of eight ejidos in the State of Quintana Roo, deforestation was greater in those ejidos that were privatized (even informally) in comparison to commonly-held ejidos. In a study at the municipal level, Bonilla-Moheno, Redo, Aide, Clark, & Grau (2013) found that municipalities where ejidos were the predominant form of land tenure suffered from higher deforestation than municipalities where land was predominantly private or owned by indigenous communities. According to the authors, these results highlight the importance of group size and composition in the deforestation decision: which are usually smaller and more homogenous in indigenous communities than in ejidos.

The second reason is that although there has been evidence of the effect that different conservation policies have on deforestation, the impact of CFM has not been greatly studied, particularly by research that focuses on a larger sample of communities over a long period of time. As such, understanding the adoption of these types of policies and the factors related to it, is a first step in expanding the knowledge about the impact of these policies. The existing evidence suggests that CFM decreases deforestation. In a systematic review from 2011, the results show that there is deforestation in both protected areas and in areas under CFM, but the rate of deforestation is lower in the latter case (Porter-Bolland et al., 2011). In another systematic review, Bowler, Buyung-Ali, Healey, et al. (2010) show that most studies find that CFM lowers deforestation and increases tree cover, although it does not seem to have a consistent effect on species richness and diversity. In a study more in line with this research, Alix-Garcia, de Janvry, & Sadoulet (2005) find that communities that decide to harvest their forest commercially (and legally) have a higher rate of deforestation than communities that choose not to. From these results, the authors suggest that forestry projects in Mexico are not profitable enough to deter land conversion and deforestation, when compared to land use in agriculture and pasture. Their results are especially important to our research question because they are based on a theoretical model of the communities' choice to harvest. It illustrates the effects of that decision on deforestation, controlling for the characteristics of the community and the forest. Their theoretical model has very clear predictions and they have a rich data set which allows for empirical testing of these predictions.

Finally, the existing literature on the factors driving the adoption of CFMs is scarce. Most studies focus on the effect that the adoption of CFM has on deforestation, and on the factors that lead to the environmental or economic success of existing CFMs. Baynes, Herbohn, Smith, Fisher, & Bray (2015) review the existing evidence, which comes largely from case studies, and identify five key factors that affect the success of community forestry: the socioeconomic status of the community, the security of property rights, the government's support to the community, the material benefits they receive from the CFM, and for them, the most important characteristic: the governance inside the community. They also highlight the importance of social capital as one of the most important factors in the success of CFM. In a similar study, and based on the principles established by Elinor Ostrom, Agrawal & Angelsen (2009) create 4 clusters of factors, and for each factor determine if it is an exogenous factor or if it is determined by the design of the policy intervention being considered. The first cluster is formed by the characteristics of the resource, the second refers to the characteristics of the community, the third to the institutional arrangements, and the fourth one to the context.

However, the factors that lead to the adoption of community forestry are not identified. To the best of our knowledge, the only study that explicitly models the adoption decision is the one by Alix-Garcia et al. (2005). In their model, a community can choose to be in a Forestry Regime (commercial and legal harvesting of the forest) or in a No Forestry Regime. The decision will depend on the total community utility under both regimes, which is the sum of the households' utility, given the household and the community level characteristics (including the characteristics of the forest). The aim of their study is to determine the effect that the participation of a community in either of the two regimes has on deforestation. For that, they use data from a survey conducted in 2002, of 450 community leaders. The nature of their data does not allow them to control for unobserved characteristics of both the households and the communities, and as such, it is challenging for them to control for the endogeneity in the participation decision. However, their estimation procedure aims to control for this endogeneity, and their results show that young communities (formed after 1975) and communities that are larger, are less likely to be in a Forestry Regime (holding the size of the forest and the altitude constant). The probability of participating in a Forestry Regime increases for communities with a larger initial forest area, with land at higher altitude, as well as those that have younger leaders.

The aim of this study is to construct and empirically test a model of the adoption decision by communities in Michoacán, and examine if the probability of adoption is significantly affected by exogenous factors such as the adoption of neighboring communities, the price of wood, and the price of main crops and agricultural supplies. The contribution to the existing literature is in the use of a large sample panel data set that allows us to control for the time-invariant unobserved characteristics of the communities and to explicitly model the spatial effects of the adoption decision. Following Ostrom (1999), I argue that this decision will depend on the expected benefit of establishing new rules and governance institutions, and on the short and long-term costs associated with the implementation of these rules. In turn, both the expected benefits and costs will depend on the attributes of the resource and the users, and on exogenous factors. We empirically test these factors using a panel data set of communities from Michoacán, and model their adoption decision using a probit model, where we control for the unobserved community level time-invariant heterogeneity by following Mundlak's approach (Mundlak, 1978).

## 2 Theoretical Framework

We base the theoretical framework on Ostrom (1999), expanding and adapting it to reflect the conditions of forest management in Michoacán. From the data, we observe the decision made by a community to adopt a forest management plan or not. Ultimately, the decision becomes one of whether or not to harvest trees legally, by getting a CFM and a harvesting permit. Behind that harvesting decision there is first a decision regarding the management and control of the community's forest: communities must first decide if the benefits of managing the forest are greater than the costs. A second decision is whether to adopt a forest management plan or not. We argue that these two decisions can be consolidated into a binary choice problem. Starting from a status-quo of no plan and individual (and illegal) harvesting of the forest by community members, communities are faced with two choices: they either decide to control the use of their forest and adopt a forest management plan, or they decide to not control the access and use of the forest, and let the community members individually decide how they will use the forestland. This implies that the community decides either to illegally clear the forest and convert this land to agricultural land, or to have no control and let individuals illegally harvest the forest. The option of controlling the use of the forest but not adopting a forest management plan is theoretically feasible but highly unlikely. Given that Mexican law does not allow harvesting of forests without a forest management plan, this option would imply that the community would incur in the costs of managing the forest but would not receive any benefit from it, since it would not be able to harvest it legally. Therefore, I do not consider this a viable option and as such the decision is binary: adopt a CFM or not[2].

The adoption decision occurs if the expected benefit from adopting is greater than the expected benefit from not adopting. Since the decision is binary, the profit function can be expressed as the expected profit from controlling the use of the forest and adopting a forest management plan, versus the expected profit from no control. The latter option

[2] Alix-Garcia (2007) mentions the possibility of having cases where even if the community did not decide to expand the agricultural frontier, communities had rules in place that controlled this expansion. This option would still fall under the status-quo choice, where the community (explicitly or implicitly) decides not to govern the forest commons.

implies that the community has the possibility to illegally clear the forest and either changes the land-use from forestry into agriculture, or does not change the land-use of the cleared land (Eq. 1, Eq. 2, Eq. 3 respectively):

$$\pi^F = P_F Y_F - \mathrm{C}(Y_F, \mathrm{Z}) - G_t(L_F, O, E, NE) - A(L_F, N, A_{t-1}, T_{t-1}) \qquad \text{Eq. 1}$$

$$\pi^A = [P_A Y_A - \mathrm{C}(Y_A, P_{AS}, Z, R)] + [P_F Y_{IF}^T - \mathrm{C}(Y_{IF}^T, Z)] - \theta F(\, Y_{IF}^T) \qquad \text{Eq. 2}$$

$$\pi^{IF} = P_F Y_{IF} - \mathrm{C}(Y_{IF}, Z) - \theta F(Y_{IF}) \qquad \text{Eq. 3}$$

Given that the average duration of a forest management plan is 10 years, we can think of the above values as representing the net present value over a 10-year period. Eq. 1 represents the profit function associated with the adoption of a CFM; Eq. 2 is the profit function for non-adoption, when the forest is taken down (illegally) and the forestland is converted into agricultural land. Finally, Eq. 3 is the profit associated with the illegal harvesting of the forest, but where the harvested area is not converted into agricultural land and the forest is not immediately taken down.

The profit derived from adopting a forest management plan and getting a harvesting permit (Eq. 1), will be a function of the volume of wood harvested $(Y_F)$, the price of wood $(P_F)$, the cost of extraction, which in turn is function of the volume of wood extracted and a vector of geophysical variables (Z), such as the elevation and the ruggedness of the terrain. The decision to adopt a forest management plan implies that the community will have to pay a forester to design the plan, which represents a fixed cost associated with the adoption decision. That fixed adoption cost $A(L_F, N, A_{t-1}, T_{t-1})$ is a function of the size of the forest $(L_F)$ and of the number of neighboring communities that have adopted a management plan (*N*), a term that captures the spillover effects of the adoption. We also hypothesize that once a plan has been adopted, the cost of adoption of subsequent plans (after the current plan has expired) will be lower. This cost will also be lower if a forester that had previously worked for the community draws up the management plan.

The cost of adoption is not the only cost that the community takes into account. There are also governance costs associated with CFM, since the community has to establish mechanisms to control the access to the forest and to ensure that the plan is being followed, so that the forest is not being over harvested. This governance cost $G_t(L_F, O, E, NE)$ is a function of the size of the forest ($L_F$), the organizational capacity that the community has ($O$) and that allows them overcome the collective action problem, the number of members with voting rights ($E$) and the number members with no voting rights ($NE$). This cost is increasing in the size of the forest and it is decreasing in the organizational capacity of the community. Regarding the number of members with voting rights ($E$) and members with no voting rights ($NE$), there is no clear prediction as to the effect that these variables have on the governance costs. Typically, it has been assumed that smaller is better when it comes the size of a community managing a common pool resource. However, there is also evidence that bigger communities have more resources (especially labor) that allows them to control the access to the forest, and so it is also possible to have a curvilinear relationship (Gibson, McKean, & Ostrom, 2000). In the case of Mexico, there are also community members who have no land and no voting rights but who can also influence the decision making process, since they can attend to community meetings. Given that they can see the forest either as a source of employment or as an obstacle to the expansion of the agricultural frontier, we assume that their effect on the governance costs is undefined.

The other option that a community has is the clearing of the forest and the conversion of that land for agricultural purposes. In this case, the community would receive a net benefit from harvesting the forest completely, discounting the expected fines from the illegal use of the forest $\theta F(Y_{IF}^T)$, where $\theta$ represents the probability of getting caught, and $F(Y_{IF}^T)$ is the total amount of the fine, which is a function of the total wood harvested. Since the land is converted into agricultural land, the community receives a profit from this agricultural activity, and this profit is a function of the prices and the total amount of crops harvested, and the cost of production of this crops. This cost of production is a function of the total production $Y_A$, the price of agricultural supplies such as fertilizers and pesticides ($P_{AS}$), the characteristics of the terrain ($Z$) and the weather in the area ($R$). This cost is increasing in agricultural supplies prices, elevation and terrain ruggedness, and is decreasing in rainfall.

Finally, for the sake of completeness, we consider the possibility of a third option, where the community does not adopt a management plan and does not control the access to the forest, but also does not allow the expansion of agricultural land. In this case, the profit derived from illegal wood harvesting will be a function of the total wood harvested, wood prices, the cost of harvesting, and the expected fine for illegal harvesting of the forest.

Thus, we can establish a very simple decision rule, where adoption happens whenever $\pi^F > \pi^A$ or $\pi^F > \pi^{IF}$. Given that not all the factors that affect the adoption decision are observable, we can express this decision in terms of the probability of adoption, and so we include a random error that captures those unobservable random events that affect this probability (as in Geoghegan, Schneider, & Vance, 2004). Based on the decision rule, for every time period $t$, the probability of adoption for community $i$ is given by

$$P(CFM_{it} = 1) = \Pr(\pi_{it}^F + \varepsilon_{Fit} > \pi_{it}^A + \varepsilon_{Ait})$$

or

$$P(CFM_{it} = 1) = \Pr(\pi_{it}^F + \varepsilon_{Fit} > \pi_{it}^{IF} + \varepsilon_{IFit}) \qquad \text{Eq. 4}$$

where $\pi_{it}^F$, $\pi_{it}^A$, and $\pi_{it}^{IF}$ are the expected profits defined by Eq. 1, Eq. 2, and Eq. 3 (respectively).

From this conceptual model, we can hypothesize what are the effects that the exogenous variables and the characteristics of the community have on the probability of adoption. Table 1 summarizes these effects.

**Table 1. Effect of exogenous and endogenous variables**

| **Exogenous Variables** | | **Community Characteristics** | |
|---|---|---|---|
| Variable | Effect on the probability of adoption | Variable | Effect on the probability of adoption |
| Price of wood ($P_F$) | (+) | Size of the forest ($L_F$) | Undefined |
| Price of crops ($P_A$) | (-) | Elevation ($Z$) | (+) |
| Price of ag. supplies ($P_{AS}$) | (+) | Terrain ruggedness ($Z$) | (+) |
| Neighbors with CFM ($N$) | (+) | Number of members ($E$) | Undefined |
| Probability of getting fined ($\theta$) | (+) | Number of nonvoting members ($NE$) | Undefined |
| Rainfall ($R$) | (-) | Organizational capacity ($O$) | (+) |

## 3 Empirical Model

The outcome of interest is the adoption of a forest management plan by a given community in charge of a forest. In its simplest form, this is a binary outcome, where a community either adopts a plan or not. Given that we have data on the adoption decision of each community from 1993 until 2013, we can estimate the probability of adoption for every community for every year, using a binary dependent variable model, such as a probit model. Furthermore, the time dimension of the data allows us to control for unobservable time-invariant characteristics that might affect the adoption decision.

Starting from the theoretical framework and assuming that the profit functions are linear in their parameters, we can estimate the indirect benefit function of adoption (Banerjee et al., 2008), for community *i* at time *t*, by estimating

$$CFM_{it} = \alpha_i + \alpha_t + X'_{it}\beta_1 + M'_{it}\beta_2 + \beta_3 \sum_{j=1}^{N} W_{ij} CFM_{jmt-1} + \varepsilon_{it} \qquad \text{Eq. 5}$$

$CFM_{it}$ is the CFM adoption variable for community *i* in year *t*, and it is equal to 1 if the underlying benefit of adoption is greater than the benefit of non-adoption (community *i* adopts a forest management plan). Parameter $\alpha_i$ is a community level fixed effect, and $\alpha_t$ is a time effect. Vector $\beta_1$ contains coefficients associated with time variant community level characteristics such as population and weather, and we also include some time-invariant characteristics of the communities, such as the number of members and non-members, and the geophysical characteristics of the community (elevation and terrain ruggedness). Vector $\beta_2$ contains coefficients associated to the prices of wood, agricultural products and agricultural supplies, which are time-variant but the same for every community. However, we interact these market prices with the inverse of the square root of the distance between the community and Morelia (the state capital) in order to get time-variant and community specific prices[3]. The reason for this transformation is that communities that are in more remote areas face higher transportation costs and as such the prices they receive for their products are lower.

[3] The results do not change if we use other specifications of the Euclidean distance besides the square root.

As discussed in the theoretical framework, it is possible to have spillovers associated to the adoption decision, and therefore it is important to take into account the spatial correlation between the adoption decisions of neighboring communities. For this, we construct a weight matrix ($W_{ij}$) that for each community assigns a weight to each of its neighboring communities. The weight assigned to each neighbor is the inverse of the distance between the two neighboring communities, such that neighbors that are further apart will have a lower weight. The weight matrix is defined as

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}}, 0 \leq d_{ij} \leq d \\ \\ 0, \quad d_{ij} > d \end{cases} \qquad \text{Eq. 6}$$

where $d_{ij}$ is the distance between community $i$ and community $j$, and $d$ is the distance cutoff. We use a 30 km distance cutoff, and as a robustness check use a 50 km distance cutoff. The weight matrix is row standardized, meaning that the sum of the weights of each row would equal to 1. This row standardization implies that the spatial lag ($SL_{it}$ henceforth) should be interpreted as the adoption rate in the area around a given community, which is determined by the distance cutoff.

We control for the time-invariant unobserved characteristics that might affect a community's decision to adopt using Mundlak's (1978) approach (Lewis, Barham, & Robinson (2011) use this approach in a similar context, where they also include a spatial lag in an adoption model). Mundlak's approach implies that community level unobserved characteristics ($\alpha_i$) are a function of the community means of the time varying variables, such that

$$\alpha_i = \alpha + \bar{X}_i\delta_1 + \bar{M}_i\delta_2 + \overline{SL}_i\delta_3 + u_i \qquad \text{Eq. 7}$$

The importance of Mundlak's procedure is that it allows us to control for the unobserved time-invariant heterogeneity and to control for the endogeneity in the spatial variable. This endogeneity arises from the spatial correlation between the adoption decisions of the communities and the unobserved characteristics shared by a given group of communities.

Furthermore, in order to avoid endogeneity in the spatial lag, we use a one period time-lagged spatial lag. This lagged variable aims to capture the dynamic effect of the adoption decision, especially since the adoption of a CFM is a process that can take up to a year. From Eq. 5 and Eq. 7 we get the estimating equation:

$$CFM_{it} = \alpha + \overline{X}_i\delta_1 + \overline{M}_i\delta_2 + \overline{SL}_i\delta_3 + \alpha_t + \rho_1 D_i$$

$$+ X'_{it}\beta_1 + M'_t\beta_2 + SL'_{it-1}\beta_3 + u_i + \varepsilon_{it} \qquad \text{Eq. 8}$$

From (Eq. 8) it is important to highlight the sources of exogenous variation that affect the adoption decision. There are three main groups of exogenous variables in this equation. The first one is the spatial lag. The second one includes all the relevant prices: the prices for pinewood, the prices of the main crops in Michoacán and the price of fertilizers. To avoid endogeneity issues with the wood price data, for the price of pine wood we use the prices from Durango and Chihuahua, which together account for 52% of the total wood supply in Mexico. Finally, we include three weather variables (yearly averages of the minimum and maximum temperature and of rainfall) that we consider can have an effect on agricultural productivity. Eq. 8 is estimated using a probit a model.

# 4 Data

The data come from different sources. Part is from the censuses conducted by INEGI (the Mexican statistical office) for 1995, 2000, 2005 and 2010, and from the national agricultural registry (RAN), which has geographical data for the communities, such as the boundaries and the area for each community. The other information identifies the forest management plans adopted by each community. For this, we have a data set of all the management plans adopted by the communities in the state of Michoacán from 1993 to 2013, with the duration of the plan, the total area covered and the type of plans (SEMARNAT - department for the environment and natural resources). SEMARNAT issues two kinds of permits, a long term (typically 10 years) harvesting permit, that usually covers the whole forest and a short-term permit that is issued in case of emergencies (such as fires and pest outbreaks). The latter is not included in our estimation, but we do include a dummy variable that captures the period after such a permit is issued, since we believe this is a good predictor of the adoption of long-term permits in the future. Forest cover data come from INEGI's series of vegetation cover and land use, which started in 1985 and go until 2011. We use the 1985 forest cover data to control for baseline forest cover. We also use market data, including the average price for pine and the producer price index for sawmills and other wood products (Figure 6), and for the main crops in Michoacán (Figure 7 and Figure 8). For the pine prices, we have data from the state of Chihuahua (33% of the total supply), Durango (20% of the total supply), Michoacán (12.5%) and the average national price (Figure 5). Only pine prices are included in the analysis, given that this is the main type of wood harvested in Michoacán. These data come from the annual outlook report by CONAFOR, the national committee in charge of forests in Mexico. We also include a variable to capture the perceived level of enforcement, which reflects the perceived probability of getting fined when harvesting wood illegally. Using the total number of operations done each year by the environmental authorities, we interact it with the communities land size to get a community level enforcement proxy. We believe that larger communities attract more attention, and as such have a higher probability of being subject to a visit by the environmental authorities. Finally, we also include weather variables, and we matched the communities to the nearest of 38 weather stations throughout Michoacán (the ones with data for these years), and got yearly averages for the minimum and maximum temperature and for rainfall. The main variables are in Table 5 (in the Appendix).

The mean values of the main variables are in Table 2 for the whole sample as well as for the groups of communities that adopted a CFM in the sample period and those who never adopted. We can see that on average, communities with a CFM are usually surrounded by other adopting communities (higher spatial lag), and have a higher number of members, even if on average the total population is smaller. They also seem to be closer to Morelia than non-adopting communities, and they have a much larger area (almost twice as big). Not surprisingly, they also had more forest cover in 1985, and a lower proportion of tropical forests. The percentage of agricultural land is also lower and they seem to have a more temperate climate, with lower temperatures and higher rainfall. The differences in the averages between these two groups of communities are significant for almost all variables, with the exception of the demographic variables. In our estimation process we include all the variables from Table 2.

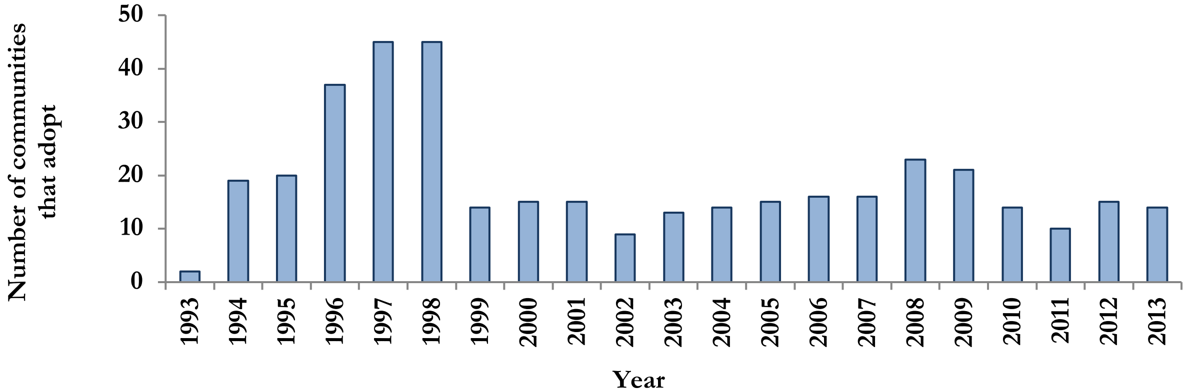
**Table 2. Community means and t-test of differences**

| | Total sample mean | Mean (no CFM) | Mean (CFM) | t-test of differences |
|---|---|---|---|---|
| Spatial Lag | 0.009 | 0.006 | 0.025 | (-19.69)*** |
| Community members | 86 | 85 | 96 | (-1.58) |
| Non-members | 25 | 23 | 39 | (-3.18)** |
| Total population | 1,837 | 1,898 | 1,417 | -1.15 |
| Male population | 880 | 908 | 685 | -1.12 |
| Young population | 662 | 676 | 561 | -0.84 |
| Older population | 109 | 112 | 85 | -1.32 |
| Year of creation | 1950 | 1950 | 1951 | (-0.33) |
| Total community area (ha) | 1,507 | 1,382 | 2,372 | (-1.96) |
| Distance to Morelia | 98 | 100 | 88 | (3.08)** |
| Forest Cover 1985 (%) | 38% | 34% | 63% | (-14.28)*** |
| Tropical forest 1985 (%) | 18% | 19% | 7% | (8.23)*** |
| Non-tropical forest 1985 (%) | 20% | 15% | 56% | (-20.50)*** |
| Agricultural land 1985 (%) | 42% | 44% | 31% | (6.56)*** |
| Elevation (m) | 1,550 | 1,474 | 2,079 | (-13.41)*** |
| Terrain ruggedness | 98.61 | 90.34 | 155.90 | (-11.36)*** |
| Min. Temp. (ºC) | 12.40 | 12.70 | 10.29 | (7.99)*** |
| Max. Temp. (ºC) | 29.16 | 29.53 | 26.58 | (11.13)*** |
| Rainfall (mm) | 825.70 | 813.50 | 910.50 | (-8.26)*** |
| No. Observations | 1785 | 1560 | 225 | |

# 5 Results

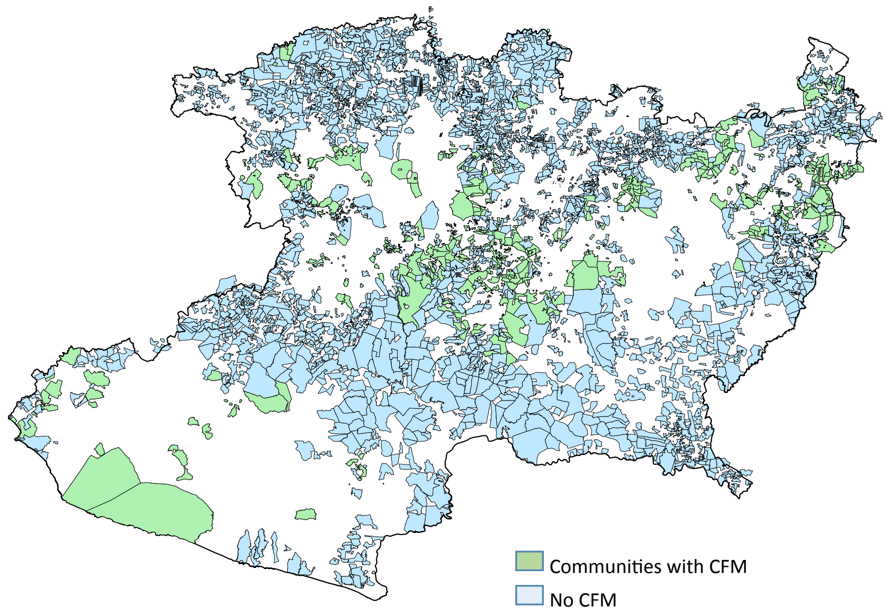
Since 1993, the adoption of CFMs has changed every year, with some years showing a higher rate of adoption than others. From Figure 1, we see that the two years with higher adoption are 1997 and 1998, and the years with the lowest adoption are 1993 and 2002. Given that most plans usually last for 10 years, there is a second peak of adoption in 2008 and 2009.

**Figure 1. Total number of communities by year of adoption**




An important aspect of the analysis is related to the spatial dynamics of the adoption of forest management plans. From the theoretical model, one of the main hypotheses is that the adoption of a forest management plan by a given community would lower the cost of adoption for neighboring communities. As such, there will be spatial correlation in the adoption decision. This spatial correlation would create clusters of communities with a forest management plan. A map showing all the communities in the state of Michoacán and whether they ever adopted a forest management plan or not would show that communities with CFMs tend to be close to each other. This is precisely what we can observe in Figure 3 in the Appendix).

**Figure 2. Clustering of forest management plans for communities in the state of Michoacán**




The spatial autocorrelation in the adoption decision is also evident from the global Moran's I statistic, which captures the degree of spatial correlation and its significance for a given variable. From Table 3, we can see that the adoption decision, the percentage of forest cover and the size of the community are all spatially correlated. The early adoption index takes the value of 1 if a community adopted a CFM in 1993 and decreases by the year of adoption. It shows that early adopters tend to be surrounded by other early adopters (Figure 1 in the Appendix shows a map of this index and Table 6 has Global Moran's I by year of adoption).

**Table 3. Global Moran's I**

| Weight Matrix | 30 km Max. distance | | 50 km Max. distance | |
|---|---|---|---|---|
| **Variables** | **Moran's I** | **p-value** | **Moran's I** | **p-value** |
| Early adoption index | 0.237 | 0.00 | 0.181 | 0.00 |
| CFM adoption | 0.246 | 0.00 | 0.188 | 0.00 |
| Forest cover '85 (%) | 0.553 | 0.00 | 0.483 | 0.00 |
| Total area of the community | 0.285 | 0.00 | 0.129 | 0.00 |
| Sum of Moran's I | 1.321 | | 0.981 | |

Given the evidence of spatial correlation, the spatial distribution of the communities must be taken into account. If the cost of adoption is lower for communities that are surrounded by other communities that already have a forest management plan, then we can say that there are spillovers related to the adoption decision. The estimation results from our model allows us confirm the existence of these spillovers. From Table 4, we have that the spatial lag is positive and significant, but that once we control for the unobserved heterogeneity, its effect is no longer significant. This means that the spatial correlation is caused by unobserved characteristics shared by the communities, and that once we control for the unobserved heterogeneity using Mundlak's device, this spatial correlation is still positive but it is no longer significant. However, we have that the time average of the spatial lag is positive and highly significant, and so this variable would be capturing the spatial correlation in the adoption decision for the sample period, allowing us to confirm the hypothesis of spatial spillovers in the adoption decision.

There is a prominent characteristic of the communities that is associated with a lower probability of adoption: the year of creation of the community. The creation of communities has increased since the Mexican revolution (1917), which gave way to legal recognition of these communal lands. To form a community (either an 'ejido' or a 'comunidad indigena'), a group of people that inhabit and work the land, will claim the land to the government and the government will officially recognize them as a community. The year of creation variable is the year when the community was officially recognized by the government. As such, the negative coefficient shows that older communities have a higher probability of adoption. This could be capturing better organizational ability that allows the communities to overcome the collective action problem. It can also reflect a greater organizational experience, which would lower the cost of adoption, just as was predicted in the theoretical model and as is mentioned by Ostrom (1999). It is important to mention that once we control for the unobserved heterogeneity, this variable is no longer significant.

**Table 4. Probit estimation results**

| | Probit - No Miundlak | Probit - Mundlak's device |
|---|---|---|
| **Variables** | **Coefficients** | **Coefficients** |
| Spatial lag | 4.945*** | 1.503 |
| Time average of spatial lag | - | 48.106*** |
| Forest Cover (%) | 3.392*** | 2.364*** |
| Tot. Area For. Cover | 0.000 | -0.000 |
| Tropical forest (%) | -1.048** | -0.687 |
| Total area of trop. For. | -0.000* | -0.000** |
| Agricultural land (%) | 1.802*** | 1.005* |
| Type of community (ejido=1) | 0.079 | 0.012 |
| Year of creation of the ejido | -0.005* | -0.006 |
| Participation in education program | -0.118* | -0.098 |
| Contingency CFM | -0.275 | -0.158 |
| Number of members (at time of creation) | 0.000 | 0.000 |
| Number of non-members (at time of creation) | 0.002** | 0.001 |
| Forest Elevation Mean | 0.000** | 0.000 |
| Tropical Forest Elevation Mean | -0.000** | -0.000 |
| Forest Terrain ruggedness (Elev. St. Dev) | -0.000** | 0.002 |
| Working age population | 0.00 | -0.000*** |
| Older population | 0.00 | 0.000** |
| Total population | 0.00 | 0.000* |
| Pine Price (national average) | 2.663** | 2.645*** |
| Oak Price (national average) | -2.563* | -2.294 |
| Maize ppi (lagged) | -16.816* | -29.001* |
| Sorghum ppi (lagged) | 59.533* | 39.551 |
| Beans ppi (lagged) | -31.529* | -17.648 |
| Wheat ppi (lagged) | 14.194 | 32.848 |
| Sugar cane ppi (lagged) | 13.902* | 24.385* |
| Cattle ppi (lagged) | 33.409* | 10.276 |
| Swine ppi (lagged) | -45.576** | -41.261* |
| Avocados cpi (lagged) | -12.086* | -7.286 |
| Average Max. Temperature (lagged) | -0.053** | -0.045 |
| Average Rainfall (lagged) | 0.00 | 0.00 |
| Constant | -10.176 | 21.046 |
| N | 33,519 | 33,519 |
| Log Likelihood | -1109.4 | -1049.4 |
| Time effects | Yes | Yes |
| Control for foresters | No | No |
| Demographic controls | Yes | Yes |
| Distance cutoff | 30 km | 30 km |

Significance levels: *** (1%), ** (5%) and * (10%)

Given that communities can be either ‘ejidos’ or indigenous communities, we include a dummy variable that captures the type of community. This is a dummy variable that takes the value of one if the community was formed as an agricultural community (‘ejido’) and zero if the community was originally formed from a traditionally indigenous community. Barnes (2009) shows that there is evidence of better governance in this type of communities, as seen from the higher attendance of members to the community meetings. However, our results do not support this conclusion (given the positive coefficient) and the effect is not significant.

From the results, we have that the main drivers of adoption are the geophysical characteristics of the community, and the relevant market prices. For the first category, we find that communities with a higher proportion of forest cover have a higher probability of adoption, however, the total of the area of the forestland does not seem to have an effect on this probability. We also find that a higher proportion of agricultural land also has a positive effect on the probability of adoption, but the total area of agricultural land does not have a significant effect on this probability. This would seem to indicate that what matters is the relative distribution of the land inside the community and not the total area of the land.

The characteristics of the terrain also seem to have a significant effect on the probability of adoption. The average elevation at which the community’s forestland is located is positively correlated with the probability of adoption, which captures the fact that temperate forests (the most commercially viable kind of forest) tend to be located at higher altitude, but it also captures the fact that the productivity of the most common crops of Michoacán, is lower at higher altitudes. Terrain ruggedness has a negative effect on the probability of adoption, since it makes it less likely that the land can be profitably used for agriculture and as such increases the value of the existing forestland, even if it increases the harvesting and transportation costs for both agricultural and nonagricultural activities. However, the effects are no longer significant once we control for the unobserved heterogeneity at the community level.

Regarding the effect of market prices, the results seem to support the predictions from the theoretical model. The price of pinewood has a positive and significant effect on the probability of adoption. An increase in the price of pinewood increases the total value of the forest, and makes legal wood harvesting more profitable, thus increasing the probability of adoption. As for the effect of agricultural prices, the results are mixed. The price of maize has a negative effect on this probability, an important result when considering that maize represents 66% of the total agricultural land in Michoacán, according to the 1990's agricultural census (65% in the 2016 census). It is also important to highlight that there is a significant effect from the prices of the most important cash crops in Michoacán, such as sugarcane, and avocado. Sugarcane prices increase the probability of adoption. However, the price of avocados has a negative effect on the probability of adoption. The result is especially relevant since anecdotal evidence from the region suggests to a possible link between deforestation and the expansion of this crop. However, the evidence from existing studies (albeit it comes from case studies) suggests that the conversion of forests to avocado orchards has been lower in forestry communities that in non-forestry communities (Barsimantov & Navia Antezana, 2012). Our estimated coefficient would indicate that as the price of avocados increases, the probability of adoption decreases. This result is especially important when considering the steep increase in the price of avocados in the last decade (Figure 7).

To interpret the results of the estimated coefficients of agricultural prices, we analyze the importance of each crop for the case of Michoacán. With these in mind, we believe that the negative effect of the price of maize on the probability of adoption is associated to the status of staple crop that maize has. Maize crops represented 66% of the total harvested land in Michoacán in 1990, 72% in 2007 and 65% in 2016 (information from the agricultural censuses). As such, when its value increases (ceteris paribus) the opportunity cost of not having more maize plots increases and is equally distributed among all the members of the community. The other crops, such as sugarcane, and avocado, can be considered as cash crops. They cover a smaller surface and therefore its production is unevenly distributed. Out of these two, avocado is the one that is grown more widely, with a total of 40.000 ha in 1990, 78.000 ha in 2007 and 91.000 ha in 2016. Just like maize for the short-term crops, avocado is the most widely grown crop out of all the perennial crops and is the one that has seen the highest increase in its price (almost a seven fold increase from its lowest to its highest point). On the other hand, sugarcane is an important crops for the revenues they generate but not for total harvested area (13.646 ha in 2016, 2% of the total harvested area). As such, we believe that its positive effect on the probability of adoption is related to the fact that they can generate revenues to cover the costs of adoption, but because of their limited scale, they do not pose a threat to the forest.

We also find that having previously adopted a short-term management plan (as a response to a negative shock), does not have a significant effect on the probability of adoption. The characteristics of these plans are very different from the long-term plans, and they usually cover a much smaller area. As such, they are not a good predictor of future adoption. Finally, contrary to the predictions from our model, we find that the enforcement proxy does not have a significant effect on the probability of adoption. This does not mean that higher enforcement does not encourage adoption but that our measure of enforcement does not seem to have a significant effect.

How do these results fit in the existing literature? As we mentioned in the introduction, the only study that explicitly models the decision by the communities to manage and harvest the forest is the one by Alix-Garcia et al. (2005). Even if they estimation procedure and the nature of the data used in this study are different, the results obtained here are similar to their results. They find that younger communities have a lower probability of being in a forestry regime (they use the year of creation of the community as proxy for forest quality, since younger communities are more likely to have received land of less quality). Similarly, they find that the availability of good agricultural land per capita, has a positive effect on the probability of being in forestry regime, a result that is similar to ours. Like us, they also find that forests at higher altitude are positively correlated to communities being in a forestry regime. Unlike us, they find that the area of the community significantly reduces the probability of participating in forestry, a result that differs from what we find for the case of Michoacán, where the total area of the community does not have a significant effect.

# 6 Conclusion

The aim of this study was to identify and analyze the factors that have a significant effect on the decision of a community to legally harvest its forest, by adopting a community forest management plan. Our focus was on the communities of the state of Michoacán (Mexico), between 1993 and 2013. Based on the existing literature, w built a simple theoretical framework based on Ostrom's (1999) contribution regarding the governance of communally owned forest, where the benefits of regulating access and managing the forest must be weighed against the costs of adoption. We use a panel data model to estimate the probability of adoption for every community for each year, where the unobserved time-invariant heterogeneity at the community level is controlled for by using the community averages of the time variant variables (following Mundlak, 1978).

The results allow us to confirm the hypotheses from the theoretical model. The probability of adoption increases with the proportion of the community's land that has forest cover and with the proportion of agricultural land in the community. This would seem to indicate that communities with both forest and crops will tend to have higher adoption, and the existence of agricultural land does not lead to the expansion of the agricultural activity into the forestland, but acts as an incentive to harvest that natural resource. The probability of adoption is also higher for communities with forestland at a higher altitude.

The market prices also seem to play an important role. The prices of pinewood have a positive and significant effect on the probability of adoption and the price of maize has a negative effect. We find that the price of avocados has a negative effect, an important result given the importance of this crop in Michoacán, and the steep increase of the price of avocados in the last decade.

The results also show that the spatial spillovers in the adoption of CFMs are positive and significant. The adoption decision of the communities has a positive effect on the adoption decision by neighboring communities. With the available data we cannot examine the mechanisms behind these spillovers, but we believe that these spillovers reduce the cost of adoption, both by removing informational hurdles and by lowering the perceived risk of adoption for the communities. However, more work is necessary to confirm the mechanisms driving these spatial spillovers.

Finally, there are two elements that highlight the importance of the results. The first one is that to the best of our knowledge this is the first study to analyze the determinants of adoption of community forest management through time, and the second one is that the results are in line with the predictions from the theoretical framework and with the results of the only existing study that addresses a similar question.

These results point toward possible future research questions. Moving forward, the effects that the adoption of community forest management has on deforestation should be evaluated, before designing or suggesting any policies that incentivize or otherwise disincentivize the adoption of these plans. If the effects are positive, then further research can focus on the mechanisms behind the spatial spillovers, as this could help in the design of policies that lead to higher adoption. It is also important to investigate what policy instruments can be used to lower the cost of adoption and increase the adoption of the communities.

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# 8 Appendix

**Table 5. Variables and data sources**

| Variable | Description | Source |
|---|---|---|
| Total population | Total population (census 1995, 2000, 2005, 2010) in each community | Census (INEGI) |
| Male population | Total male population in each community | Census |
| Female population | Total female population in each community | Census |
| Young population | Total population with ages between 0 and 14 years of age in each community | Census |
| Working age population | Total working age population in each community (15 - 64 years) | Census |
| Older population | Total population with 65 years or more in each community | Census |
| Number of houses | Total number of inhabited houses in each community (census 1995, 2000, 2005, 2010) | Census |
| Houses with electricity | Total number of inhabited houses with access to electricity (census 1995, 2000, 2005, 2010) | Census |
| Houses with water | Total number of inhabited houses with access to piped water (census 1995, 2000, 2005, 2010) | Census |
| Type of community | Type of community as registered in the national agricultural registry ("EJIDO" ó "COMUNIDAD") | RAN (national agricultural registry) |
| Distance | Euclidean distance between the centroid of the community and state capital (Morelia) | Own calculations |
| CFM adoption | Adoption of a forest management plan for any given period and details about the plan | SEMARNAT |
| Spatial lag | Spatial lag constructed using a 30 and 50 km distance weight matrix and the cfm variable. This variable is also lagged for one year. | Own calculations |
| Operations against illegal forestry (enforcement proxy) | Total number of operations for the whole country (by year) by the Mexican environmental authorities (PROFEPA) | PROFEPA |
| Pine prices | Average pine prices interacted with the inverse distance from each community to Morelia. | CONAFO |
| Producer Price Index (PPI) for the crops and livestock | Avocado, lemon, sugar cane, maize, sorghum, beans, wheat, fertilizer, cattle, swine and poultry | INEGI |
| PPIf or Sawmills and other wood products | Index for the price of wood paid by sawmills and by other wood producers (2012 = 100) | INEGI |
| Weather (Min. Temp., Max. Temp., Rainfall) | The yearly average minimum and maximum temperature, and the rainfall from 1992 to 2013. | National meteorogical system |

| | | |
|---|---|---|
| Average elevation | From INEGI's digital elevation model, which has a resolution of 15x15 meters | INEGI – own calculations |
| Terrain ruggedness | Corresponds to the standard deviation of the elevation for each polygon of each community | INEGI – own calculations |

### Data construction

Mexico is a federal state, where states are the largest geographical unit. Each state is composed by municipalities and each municipality is composed by localities. Localities are usually small groups of houses, both in the rural and the urban area. Given that there are no population data for each community, we constructed the data by matching localities to communities, through a spatial intersection process. Taking the polygons of each community and the geolocation of the localities, we matched a locality to a community if that locality was within the community. Localities outside the border of the community but within 1 km were also assigned to the closest community. Localities and communities that share the same name and are within a distance no greater that 7 km are also matched[4]. The available census data are at the locality level, and so in order to get the total population and its characteristics for each community, we aggregated the information from the locality to the community level. Given that the census data is only available for certain years, for each year with no data, the data of the closest census is imputed for that year. So, 1993 to 1997 use data from the 1995 census, 1998 to 2002 use data from the 2000 census, 2003 to 2007 use data from the 2005 census and 2008 to 2013 use data from the 2010 census.

The procedure by which localities are assigned to communities has not been used before (to the best of our knowledge). For this study it is necessary to have data for several years for each community, and the only available population data for communities is from the population censuses. We use the matching procedure assuming that inhabitants of localities within and close to a community will also belong to that community. It is a reasonable assumption, although it has a caveat. For some communities, it is possible that the members of the community live in localities outside the community, mainly in the urban areas of the municipalities.

[4] By law, no land could be given to a community that is more than 7 km away from the land they are claiming.