Optimal Forest Management for Interdependent Products:
A Nested Stochastic Dynamic Bioeconomic Model and Application to Bamboo[1,2]

Tong Wu, David R. Just, C.-Y. Cynthia Lin Lawell, Ariel Ortiz-Bobea, Jiancheng Zhao

Abstract

Sustainable forest management is a complex dynamic problem, and an important issue worldwide. Forests supply the world's population with a variety of forest products, including renewable products such as fruits, nuts, and maple syrup that can be harvested at more frequent intervals than the trees themselves. When there is both uncertainty and interdependent forest products, the interaction between these two phenomena leads to a complicated set of trade-offs. We develop a nested stochastic dynamic bioeconomic model of optimal forest management under uncertainty for interdependent products that differ in their growth cycles, rates of growth, lengths of growing periods, and potential harvest frequency. We use our model to assess the optimality of actual decisions made by forest managers and to develop a dynamic structural econometric model to understand the beliefs and perceptions that underlie and rationalize their management strategies. We apply our model to bamboo forests, which generate two interdependent products: bamboo shoots and bamboo stems. Our methodology is relevant and applicable to the sustainable management of a variety of renewable resources that generate multiple interdependent products.

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[1]Wu: Natural Resources Institute Finland (Luke); tong.wu@luke.fi. Just: Cornell University; drj3@cornell.edu. Lin Lawell: Cornell University; clinlawell@cornell.edu. Ortiz-Bobea: Cornell University; ao332@cornell.edu. Zhao: Zhejiang Academy of Forestry; jiancheng68@163.com.

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1. Introduction

Sustainable forest management is a complex dynamic problem, and an important issue worldwide. Forests supply the world's population with timber as well as renewable non-timber forest products such as fruits, nuts, and maple syrup that can be harvested at more frequent intervals than the trees themselves. This paper develops a nested stochastic dynamic bioeconomic model of optimal forest management under uncertainty for interdependent products.

When forest products are interdependent, the harvest of one product may affect the availability or growth of another product. For example, after harvesting a tree, one will no longer be able to grow or harvest products that grow on the tree. Furthermore, the timing of the harvest of one product may affect how it affects another product. For example, harvesting a tree may have less of an effect on the tree crops that season if the tree harvest takes place after the tree crops have already been harvested.

There is an interesting trade-off that arises for forest management under uncertainty. Under some forms of uncertainty (e.g., uncertainty in prices or precipitation), since harvests are irreversible, there may be an option value to waiting before harvesting that is akin to the option value to waiting in most problems of investment under uncertainty (Dixit and Pindyck, 1994). Thus, all else equal, a forest manager facing these forms of uncertainty may find it optimal to delay harvests. On the other hand, the opposite happens when there is uncertainty over the survival of a forest product. Since any death, decay, or damage to the forest product is irreversible, all else equal, a forest manager facing the possibility that a forest product may die, decay, be damaged, or be infested by pests may find it optimal to harvest earlier. Thus, a forest manager under uncertainty faces two different types of irreversibilities – in harvests on the one hand; and in death or damage on the other – which leads to a tension between delaying versus expediting harvests. This tension is akin to the countervailing forces that arise in environmental policy adoption, wherein on the one hand, environmental policy may induce regulatees (e.g., firms, households, individuals, society) to make irreversible investments in order to comply, and there is an option value to waiting before making these irreversible investments; while on the other hand, delaying climate policy may lead to environmental damage that may be at least partially irreversible, which all else equal would favor expediting climate change policy and adaptation (Dixit and Pindyck, 1994).

When there is both uncertainty and interdependent forest products, the interaction between these two phenomena leads to a complicated set of trade-offs; and developing a model at this nexus is the primary innovation of our paper. On the one hand, reasons for a forest manager to harvest a forest product sooner rather than later may include high prices, low costs, and uncertainty over the survival of the product. On the other hand, reasons for a forest manager to delay the harvest of a forest product include allowing the product more time to grow in size, ripeness, or quality; uncertainty over prices; uncertainty over costs; uncertainty over precipitation; and allowing an interdependent product to grow.

In this paper, we develop a nested stochastic dynamic bioeconomic model of the optimal management of forests that generate interdependent products that differ in their growth cycles, rates of growth, lengths of growing periods, and potential harvest frequency. Our model helps inform optimal forest harvest decision-making under uncertainty when forest products are interdependent, and the optimal strategies from the model can be compared with actual harvesting decisions. We also use our nested stochastic dynamic bioeconomic model to develop a dynamic structural econometric model to understand the beliefs and perceptions of forest managers that underlie and rationalize their actual harvesting decisions. We then use our model to assess sources of any potentially sub-optimal behavior, and suggest possible ways to address them. Our model has important implications for the sustainable management of forests worldwide, particularly when the forests produce products that can be harvested at more frequent intervals than the trees themselves.

We apply our nested stochastic dynamic bioeconomic model to bamboo forests, which generate two interdependent products: bamboo shoots and bamboo stems. Bamboo is a fast growing, renewable, versatile, and easy-to-grow resource touted for its environmental and sustainability benefits (Econation, 2025; Lewis Bamboo, 2025; Guadua Bamboo, 2025). Bamboo shoots are a traditional food source, and bamboo stems are used as timber for paper making, flooring, and construction (Fu, 2001). Moso bamboo (*Phyllostachys edulis*) is the single most important bamboo species in China, accounting for 74% of China's bamboo forest area (China Forestry and Grassland Administration, 2018), as well as the third most important source of timber in China.

Optimal bamboo forest management is a complex dynamic problem, and involves making decisions about the timing and quantity of bamboo stem harvests and bamboo shoot harvests. The harvesting of bamboo stems entails cutting down the bamboo plant, while the harvesting of bamboo shoots does not. Bamboo shoots grow annually from a bamboo plant's underground rhizomes. Owing to their tender taste and to difficulties in harvesting underground shoots, winter shoots – which are young bamboo shoots that are just beginning to grow underground during the winter months – have a higher market price than the older spring shoots that emerge above ground during the later spring months. Bamboo shoots grow into bamboo stem after the end of spring shooting (Shi et al., 2013), and these bamboo stems continue to grow each year until age 4-5 years (Zhang et al., 2014; Zhuang et al., 2015). Bamboo shoots only grow within a year. Bamboo shoots prices vary day to day and are hard to predict, while the bamboo stem price does not vary much over the course of a year. Winter shoots are more expensive than spring shoots, and both winter shoots and spring shoots are more expensive than bamboo stem.

There are several trade-offs involved in determining the optimal bamboo shoots harvesting strategy that arise from uncertainty and the interdependence of shoots and stem. On the one hand, factors that may lead bamboo farmers to harvest shoots sooner rather than later include a high shoots price, low shoots harvest costs, and uncertainty over shoots survival. On the other hand, bamboo farmers may wish to delay the shoots harvest in order to give shoots more time to grow in biomass, and also to wait for the possibility of a higher shoots price (since shoots prices are uncertain). Furthermore, bamboo farmers may forego harvesting some or all of their bamboo shoots if shoots prices are low, if shoots harvests costs are high, if they wish to have more bamboo stem the following year (since unharvested shoots grow into bamboo stem at the end of the year), and/or if there is uncertainty over precipitation (which affects how many shoots will grow the following year from any stem that resulted from unharvested shoots the previous year).

Likewise, there are several trade-offs involved in determining the optimal bamboo stem harvesting strategy. On the one hand, reasons to harvest bamboo stem sooner rather than later include high stem prices and low stem harvest costs. On the other hand, bamboo farmers may wish to delay harvesting bamboo stem in order to give the stem more time to grow in biomass, if stem prices are low, if stem harvest costs are high, to allow shoots to grow annually from the bamboo plant, and/or if they face uncertainty over precipitation (which affects how many shoots will grow from the stem remaining at the beginning of the year).

To solve for the optimal bamboo stem harvest and bamboo shoot harvest policy, our nested stochastic dynamic bioeconomic model nests an inner finite-horizon within-year daily dynamic programming problem within an outer finite-horizon between-year annual dynamic programming problem. The inner finite-horizon within-year daily dynamic programming problem captures daily bamboo shoot growth within a year. The outer finite-horizon between-year annual dynamic programming problem captures annual bamboo stem growth from year to year. We use a Chapman-Richards growth function as our model for bamboo biomass accumulation. To incorporate uncertainty, we allow precipitation, prices, and the possibility of bamboo shoots death to all be stochastic.

We use an iterative approach to developing and refining our model to ensure that it best reflects reality (Figure 1). We use research and information on Moso bamboo from the biological sciences, economic data, and interviews we conducted with bamboo forest managers to develop our model and calibrate the parameters. We compare the optimal strategy given by our model to data on actual bamboo shoot and bamboo stem harvests we collected from multiple bamboo plots in Zhejiang province in China. After obtaining initial results from our numerical model, we then went back to Zhejiang province in China to interview farmers to better understand their beliefs, perceptions, and decision-making, and used that information to further refine our model and better reconcile our model with the actual data. Then, to further understand the beliefs and perceptions of bamboo farmers that underlie and rationalize their bamboo shoot and bamboo stem harvesting decisions as revealed in the data, and to help us assess and mitigate sources of differences between actual behavior and the optimal strategy given by our model, we use our nested stochastic dynamic bioeconomic model to develop a dynamic structural econometric model to estimate different subsets of the parameters econometrically.

Since there is a large set of parameters in our nested stochastic dynamic bioeconomic model, we are unable to identify the entire set of parameters simultaneously. Instead, we run several different specifications of our structural model, each focusing on estimating a different set of structural parameters, holding the remaining parameters fixed at the values we calibrated for our numerical model based on research and information on Moso bamboo from the biological sciences and in economic data. For each specification, the respective structural parameters provide suggestive evidence for the beliefs and perceptions of bamboo farmers regarding that parameter. We use any differences between the estimated structural parameters and the respective values we calibrated based on biological sciences and economic data to help us assess and mitigate sources of differences between actual behavior and the optimal strategy given by our model.

After applying the iterative strategy above to refine our model to ensure that it best reflects reality, we find that the actual bamboo stem and bamboo shoot harvests come close to approximating the optimal harvesting strategy, though some differences remain. Our results have important implications for bamboo forest management and, to the extent that some of the differences between actual harvests and optimal bamboo harvests reflect possible sub-optimal behavior on the part of bamboo forest managers, for ways to improve bamboo forest management and policy.

More generally, the methodology we develop and employ -- including our novel nested stochastic dynamic bioeconomic model, our dynamic structural estimation, as well as our iterative approach to model development and refinement (Figure 1) -- is relevant and applicable to a variety of production processes that generate multiple interdependent products, including forests that produce products (such as fruits, nuts, and maple syrup) that grow on trees, agroforestry, and cattle production. In addition, our iterative approach to model development and refinement (Figure 1) may serve as a blueprint for integrating other insights from natural sciences into economics.

The balance of our paper proceeds as follows. We discuss the previous literature in Section 2. Section 3 summarizes our biological and economic setting. We describe our numerical dynamic model of bamboo forest management in Section 4. Section 5 presents the results of our numerical dynamic model. In Section 6, we compare the dynamically optimal harvesting strategies derived from our model with our data on actual bamboo shoot and bamboo stem harvests. Section 7 presents our dynamic structural econometric model and its results. We conclude in Section 8.

2. Previous Literature

We build on the seminal models of optimal forest management developed by Faustmann (1849) for multiple timber harvests and Wicksell ([1901] 1934) for a single timber harvest, elaborated upon by Samuelson (1976), and subsequently extended in many ways (Kant and Alavalapati, 2014; Wu et al., 2024), including related extensions to allow for additional non-timber sources of forest value (Hartman, 1976; Nguyen, 1979; Berck, 1981; Krutilla and Bowes, 1989; Strang, 1983; Buongiorno, and Gilless, 2003; Yousefpour and Hanewinkel, 2009; Kim and Langpap, 2015; Lintunen, Rautiainen and Uusivuori, 2022), prices and costs that change over time (Chang, 1983; McConnell, Daberkow and Hardie, 1983; Newman, Gilbert and Hyde, 1985), risk of tree death or damage (Reed, 1984; Sims, 2013), and applications to specific tree species (Brodie, Adams, and Kao, 1978; Calish, Fight and Teeguarden, 1978; Riitters, Brodie and Hann, 1982; Tyler, Macmillan, and Dutch, 1996); as well as on the literature on deforestation (Démurger, Hou and Yang, 2009; Souza-Rodrigues, 2019; Oldekop et al., 2019; Balboni et al., 2023; Wang, Amacher and Xu, 2025). We innovate on this literature by developing a model of optimal forest management under uncertainty for interdependent forest products; and also by analyzing forest management in a developing country.

There are multiple available models to measure the growth and productivity of a Moso bamboo plant. Allometric equations and logistic functions have been used for characterizing bamboo growth. An allometric model predicts biomass using diameter at breast height. Biological studies suggest using the Chapman-Richards model (Richards, 1959), which is a flexible growth model for plants (Liu and Li, 2003), and has been used to predict Moso bamboo height (Yen, 2016). Bamboo shoot biomass accumulation has been described using a logistic curve (Zhou, 1998). The literature constructing a growth model for bamboo shoots is sparse, however, and even less is known about underground winter shoot growth. Thus, as the Chapman-Richards model is a generalized logistic curve, and since bamboo shoots are young bamboo plants, we adopt and separately parameterize separate Chapman-Richards models for bamboo stem growth, winter shoot growth, and spring shoot growth.

The dynamics and interdependence of bamboo stem and bamboo shoots share similar characteristics to the dynamics and interdependence of cows and calves, and the resulting cattle cycle (USDA, 2025); our nested stochastic dynamic bioeconomic modeling framework therefore contributes to the literature on cattle management and cattle cycles (Rosen, Murphy and Scheinkman, 1994; Hadley, Wolf and Harsh, 2006; Tonsor, 2011). In Wu et al. (2025b), we develop an analogous notion of a bamboo cycle.

Our paper also contributes to the literature on dynamic structural econometric models, spawned by the seminal work of Rust (1987), and their applications, including related applications to natural resources (Timmins, 2002; Huang and Smith, 2014; Aguirregabiria and Luengo, 2016; Reeling, Verdier and Lupi, 2020; Oliva et al., 2020; Burlig, Preonas and Woerman, 2025; Sears, Lin Lawell and Walter, 2025; Araujo, Costa, and Sant'Anna, 2020; Sears et al., 2025a; Sears et al., 2025b), the environment and energy (Rapson, 2014; Blundell, Gowrisankaran and Langer, 2020; Cook and Lin Lawell, 2020; Feger, Pavanini and Radulescu, 2020; Donna, 2021; Gillingham et al., 2022; Langer and Lemoine, 2022; Li, Liu and Wei, 2022; Weber, 2022; Gerarden, 2023; Toyama, 2024; Bradt, 2024; Thome and Lin Lawell, 2025; Kheiravar, Lin Lawell and Jaffe, 2025), agriculture (Scott, 2013; Carroll et al., 2019; Meneses et al., 2025a; Carroll et al., 2025b; Yeh, Gómez and Lin Lawell, 2025; Meneses et al., 2025b; Carroll et al., 2025a; Sambucci, Lin Lawell and Lybbert, 2025), health (Iskhakov, 2010; Agarwal et al., 2021), development (Duflo, Hanna and Ryan, 2012; Rojas Valdés, Lin Lawell and Taylor, 2025), and consumer behavior (Gowrisankaran and Rysman, 2012; Ching and Osborne, 2020). Misra and Nair (2011) provide evidence that dynamic structural econometric models can help significantly improve decision-making and outcomes.

We innovate on the literature on dynamic structural econometric models by nesting our nested stochastic dynamic bioeconomic model within the maximum likelihood estimation, thereby yielding an expanded technique we refer to as "nested nested fixed point maximum likelihood estimation". We also innovate on the literature on dynamic structural econometric modeling, and structural econometric modeling more generally, by using research and knowledge from the biological and plant sciences to inform our modeling and to calibrate the biological parameters in our model. Owing to intertwined feedback links between biological and economic systems, bioeconomic modeling is challenging, and there is a considerable need for studies that couple economic models of decision-making with biophysical models to provide policy-relevant implications (Kling et al., 2017).

3. Biological and Economic Setting

3.1. The dynamics and interdependence of bamboo stem and bamboo shoots

Moso bamboo (*Phyllostachys pubescens*) is the single most important bamboo species in China, accounting for 74% of China's bamboo forest area (China Forestry and Grassland Administration, 2018). Moso bamboo distributes mostly in subtropical provinces including Fujian, Hunan, Zhejiang, and Jiangxi.

Bamboo shoots grow annually from a bamboo plant's rhizomes, which are underground bamboo stem structures. Bamboo shoots are buds of new bamboo. A bamboo growth year begins on September 1, the first day of winter shooting. The number of bamboo shoots at the beginning of the bamboo growth year is positively correlated with the number of bamboo stem: the more bamboo stem, the more rhizomes there are underground, and the more bamboo shoots that can grow (Li et al., 2016; Zhang and Ding, 1997). The number of bamboo shoots is also positively correlated with precipitation in July and August of the previous bamboo growth year, when bamboo shoots are being formed (Zhang and Ding, 1997).

As long as the shoots are underground and have not emerged above ground, they are called winter shoots. Winter shoots remain dormant during the coldest winter days in January and February, and emerge above ground as spring shoots in March when the temperature rises (Su, 2012). Winter shoots can be harvested and sold on the market for a high winter shoots price until they emerge above ground and start to be called spring shoots. Spring shoots continue to grow very fast until the end of the bamboo growth year (Song et al., 2016).

Bamboo shoots either degenerate, are harvested, or are left in the ground and grow into a newly grown bamboo stem (personal communication, bamboo specialist at Zhejiang Provincial Key Laboratory of Bamboo of Zhejiang Provincial Academy of Forestry, August 2018). More than half of the shoots will degenerate and die naturally before they grow into bamboo stem (Jiang, 2007).

Bamboo shoots grow into bamboo stem after the end of spring shooting (Shi et al., 2013). The number of newly grown bamboo stem is the number of surviving bamboo shoots minus number of shoots harvested. Moso bamboo stems reach their maximum biomass at age 4-5 years (Zhang et al., 2014; Zhuang et al., 2015), do not increase significantly in biomass after 4.62 years (Zhuang et al., 2015), and mature at age 5-6 years (Yen and Lee, 2011).

3.2. Bamboo market

The bamboo market in China is arguably characterized by perfect competition. The cultivation of bamboo forests is done by individual bamboo farmers on their own land (personal communication, Mr. Jianping Pan, manager of Fumin Bamboo Shoot Specialized Cooperative, August 2018), and the number of bamboo farmers in China is quite high. There were 7.14 million bamboo farmers in 2010 (International Bamboo and Rattan Organisation, 2012). In Anji County of Zhejiang province alone, there were approximately 110,000 farmers growing bamboo and another 11,000 people working in the bamboo-processing industry in the county in 1999 (Pérez et al., 1999). Bamboo farmers in Zhejiang province are small peasants who own a relatively small amount of land per family. The average land area managed by a family in Anji County is 21.2 mu, of which 14.9 mu (70%) is allocated to bamboo plantations (Pérez et al., 1999). Bamboo shoots produced in Zhejiang, Hunan, Fujian, Jiangxi, and Sichuan provinces all compete for the same consumers (People.cn, 2014).

Bamboo shoots prices vary day to day and are hard to predict, while the bamboo stem price does not vary much over the course of a year. Bamboo shoot prices also differ for spring bamboo shoots and winter bamboo shoots. Due to difficulties of locating and harvesting underground winter bamboo shoots, as well as popular preference over more tender taste, winter bamboo shoots have higher market price than spring bamboo shoots. Both winter shoots and spring shoots are more expensive than bamboo stem (Wu et al., 2025a).

The bamboo shoot and bamboo stem harvest cost is determined by labor costs (Wu and Cao, 2016) as well as land specific characteristics such as the slope of forest land (Wu and Cao, 2016; Dong et al., 2015). Due to decreasing profits from bamboo forests, younger workers in rural areas have left their hometown and started to find jobs in large cities such as Hangzhou and Shanghai, leaving less labor to manage bamboo forests in rural areas of Zhejiang province; this insufficient labor supply has resulted in increasing labor costs in recent years (Jiang, 2020).

3.3. Data on harvests

We collect, translate, and transcribe individual hard-copy handwritten Chinese records on actual bamboo shoot harvest and bamboo stem harvest decisions on 20 meter by 20 meter bamboo plots in Shanchuan Township and Sian Township in Zhejiang province in China. Our data set includes 35 bamboo plots over 2 bamboo growth years from March 1, 2017 to August 31, 2018: 20 bamboo plots in Sian Township and 15 bamboo plots in Shanchuan Township. We describe and discuss our data in more detail in Appendix B, and present plots of the data on actual harvests in Section 6.

For additional background information regarding China's forests, bamboo forests, and Moso bamboo, see Wu et al. (2025a).

4. Dynamic Model of Moso Bamboo Management

We solve for the optimal bamboo stem and bamboo shoot harvest policy using a numerical dynamic model that nests an inner finite-horizon within-year daily dynamic programming problem within an outer finite-horizon between-year annual dynamic programming problem. The inner finite-horizon within-year daily dynamic programming problem captures daily bamboo shoot growth within a year. Sources of daily variation include the daily shoots biomass, the daily shoots price, the daily number of shoots, daily shoots death, and daily precipitation. The outer finite-horizon between-year annual dynamic programming problem captures annual bamboo stem growth from year to year.[3]

We model the harvesting of bamboo that was all planted at the same time (and therefore of the same age class). The daily control (action) variables are the bamboo shoots harvest a_s (in units of number of bamboo shoots) and bamboo stem harvest a_b (in units of number of bamboo stem). The daily state variables include the number of bamboo stem n_b; the number of bamboo shoots n_s; our precipitation state *precip*, which is a dummy for the cumulative daily precipitation over July and August of that bamboo growth year exceeding a high precipitation threshold that day; and the shoots price p_s. The time variables are year y and day-in-year d.

To incorporate uncertainty, we allow precipitation, bamboo shoot prices, and the possibility of bamboo shoots death to all be stochastic. For both precipitation and prices, we use the empirical distribution of precipitation and prices in the data. In particular, we draw the daily winter shoots price from the empirical distribution of daily winter shoots price, we draw the daily spring price from the empirical distribution of daily spring shoots price, and we draw the daily high precipitation dummy *precip* from the daily empirical probability of high precipitation (*precip* = 1) for each township. For the possibility of bamboo shoots death, we calibrate the probability of death using data and information from previous studies of bamboo growth in the scientific, biological, and plant science literature.[4]

We use a separate Chapman-Richards model (Richards, 1959) for the growth of each of the three types j of bamboo products: winter shoots s_w, spring shoots s_s, and bamboo stem b. The Chapman-Richards model is given by:

$$Y_j = A_j \cdot \left(1 - Q_j e^{-\alpha_j t_j}\right)^{1/(1-v_j)},$$

where Y_j is the total biomass for bamboo product j in a single bamboo plant; t_j is the age of bamboo (in days for winter and spring shoots, and in years for bamboo stem); and A_j, α_j , Q_j, v_j are parameters whose interpretation and values for each of the bamboo product types j are discussed in more detail in Appendix A. Figures A.1 and A.2 in Appendix A plot our calibrated Chapman-Richards growth functions for bamboo shoots and bamboo stem, respectively.

[3] As explained in more detail in Appendix B, we set the finite horizon for the outer between-year annual dynamic programming problem to 11 years, well past the age 4-5 years at which Moso bamboo stems reach their maximum biomass (Zhang et al., 2014; Zhuang et al., 2015).

[4] We describe the empirical distributions and probabilities we use for our stochastic variables in more detail in Appendix B.

The per-period profit function is:

$$\pi(s,a,d,y) = \pi_b(s,a,d,y) + \pi_s(s,a,d,y),$$

where $\pi_b(s,a,d,y)$ is the profit from harvesting bamboo stem and $\pi_s(s,a,d,y)$ is profit from harvesting bamboo shoot. Given the large number of bamboo farmers and the other features of the bamboo market described in Section 3 and further elaborated on in Wu et al. (2025a), we assume that the bamboo market is perfectly competitive and that bamboo farmers are therefore price takers.

The profit $\pi_b(s,a,d,y)$ from bamboo stem harvest is given by:

$$\pi_b(s,a,d,y) = (p_b - c_b)\tau a_b Y_b,$$

where p_b is the bamboo stem price, c_b is the unit cost of bamboo stem harvest, and τ is the conversion coefficient to convert bamboo stem price and bamboo stem quantity $a_b Y_b$ to comparable units.[5]

The profit $\pi_s(s,a,d,y)$ from bamboo shoot harvest is given by:

$$\pi_s(s,a,d,y) = (p_s - c_s)\tau a_s Y_s,$$

where p_s is the bamboo shoots price, c_s is the unit cost of bamboo shoot harvest, and τ is a conversion coefficient to convert bamboo shoots price and bamboo shoots quantity $a_s Y_s$ to comparable units. We allow the bamboo shoots price p_s and the bamboo shoots harvest cost c_s to differ for winter shoots and spring shoots. Since winter shoots price and spring shoots price tend to vary a lot within and across seasons, we also allow the shoots price to be stochastic. In particular, we draw the daily winter shoots price from the empirical distribution of daily winter shoots price, and we draw the daily spring price from the empirical distribution of daily spring shoots price.

In our base case specification, we assume that the bamboo farmer is risk neutral, and therefore that the bamboo farmer's per-period payoff (or utility) $U(\cdot)$ is linear in per-period profit $\pi(s,a,d,y)$:

$$U\big(\pi(s,a,d,y)\big) = \pi(s,a,d,y).$$

Since the bamboo farmer faces multiple sources of uncertainty (precipitation, weather, and shoots death), in an alternative specification we allow the bamboo farmer to be risk averse, and

[5] The Chapman-Richard's model predicts biomass Y_b and Y_s in units of kilograms of dry weight. In contrast, our shoots and stem price are in units of yuan per kilogram of actual weight, which contains both biomass and water. We use a conversion coefficient τ to convert biomass in dry weight into its actual weight (which contains both biomass and water).

use a constant relative risk aversion (CRRA) functional form for the farmer's per-period payoff (or utility) $U(\cdot)$ as a function of per-period profit $\pi(s,a,d,y)$:

$$U\big(\pi(s,a,d,y)\big)=\frac{\pi(s,a,d,y)^{1-\eta}}{1-\eta},$$

where η is the coefficient of constant relative risk aversion. When $\eta=0$, the bamboo farmer is risk neutral, and the per-period payoff corresponds to the linear per-period payoff function from our base case specification.

The bamboo forest manager chooses the bamboo stem harvest strategy and the bamboo shoot harvest strategy to maximize the present discounted value (PDV) of the entire stream of per-period payoffs. The value function, which is the present discounted value of the entire stream of per-period payoffs when the bamboo shoot harvest and bamboo stem harvest decisions are chosen optimally, is given by the following Bellman equation:

$$V(s,d,y)=\max_{a=(a_b,a_s)}U\big(\pi(s,a,d,y)\big)+\beta E[V(s',d',y')|s,a,d,y].$$

Since we nest an inner finite-horizon within-year daily dynamic programming problem within an outer finite-horizon between-year annual dynamic programming problem, we use two different discount factors β: a daily discount factor β_d and an annual discount factor β_y. We set the daily discount factor to be $\beta_d={\beta_y}^{1/365}$, which yields an annual discount factor of β_y over 365 days.

For the transition density for number of bamboo shoots within a year: during each year y, the number of bamboo shoots will change via the bamboo shoots harvest decision a_s. For the transition density for number of bamboo plants, the number of bamboo stems n_b changes via the bamboo stem harvest decision a_b. Bamboo stem harvest can occur any day of year. In addition, since bamboo shoots grow into bamboo stem after the end of spring shooting, the number of bamboo stems n_b also increases by the number of bamboo shoots that remain at the end of the last day of spring shooting.

The transition density for number of bamboo shoots between years is more complicated. The number of bamboo shoots at the beginning of the year depends on the number of remaining bamboo stem at the beginning of the year (remaining after bamboo stem are harvested the previous year): the more bamboo stem, the more rhizomes there are underground, and the more bamboo shoots that can grow (Li et al., 2016; Zhang and Ding, 1997). In addition, to capture the positive correlation of the number of bamboo shoots with precipitation during the months of July and

August of the previous bamboo growth year (Zhang and Ding, 1997), we allow rain to be stochastic and include a state variable, *precip*, which is a dummy for the cumulative daily precipitation over July and August of that bamboo growth year exceeding a high precipitation threshold that day. For each township, for each day in July and August, we take a draw from the daily empirical probability of high precipitation (*precip* = 1) for that township.[6] The number of bamboo shoots n_s is bounded below by 0 and bounded above by an upper bound $\overline{n_s}$ that reflects in part the carrying capacity for bamboo plants.

Since this is a finite horizon problem, the value functions and policy functions are functions of both measures of time, year y and day-in-year d. The terminal condition for the outer annual backwards iteration is that there is no continuation value after the last day of the last year. The terminal condition for the inner day-in-year backwards iteration is that, except in the last year, when there is no continuation value after the last day of the last year, the continuation in the last day of the year is the expected value of the value function on the first day of the next year.

We describe our base case parameter values in Appendix B. We run several specifications of our numerical model that vary the values of the parameters. For each specification, we solve for the value function, the bamboo shoot harvest policy function, and the bamboo stem harvest policy function, each as a function of the state variables (number of bamboo stem n_b, number of bamboo shoots n_s, high precipitation dummy *precip*, and shoots price p_s). Since our dynamic model nests an inner finite-horizon within-year daily dynamic programming problem within an outer finite-horizon between-year annual dynamic programming problem, there is a separate value function and policy function (as functions of state variables) for each day of each year.

5. Results of Numerical Model

Our numerical model yields several notable results. For the optimal bamboo stem harvest, we find that it is generally optimal to wait to harvest any bamboo stem until the fourth bamboo growth year or later, after their growth has begun to slow down, and to harvest bamboo stem at the beginning of the year (Figures C.1 and C.2 in Appendix C). The intuition is as follows. Since bamboo stems continue to grow each year until age 4-5 years, and bamboo stem growth begins to slow down around the end of the fourth year and beginning of the fifth year (Zhang et al., 2014;

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[6] We describe how we model stochastic rain and estimate the daily probability of high precipitation for each township in more detail in Appendix B.

Zhuang et al., 2015), and since the number of bamboo shoots at the beginning of each year depends on the number of bamboo stem remaining at the beginning of each year (Li et al., 2016; Zhang and Ding, 1997), it is optimal to wait until the fourth year or later to harvest any bamboo stem in order to allow bamboo stem biomass to accumulate, and to make bamboo shoots harvest possible for multiple years. Moreover, after bamboo stem growth has slowed down, any increase in bamboo stem biomass from delaying bamboo stem harvest past the beginning of the year will be small since the number of bamboo shoots at the beginning of that year was already determined by the number of bamboo stem remaining at the beginning of that year; it is therefore optimal to harvest bamboo stem at the beginning of the bamboo growth year it is being harvested.

For the optimal bamboo shoot harvest (Figure 2), we find that it is generally optimal to harvest bamboo shoots each year that there are bamboo shoots, starting from the second bamboo growth year. The intuition is as follows. The number of bamboo shoots at the beginning of each year depends on the number of bamboo stem remaining at the beginning of each year. In the first year, when all the bamboo is in the form of bamboo shoots, it is generally optimal to forego harvests so that the bamboo shoots can grow into bamboo stem at the end of the first year, which would then result in there being both bamboo shoots and bamboo stem at the beginning of the second year. It is then optimal to harvest the bamboo shoots each year for which there are bamboo shoots, since starting from the second bamboo growth year onwards the number of bamboo shoots at the beginning of each year is not affected by the bamboo shoot harvest in the previous year, but depends instead on number of bamboo stem remaining at the beginning of each year.

In terms of within-year timing for any winter shoots harvest, we find that even if there is a possibility of shoots death, it is generally optimal to wait at least until end of October and when winter shoots price is high to do any winter shoots harvest. This is because over 50% of winter shoots growth takes place during November (Wei et al., 2017). This result is consistent with the traditional bamboo management guidance to avoid harvesting too many winter shoots before spring shoots emerge, in order to foster a new bamboo forest (Forestry Department of Hunan Province, 2008).

If the number of shoots is very low, however, the winter shoots price is high, and there is a possibility of shoots death, it may be optimal to harvest some winter shoots earlier, including in the first bamboo growth year (Figure C.3 in Appendix C). The intuition is that with very few winter shoots and the possibility of shoots death, it may be worthwhile to harvest earlier if the winter shoots price is high even though the shoots have less biomass because the farmer faces a non-trivial possibility that all of the very few shoots may die before they are harvested.

Likewise, if the bamboo farmer is risk averse and there is a possibility of shoots death, it may be optimal to harvest some winter shoots earlier even when the winter shoots price is low (Figure C.4 in Appendix C). With the possibility of shoots death, it may be worthwhile to harvest earlier even though the shoots have less biomass for a risk averse farmer since the expected marginal utility from waiting for the shoots to accumulate more biomass may be lower than the opportunity cost from any foregone sure profits from harvesting winter shoots earlier before they die.

In terms of within-year timing for any spring shoots harvest, we find that, unless the spring shoots price is high, it is optimal to wait until last days of spring shooting for which spring shoots are marketable to do any spring shoots harvest. The intuition is that the more time the spring shoots are given to grow during spring shooting, the more biomass there is.

Figure 3 presents a sample set of optimal trajectories for bamboo stem harvest, shoots harvest, number of bamboo stem, and number of shoots. Our solution for optimal bamboo forest management might also characterize the optimal forest management policy for other forests that produce products (such as fruits, nuts, sap, and maple syrup) that grow on trees that are renewable and can be harvested at more frequent intervals than the trees themselves.

6. Comparing Optimal Bamboo Management with Actual Harvest Decisions

We compare the optimal bamboo shoot and bamboo stem harvest policy as given by our numerical dynamic model with our data on actual bamboo shoot and bamboo stem harvests on 35 bamboo plots in Zhejiang province.

Figure 4 presents time series plots of the optimal vs. actual number of bamboo stem harvested by initial age class on each bamboo plot. Actual bamboo stem harvests tend to be close to what our model stipulates to be optimal: bamboo stem harvests do not take place until the fourth bamboo growth year or later. Nevertheless, given the relatively low bamboo stem prices during the time period of our data, farmers might do even better by waiting even more years before harvesting bamboo stem.

Figure 5 presents time series plots of the optimal vs. actual number of bamboo shoots harvested, as imputed above, on each bamboo plot. Actual shoots harvests also tend to be close to what our model deems to be optimal: bamboo shoots harvest take place when shoots prices are high; and if the number of shoots is very low and there is a possibility of winter shoots death, winter shoots are harvested earlier when the shoots price is high, including in the first bamboo growth year. Nevertheless, the frequency and/or quantity of actual winter shoots harvests might be higher than optimal.

Previous anecdotal evidence suggests that winter shoots have sometimes been over-harvested for high profit, leaving too few shoots for future bamboo forest development (Wu et al., 2025a). We find that, for the bamboo plots in our data set, even when there are few shoots, and even with the possibility of winter shoots death and high winter shoots prices, the frequency and/or quantity of winter shoots harvest might be higher than optimal.

Thus, results of our comparison between the optimal bamboo stem harvest and bamboo shoot harvest given by our dynamic model with the data on actual bamboo stem harvests and bamboo shoots harvest is that actual bamboo stem and bamboo shoot harvests come close to approximating the optimal harvesting strategy, but have some features that differ from what our model suggests to be optimal.

We also compare actual and optimal net present value (NPV), where net present value (NPV) is defined as the present discounted value (PDV) of the entire stream of daily profits. First, we calculate and compare actual and optimal NPV during the days with data, where optimal NPV during the days with data is calculated using the actual initial states and actual daily prices and precipitation; and the actual NPV during the days with data is calculated using the actual daily actions, states, prices, and precipitation. Second, we calculate and compare optimal expected NPV over the entire 11-year horizon, where optimal expected NPV over the entire 11-year horizon is given by the value function evaluated at the initial states, and takes an expectation over stochastic shoots prices and precipitation; and where actual expected NPV over the entire 11-year horizon is the actual NPV during the days with data calculated above plus the discounted continuation value evaluated at the actual state at end of data and assumes optimal behavior after the last day of data.

As seen in the NPV results in Table 1, the optimal strategy yields a higher NPV than actual harvests do, both during the days with data, and also in expectation over the entire 11-year horizon. The optimal strategy does even better than actual harvests in expectation over the 11-year horizon, since the optimal strategy may involve forgoing some profits in the short run in order to benefit from higher and more sustained profits in the long run, and thus we see even more benefits of the optimal strategy in expectation over 11 years than we see in just the 2 years of our data.

7. Dynamic Structural Econometric Model

To understand the beliefs and perceptions of bamboo farmers that underlie and rationalize their bamboo shoot and bamboo stem harvesting decisions as revealed in the data, and to help us assess and mitigate sources of differences between actual behavior and the optimal strategy given by our model, we use our nested stochastic dynamic bioeconomic model to develop a dynamic structural econometric model. We innovate upon the nested fixed point maximum likelihood estimation developed by Rust (1987, 1988) by nesting our nested stochastic dynamic bioeconomic model within the maximum likelihood estimation, so that the nested fixed point calculation itself also involves a nest, thereby yielding an expanded technique we refer to as "nested nested fixed point maximum likelihood estimation".

Since there is a large set of parameters in our nested stochastic dynamic bioeconomic model, we are unable to identify the entire set of parameters simultaneously. Instead, we run several different specifications of our structural model, each focusing on estimating a different set of structural parameters θ, holding the remaining parameters fixed at the values we calibrated for our numerical model based on research and information on Moso bamboo from the biological sciences and in economic data. For each specification, the respective structural parameters θ provide suggestive evidence for the beliefs and perceptions of bamboo farmers regarding that parameter θ. We use any differences between the estimated structural parameters θ and the respective values we calibrated based on biological sciences and economic data to help us assess and mitigate sources of differences between actual behavior and the optimal strategy given by our model.

7.1. Nested nested fixed point maximum likelihood estimation

To account for unobservable state variables that bamboo farmers observe (but we do not observe) when they make their spraying and harvesting decisions, we next expand the per-period payoff to each choice a to include both a deterministic component $U_0(\pi(s,a,d,y);\theta)$ and a stochastic component $\varepsilon(a)$. The deterministic component $U_0(\pi(s,a,d,y);\theta)$ of the per-period payoff in our structural model is equal to the bamboo farmer's per-period payoff $U\big(\pi(s,a,d,y)\big)$

from the numerical model; as before, we assume the bamboo farmer is risk neutral in the base case and allow for risk aversion in an alternative specification. The stochastic component to the per-period payoff to each action is an unobserved shock $\varepsilon(a)$ associated with that action choice a that is assumed to be distributed i.i.d. extreme value across days d, years t, farmers i, and actions a. The value function incorporating these unobserved shocks $\varepsilon(a)$ is now given by:

$$V(s,d,y;\theta) = \max_{a=(a_b,a_s)} U_0(\pi(s,a,d,y);\theta) + \varepsilon(a) + \beta E[V(s',d',y';\theta)|s,a,d,y].$$

The conditional choice probabilities $\Pr(a|s,d,y;\theta)$are given by:

$$\Pr(a|s,d,y;\theta) = \frac{\exp\big(U_0(\pi(s,a,d,y);\theta)+\beta V^c(s,a,d,y;\theta)\big)}{\sum_{\tilde{a}}\exp\big(U_0(\pi(s,\tilde{a},d,y);\theta)+\beta V^c(s,\tilde{a},d,y;\theta)\big)},$$

where $V^c(s,a,d,y;\theta)$ is the continuation value, which is the expected value of the value function next period given the states and actions this period:

$$V^c(s,a,d,y;\theta) = E[V(s',d',y';\theta)|s,a,d,y].$$

We use a nested fixed point maximum likelihood estimation to find the parameters θ that maximize the log-likelihood function $L(\theta)$, which is the following function of the conditional choice probabilities $\Pr(a|s,d,y;\theta)$:

$$L(\theta) = \sum_i \sum_d \sum_y \ln \Pr(a_{idy}|s_{idy},d,y;\theta).$$

Building on the nested fixed point maximum likelihood estimation technique developed by Rust (1987, 1988), our maximum likelihood estimation methodology nests an inner finite-horizon within-year daily dynamic programming problem within an outer finite-horizon between-year annual dynamic programming problem to solve for the continuation values and conditional choice probabilities for each day d in each year y at each evaluation of the likelihood function. Thus, the nested fixed point calculation itself involves a nest -- our nested stochastic dynamic bioeconomic model, an expanded technique we thereby refer to as "nested nested fixed point maximum likelihood estimation".

In one specification, the structural parameter θ we estimate is the growth rate α_{s_w} for winter shoots. In a second specification, the structural parameters θ we estimate are parameters in the shoots harvesting cost, namely the winter shoots harvest cost parameter c_{s_w}, the spring shoots harvest cost parameter c_{s_s}, and the shoots harvest cost convex cost parameter c_{s_2}. In a third specification, the structural parameter θ we estimate is the daily shoots decline probability during winter shooting. In a fourth specification, we allow for risk aversion and the structural parameter θ we estimate is the coefficient of constant relative risk aversion η.

Identification of the parameters θ comes from the differences between per-period payoffs across different action choices, which in finite-horizon dynamic discrete choice models are identified when the discount factor β, the distribution of the choice-specific shocks $\varepsilon(a)$, and the final period continuation value are fixed (Rust, 1994; Magnac and Thesmar, 2002; Abbring, 2010). In particular, because the discount factor β and the distribution of the choice-specific shocks $\varepsilon(a)$ are fixed and the final period continuation value is zero, the parameters in our model are identified because each term in the deterministic component $\pi_0(s, a, d, y; \theta)$ of the per-period payoff depends on the action a being taken in day d in year y, and therefore varies based on the action taken; as a consequence, the parameters do not cancel out in the differences between per-period payoffs across different action choices and are therefore identified. For example, the winter shoots harvest cost parameter c_{s_w} is identified in the difference between the per-period payoff from choosing to harvest winter shoots and the per-period payoff from any daily action choice a that does not involve harvesting winter shoots.

In a fifth specification, the structural parameter θ we estimate is the annual discount factor β_y. In general, the discount factor β is not identified in dynamic structural econometric models. In order to identify the discount factor β in a dynamic structural econometric model, one needs a variable that affects the transition density of state variables that affect per-period profits, but does not itself directly affect the per-period profits except through its effect on the transition density (Fang and Wang, 2015). In our case, our variable for precipitation over the months of July and August does not directly affect daily profits except through its effect on the number of bamboo shoots at the beginning of the subsequent bamboo growth year. Thus, in our case, we can potentially identify the discount factor β_y.

Standard errors are formed by a non-parametric bootstrap. Bamboo plots are randomly drawn from the data set with replacement to generate 100 independent panels each with the same number of bamboo plots as in the original data set. The structural model is run on each of the new panels. The standard errors are then formed by taking the standard deviation of the parameter estimates from each of the panels.

7.2. Results

Table 2 presents the results of the specification of the dynamic structural model in which the structural parameter θ we estimate is the growth rate α_{s_w} for winter shoots. Our structural parameter estimate for the winter shoots growth rate α_{s_w} of 0.272 for the pooled sample is larger than the winter shoots growth rate α_{s_w} we calibrated based on biological research and information on winter shoots to be 0.016. Thus, the harvesting behavior of the bamboo farmers in our data can be rationalized by high perceived growth rate for winter shoots. In other words, bamboo farmers are acting as if they perceive or believe the growth rate for winter shoots to be higher than may actually be the case based on data and information on winter shoots from plant scientists. Figure C.5 in Appendix C plots the bamboo farmers' perceived Chapman-Richards growth function for winter shooting and spring shooting based on our structural parameter estimates for the winter shoots growth rate. Thus, the high quantity and frequency of winter shoots harvests we see in the data can be rationalized by perceived growth rate for winter shoots that is higher than may actually be the case based on data and information on winter shoots from plant scientists.

Table 3 presents the results of the specification of the dynamic structural model in which the structural parameters θ we estimate are parameters in the shoots harvesting cost, namely the winter shoots harvest cost parameter c_{s_w}, the spring shoots harvest cost parameter c_{s_s}, and the shoots harvest cost convex cost parameter c_{s_2}. We find that the bamboo farmers in our data are acting as if they perceive or believe spring shoots harvest costs to be lower higher than the actual monetary cost, and that they perceive or believe high convex costs to shoots harvest. The high perceived convex costs to shoots harvest may explain why we see a high frequency of winter shoots harvests in the data.

Table C.1 in Appendix C presents the results of the specification of the dynamic structural model in which the structural parameter θ we estimate is the daily shoots decline probability during winter shooting. We find that the harvesting behavior of the bamboo farmers in our data can be rationalized by a daily winter shoots decline probability of zero. We rerun our numerical nested stochastic dynamic bioeconomic model using a daily winter shoots decline probability of zero. Figure C.6 in Appendix C compares the resulting optimal bamboo shoots harvests with the actual data (optimal bamboo stem harvests remain unchanged from before, and the respective figure is identical to Figure 4), and Table C.2 in Appendix C compares resulting optimal NPV with actual NPV. Results suggest that using the perceived daily winter shoots decline probability of zero estimated from the structural model does not substantially improve the fit of the model; while the optimal strategy may better match spring shoots harvest during the second year of our data set (see, for example, initial age class 0 in the second year of data following the second dashed red vertical line) when using the structural parameter estimate (Figure C.6), the calibrated parameter better explains the actual winter shoots harvest (Figure 5). In addition, the difference between optimal and actual NPV is higher under the structural parameter estimate (Table C.2) than under the calibrated parameter (Table 1). Moreover, the most cited reason among bamboo farmers we interviewed for harvesting bamboo shoots earlier during winter shooting is the probability that shoots might not survive (Wu et al., 2025a). For these reasons, it is unlikely that the discrepancy between actual and optimal decisions is due to bamboo farmers misperceiving the daily winter shoots decline probability to be zero.

Table 4 presents the results of the specification of the dynamic structural model in which we allow for risk aversion and the structural parameter θ we estimate is the coefficient of constant relative risk aversion η. We find that the harvesting behavior of the bamboo farmers in our data for the pooled sample and for Sian Township can be rationalized by a coefficient of constant relative risk aversion of $\eta = 0.8$. In contrast, bamboo farmers in Shanchuan Township appear to be risk neutral, as the coefficient of constant relative risk aversion η for the subsample of farmers in Shanchuan Township is statistically insignificant. We rerun our numerical nested stochastic dynamic bioeconomic model using a coefficient of constant relative risk aversion of $\eta = 0.8$. Figure C.7 in Appendix C compares the resulting optimal bamboo shoots harvests with the actual data (optimal bamboo stem harvests remain unchanged from before, and the respective figure is identical to Figure 4), and Table C.3 in Appendix C compares resulting optimal welfare with actual welfare, where welfare is defined as the present discounted value (PDV) of the entire stream of daily payoffs. When farmers are risk averse (with $\eta = 0.8$), the optimal winter shoots harvests are higher in frequency and quantity, which may better match the actual winter shoots harvests (Figure C.7), though risk neutrality (Figure 5) better matches the actual spring shoots harvest during the second year of our data set (see, for example, initial age class 3 in the second year of data following the second dashed red vertical line).

Table C.4 in Appendix C presents the results of the specification of the dynamic structural model in which the structural parameter θ we estimate is the annual discount factor β_y. Results show the discount factor β_y is close to 1, so the bamboo farmers in our data set do care about the future, which rules out myopic behavior as a possible source of discrepancy between actual and optimal decisions.

7.3. Discussion and policy implications

Results of our dynamic structural econometric model suggest three possible sources of differences between actual and optimal harvests: a higher perceived winter shoots growth rate, more convex costs to shoots harvest, and risk aversion. Each of these three channels would explain why actual winter shoots harvests in the data are higher and more frequent than our model suggests is optimal.

Since the winter shoots growth rate we calibrate is based on research and information on Moso bamboo from biological science, the parameter value we use likely reflects actual winter shoots growth. Thus, if bamboo farmers perceive the winter shoots growth rate to be higher than the what it actually is, this is a misperception that leads to a loss in farmer NPV (as seen in Table 1) and can be addressed via programs and policies that better inform farmers about winter shoot growth.

As for the high convex costs to harvesting shoots, since we have less information on costs and since costs can vary by farmer, we therefore feel less confident that the convexity parameter we use for our model reflects the true convexity of costs for all bamboo farmers; it is therefore very possible that the structural estimate for the convexity of shoots harvesting costs may better reflect the convexity of all shoots harvesting costs, monetary and otherwise, that farmers face. Nevertheless, as the high convexity of costs leads to a loss in farmer NPV, there may be scope for improving bamboo farmer profits and sustainability through initiatives that address the reason costs are so convex. For example, if the convex costs arise due to labor shortages or labor constrains that preclude a farmer from harvesting a large quantity of shoots at one time, then policies that alleviate the labor market frictions might be beneficial.

As for risk aversion, results of our structural model suggest that bamboo farmers in Sian Township are risk averse while the bamboo farmers in Shanchuan Township are not. As risk aversion leads to lower profits, there may be scope for improving bamboo farmer profits and sustainability through initiatives, such as crop insurance, that help farmers reduce, share, or manage the risk they face.

8. Conclusion

When there is both uncertainty and interdependent forest products, the interaction between these two phenomena leads to a complicated set of trade-offs; developing a model at this nexus is the primary innovation of our paper. In particular, we develop a nested stochastic dynamic bioeconomic model of optimal forest management under uncertainty for interdependent products that differ in their growth cycles, rates of growth, lengths of growing periods, and potential harvest frequency. Our model enables us to assess the optimality of actual decisions made by forest managers and to develop a dynamic structural econometric model to understand the beliefs and perceptions that underlie and rationalize their management strategies. As depicted in Figure 1, we use an iterative approach to developing and refining our model to ensure that it best reflects reality.

We apply our model to bamboo forests, which generate two interdependent products: bamboo shoots and bamboo stems. We compare the optimal bamboo stem harvest and bamboo shoot harvest policy with actual data on bamboo shoot and bamboo stem harvests in China. We find that the actual bamboo stem and bamboo shoot harvests come close to approximating the optimal harvesting strategy, though some differences remain. First, given relatively low bamboo stem prices, farmers might do even better by waiting even more years before harvesting bamboo stem. Second, for the bamboo plots in our data set, even when there are few shoots, and even with the possibility of winter shoots death and high winter shoots prices, the frequency and/or quantity of winter shoots harvest might be higher than optimal, and contrary to the traditional bamboo management guidance to avoid harvesting too many winter shoots before spring shoots emerge, in order to foster a new bamboo forest (Forestry Department of Hunan Province, 2008). The results are consistent with anecdotal evidence that winter shoots have sometimes been over-harvested for high profit, leaving too few shoots for future bamboo forest development.

To further understand the beliefs and perceptions of bamboo farmers that underlie and rationalize their bamboo shoot and bamboo stem harvesting decisions as revealed in the data, and to help us assess and mitigate sources of differences between actual behavior and the optimal strategy given by our model, we use our nested stochastic dynamic bioeconomic model to develop a dynamic structural econometric model to estimate different subsets of the parameters econometrically. Results of our dynamic structural econometric model suggest three possible sources of differences between actual and optimal harvests: a higher perceived winter shoots growth rate, more convex costs to shoots harvest, and risk aversion. To the extent that the overharvesting of winter shoots and its resulting loss in farmer NPV is due to farmers misperceiving the winter shoots growth rate, this inefficiency can be addressed via programs and policies that better inform farmers about winter shoot growth. Similarly, if farmers are facing highly convex costs due to labor shortages or labor constraints that preclude them from harvesting a large quantity of shoots at one time, then policies that alleviate the labor market frictions might be beneficial. Likewise, there may be scope for improving bamboo farmer profits and sustainability through initiatives, such as crop insurance, that may make bamboo farmers less risk averse.

There are several important features of bamboo forest management that are at least partially captured by our model. These include winter shoots growth, variation in bamboo shoot price and bamboo stem price over time; capacity and/or labor constraints on the amount that is feasible to harvest in one day; the possibility of shoots death; risk aversion; and parameter values that differ from the ones we use in the model. The remaining differences between actual harvests and optimal bamboo harvests may reflect features that we do not capture in our model, including liquidity constraints and/or alternative crops or uses of the land. If some of the differences between actual harvests and optimal harvests arise because of economic constraints such as liquidity constraints, it is possible that some of these constraints can be ameliorated by well-designed institutions or policies. Our results have important implications for bamboo forest management and, to the extent that some of the differences between actual harvests and optimal bamboo harvests reflect possible sub-optimal behavior on the part of Moso bamboo forest managers, for ways to improve Moso bamboo forest management and policy.

The methodology we develop and employ – including our novel nested stochastic dynamic bioeconomic model, our "nested nested fixed point maximum likelihood estimation" technique, as well as our iterative approach to model development and refinement (Figure 1) – is relevant and applicable to the sustainable management of forests under uncertainty in a variety settings wherein the forests produce products (such as fruits, nuts, and maple syrup) that grow on trees, that are renewable, and can be harvested at more frequent intervals than the trees themselves. Our methodology may also be helpful in the examination of other production processes that generate multiple interdependent products, such as cattle production (Wu et al., 2025b). In addition, our iterative approach to model development and refinement (Figure 1) may serve as a blueprint for integrating other insights from natural sciences into economics. Finally, the notion of using structural models to provide suggestive evidence for the beliefs and perceptions of decision-making agents regarding various scientific and economic parameters, and to help assess and mitigate sources of differences between actual behavior and the optimal strategy given by an economic model, may provide an important role for structural models in economic analysis in contexts wherein information about parameter values may already be available, for example from the natural sciences or economic data.

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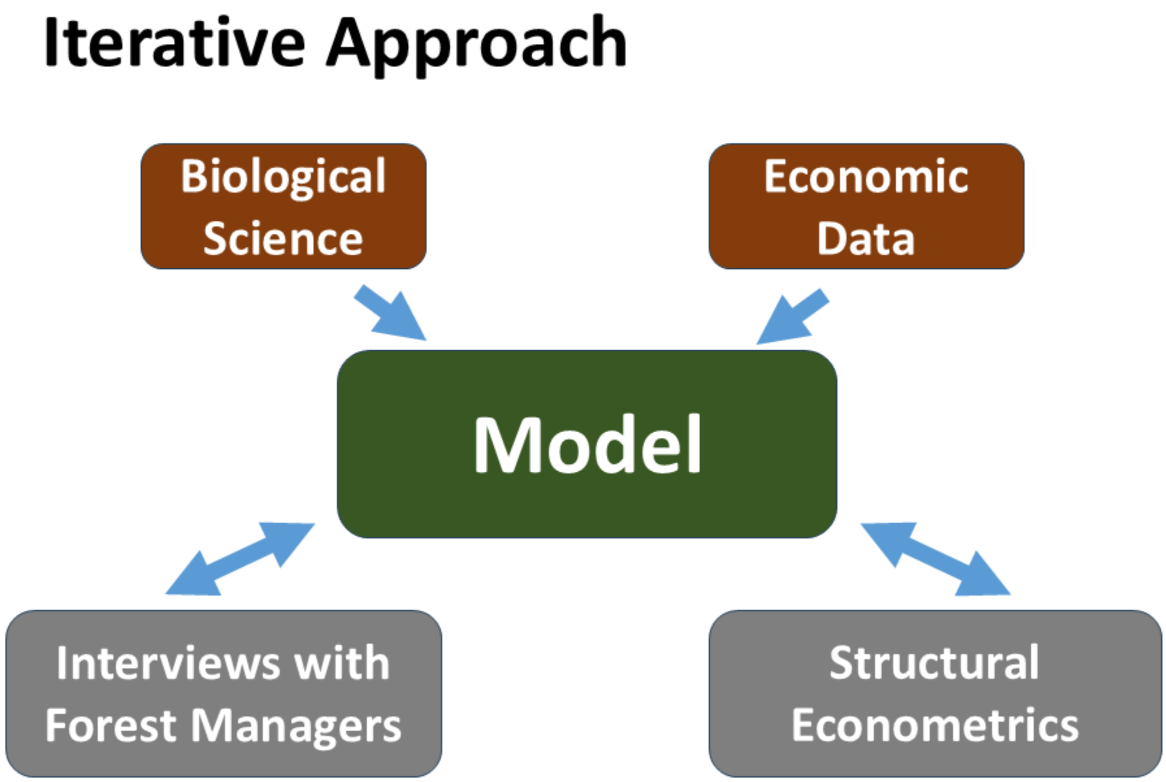
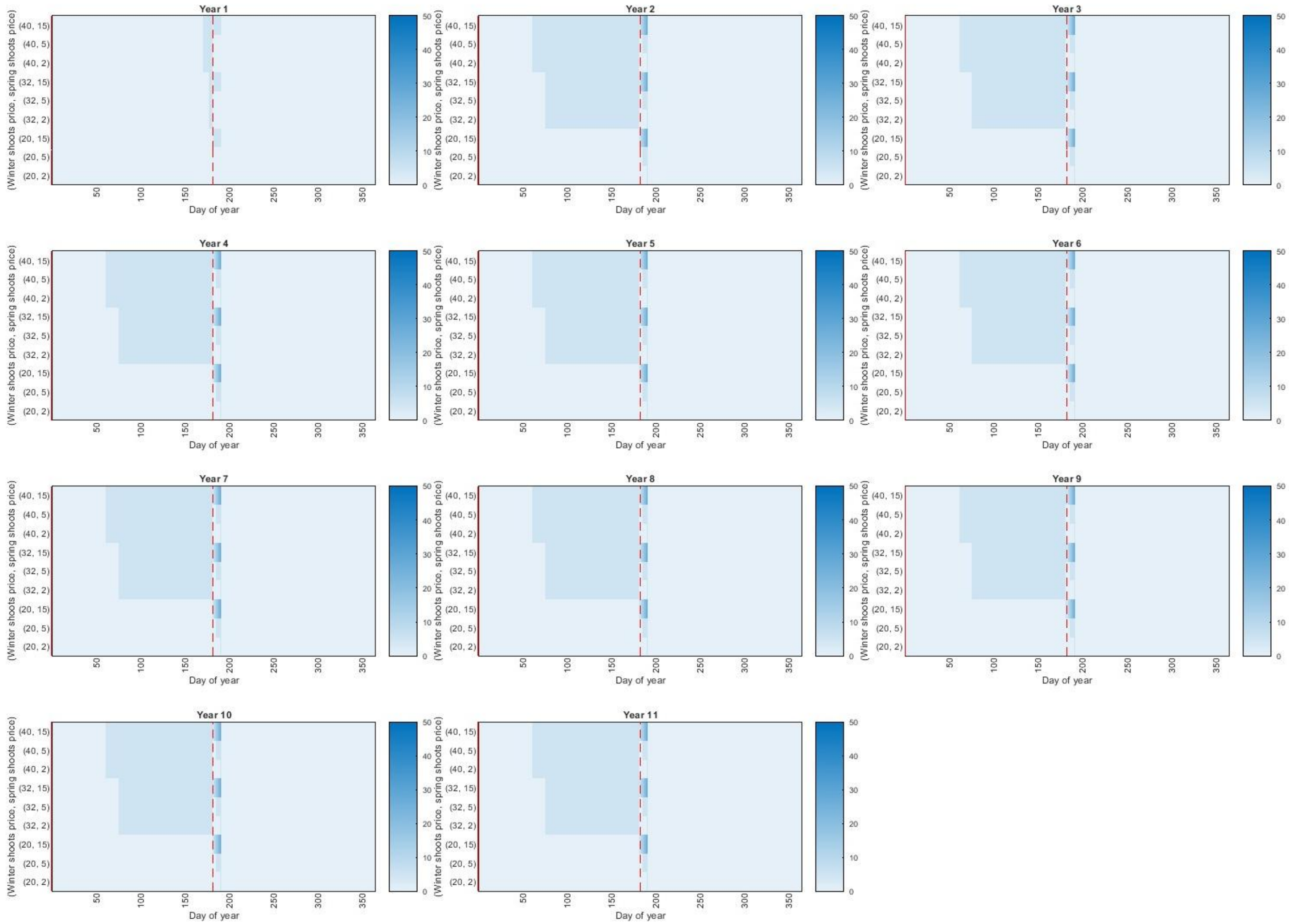
Figure 1. Iterative Approach to Model Development and Refinement



Notes: We use an iterative approach to developing and refining the model to ensure that it best reflects reality. We use research and information on Moso bamboo from the biological sciences, economic data, and interviews we conducted with bamboo forest managers to develop our model and calibrate the parameters. We compare the optimal strategy given by our model to data on actual bamboo shoot and bamboo stem harvests. After obtaining initial results from our numerical model, we then went back to Zhejiang province to interview farmers to better understand their beliefs, perceptions, and decision-making, and used that information to further refine our model and better reconcile our model with the actual data. Then, to further understand the beliefs and perceptions of bamboo farmers that underlie and rationalize their harvesting decisions, and to help us assess and mitigate sources of differences between actual behavior and the optimal strategy given by our model, we use our nested stochastic dynamic bioeconomic model to develop a dynamic structural econometric model to estimate different subsets of the parameters econometrically. Since there is a large set of parameters in our nested stochastic dynamic bioeconomic model, we are unable to identify the entire set of parameters simultaneously. Instead, we run several different specifications of our structural model, each focusing on estimating a different set of structural parameters, holding the remaining parameters fixed at the values we calibrated for our numerical model based on research and information on Moso bamboo from the biological sciences and in economic data. For each specification, the respective structural parameters provide suggestive evidence for the beliefs and perceptions of bamboo farmers regarding that parameter. We use any differences between the estimated structural parameters and the respective values we calibrated based on biological sciences and economic data to help us assess and mitigate sources of differences between actual behavior and the optimal strategy given by our model.

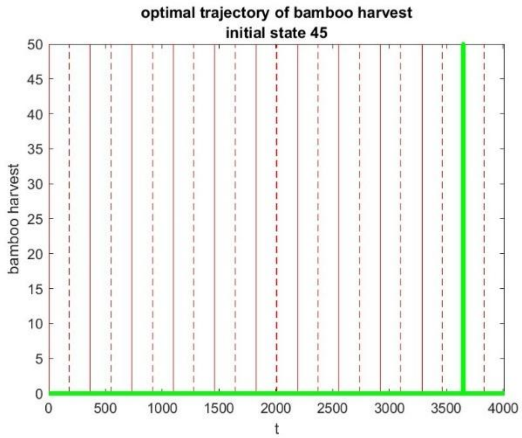
Figure 2. Daily Bamboo Shoots Harvest Policy Function



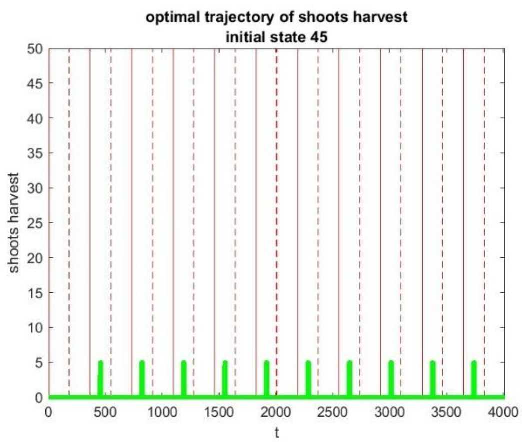
Notes: Figure presents bamboo shoots harvest policy function for each day for each year as a function of daily shoots price when the number of shoots is a medium quantity ($n_s = 25$) and cumulative daily precipitation is low ($precip = 0$), and when parameters are set at their base case values. For each bamboo growth year, dashed vertical lines in red that go from the top to the bottom of the graph denote March 1 (first day of spring shooting) of each year.

Figure 3. Example of Optimal Trajectories

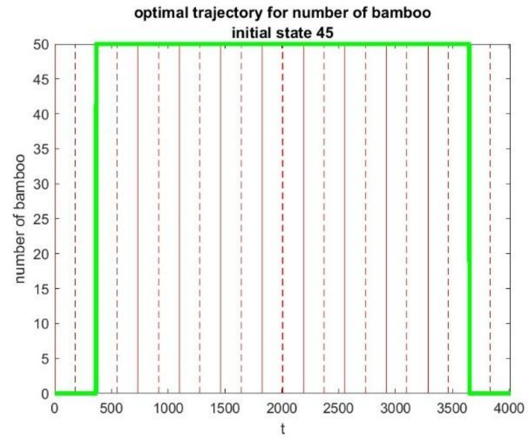
a) Bamboo Stem Harvest



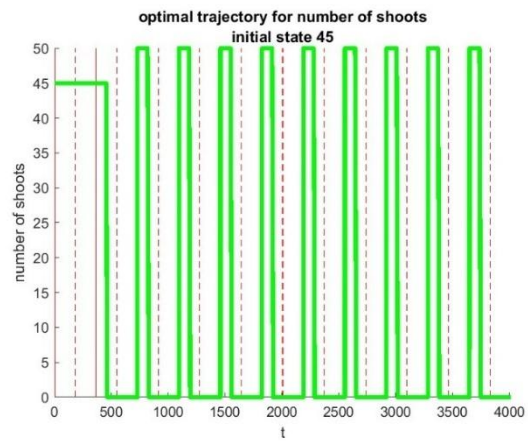
b) Shoots Harvest



c) Number of Bamboo Stem

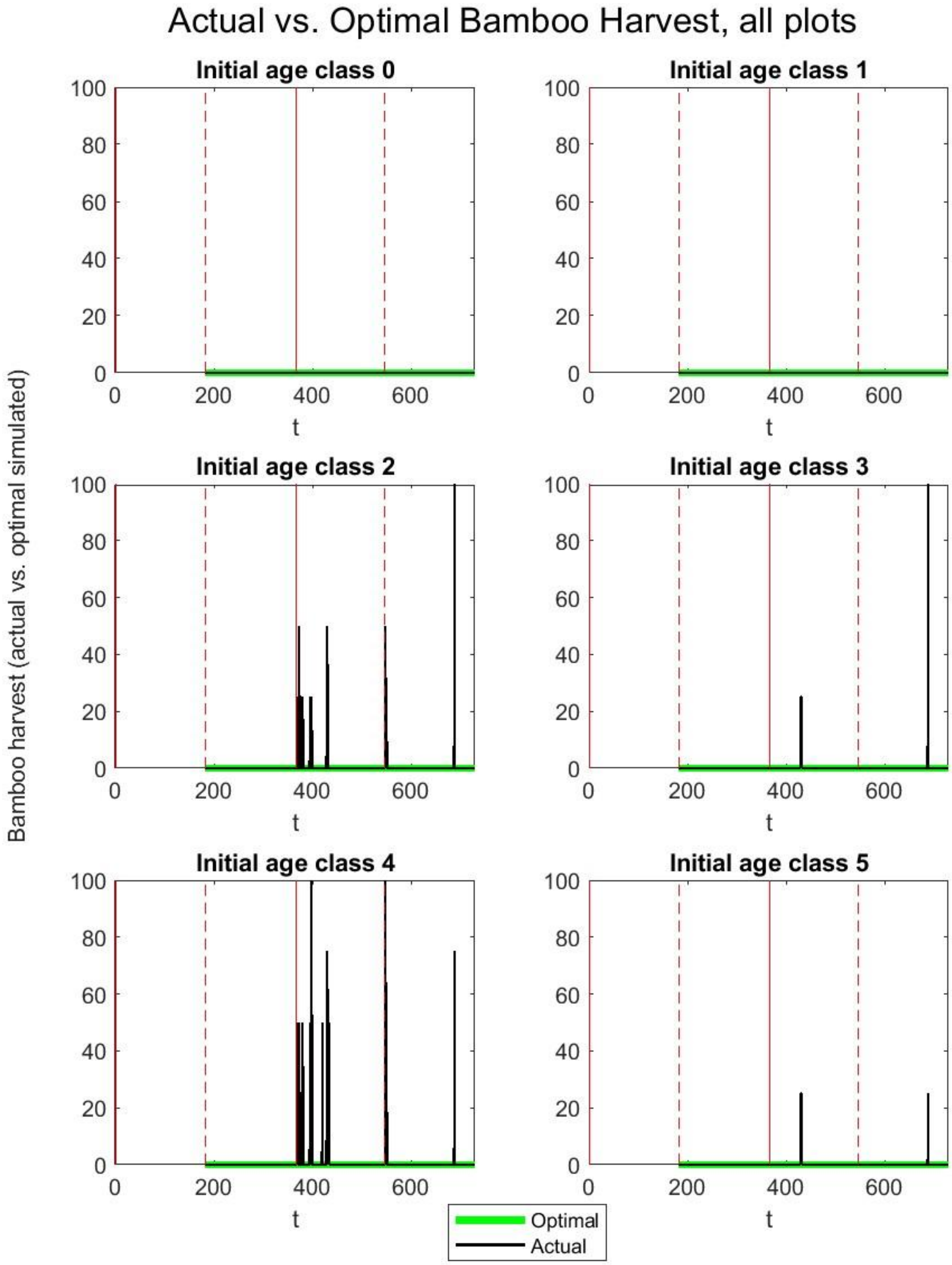


d) Number of Shoots



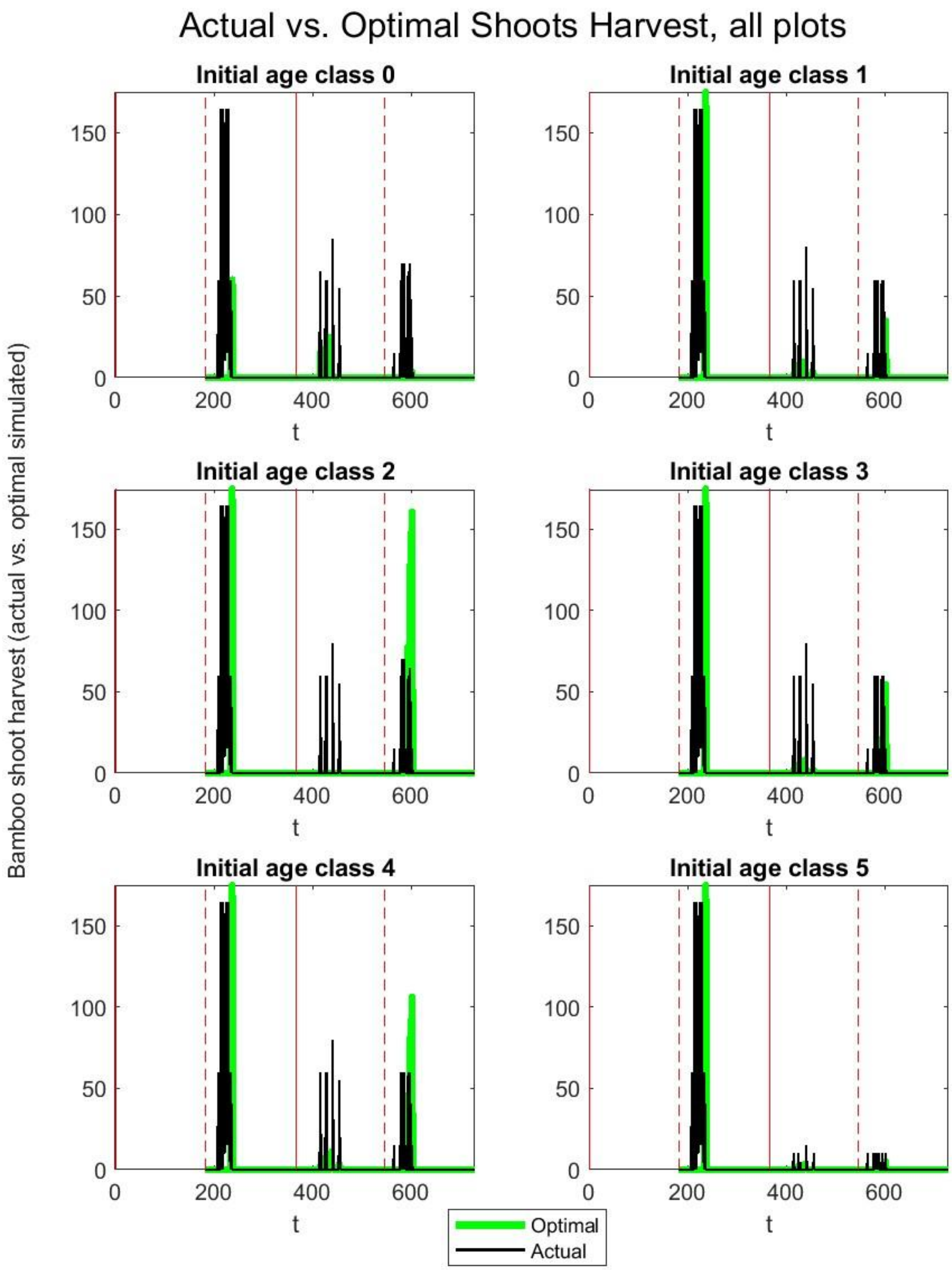
Notes: Figure presents a simulated set of optimal trajectories for bamboo stem harvest, bamboo shoots harvest, number of bamboo stem, and number of bamboo shoots for each day of each year starting from a large initial number of bamboo shoots ($n_s = 45$) on the first day of the first bamboo growth year, when parameters are set at their base case values. Vertical lines in red that go from the top to the bottom of the graph denote September 1 (first day of winter shooting) of each year. Dashed vertical lines in red that go from the top to the bottom of the graph denote March 1 (first day of spring shooting) of each year.

Figure 4. Optimal vs. Actual Bamboo Stem Harvests



Notes: Time series plots of the optimal and actual number of bamboo stem harvested by initial age class. Vertical lines in red that go from the top to the bottom of the graph denote September 1 (first day of winter shooting) of each year. Dashed vertical lines in red that go from the top to the bottom of the graph denote March 1 (first day of spring shooting) of each year.

Figure 5. Optimal vs. Actual Shoots Harvest



Notes: Time series plots of the optimal vs. actual number of bamboo shoots harvested on each bamboo plot. Vertical lines in red that go from the top to the bottom of the graph denote September 1 (first day of winter shooting) of each year. Dashed vertical lines in red that go from the top to the bottom of the graph denote March 1 (first day of spring shooting) of each year.

Table 1. Actual vs. Optimal Net Present Value (NPV)

(a)

NPV during days with data	Mean (Yuan)
Optimal	272
Actual	127
Optimal minus Actual	145

(b)

Expected NPV over 11-year horizon	Mean (Yuan)
Optimal	5,529
Actual	4,007
Optimal minus Actual	1,522

Notes: Table compares actual and optimal net present value (NPV), where net present value (NPV) is defined as the present discounted value (PDV) of the entire stream of daily profits. Panel (a) compares actual and optimal NPV during the days with data, where optimal NPV during the days with data is calculated using the actual initial states and actual daily prices and precipitation; and the actual NPV during the days with data is calculated using the actual daily actions, states, prices, and precipitation. Panel (b) compares optimal expected NPV over the entire 11-year horizon, where optimal expected NPV over the entire 11-year horizon is given by the value function evaluated at the initial states, and takes an expectation over stochastic shoots prices and precipitation; and where actual expected NPV over the entire 11-year horizon is the actual NPV during the days with data calculated above plus the discounted continuation value evaluated at the actual state at end of data and assumes optimal behavior after the last day of data.

Table 2. Dynamic Structural Model Results: Winter Shoot Growth

Structural Parameter	Actual (Assumed Value)	All	Sian	Shanchuan
		(1)	(2)	(3)
Winter shoots growth rate α_{s_w}	0.016	0.272 ***	0.292 ***	0.202 ***
		(0.005)	(0.045)	(0.009)
# Observations		115,290	65,880	49,410
# Bamboo plots		35	20	15

Notes: The structural parameter estimates are the parameter estimates from our specification of the structural model estimating the winter shoot growth parameter only for the entire sample ("All"), Sian Township only ("Sian"), and Shanchuan Township only ("Shanchuan"). The actual value is the assumed base case parameter value we calibrated based on biological sciences and economic data. Bootstrapped standard errors in parentheses. Significance codes: *** p<0.001, ** p<0.01, * p<0.05

Table 3. Dynamic Structural Model Results: Shoots Cost Parameters

Structural Parameter	Actual (Assumed Values)	All (1)
Winter shoots harvest cost parameter c_{s_w}	15	14.71*** (4.504)
Spring shoots harvest cost parameter c_{s_s}	1.5	0.61*** (0.117)
Shoots harvest cost convex cost parameter c_{s_2}	50	114.28*** (1.321)
# Observations		115,290
# Bamboo plots		35

Notes: The structural parameter estimates are the parameter estimates from our specification of the structural model estimating the shoots cost parameters only for the entire sample ("All"). The actual values are the assumed base case parameter values we calibrated based on biological sciences and economic data. Bootstrapped standard errors in parentheses. Significance codes: *** p<0.001, ** p<0.01, * p<0.05

Table 4. Dynamic Structural Model Results: Coefficient of Constant Relative Risk Aversion

Structural Parameter	Actual (Assumed Value)	All	Sian	Shanchuan
		(1)	(2)	(3)
Coefficient of constant relative risk aversion η	0	0.805 ***	0.788 ***	0.121
	(risk neutral)	(0.008)	(0.002)	(0.138)
# Observations		115,290	65,880	49,410
# Bamboo plots		35	20	15

Notes: The structural parameter estimates are the parameter estimates from our specification of the structural model allowing for risk aversion and estimating the coefficient of constant relative risk aversion parameter only for the entire sample ("All"), Sian Township only ("Sian"), and Shanchuan Township only ("Shanchuan"). The actual value is the assumed base case parameter value. Bootstrapped standard errors in parentheses. Significance codes: *** p<0.001, ** p<0.01, * p<0.05

Appendix

Appendix A. Chapman-Richards Growth Model

There are multiple available models to measure the growth and productivity of a Moso bamboo plant. Allometric equations and logistic functions have been used for characterizing bamboo growth. An allometric model predicts biomass using diameter at breast height. Biological studies suggest using the Chapman-Richards model (Richards, 1959), which is a flexible growth model for plants (Liu and Li, 2003), and has been used to predict Moso bamboo height (Yen, 2016). In addition to a model for bamboo stem growth, we also need a model for bamboo shoot growth. Bamboo shoot biomass accumulation has been described using a logistic curve (Zhou, 1998). The literature constructing a growth model for bamboo shoots is sparse, however, and even less is known about underground winter shoot growth. Thus, as the Chapman-Richards model is a generalized logistic curve, and since bamboo shoots are young bamboo plants, we adopt and separately parameterize separate Chapman-Richards models for winter shoot growth and spring shoot growth as well.

We therefore use a separate Chapman-Richards model for the growth of each of the three types j of bamboo products: winter shoots s_w, spring shoots s_s, and bamboo stem b. The Chapman-Richards model is given by:

$$Y_j = A_j \cdot \left(1 - Q_j e^{-\alpha_j t_j}\right)^{1/(1-v_j)},$$

where Y_j is the total biomass for bamboo product j in a single bamboo plant; t_j is the age of bamboo (in days for winter and spring shoots, and in years for bamboo stem); and A_j, α_j , Q_j, v_j are parameters whose interpretation and values for each of the bamboo product types j are discussed in more detail below. The Chapman-Richard's model predicts biomass Y_b and Y_s in units of kilograms of dry weight. In contrast, our shoots and stem price are in units of yuan per kilogram of actual weight, which contains both biomass and water. We use a conversion coefficient τ to convert biomass in dry weight into its actual weight (which contains both biomass and water).

Our calibrated piecewise Chapman-Richards growth function for bamboo shoots, which combines a Chapman-Richards growth function for winter shoots with a separate Chapman-Richards growth function for spring shoots, is presented in Figure A.1. Our calibrated Chapman-Richards growth function for bamboo stem growth is presented in Figure A.2. We discuss our calibration in more detail below.

A.1. Parameters in Chapman-Richards model of bamboo shoot growth for winter shoots

To date there have been very few studies on Moso bamboo underground development, winter shoots biomass, and winter shoots growth. We calibrate our model for winter shoots growth to capture what previous research has found about winter shoots, and also to better match the actual winter shoots harvest decisions in our data. In particular, previous research that has found winter shoots are dormant from December onwards (Su, 2012; Sun et al. 2017; Wei et al., 2017; Hu et al., 2020) and that over half of winter shoots growth happens during November (Wei et al., 2017). In our data, some bamboo plots have harvested winter shoots as early as late October when the winter shoots price is very high, which our dynamic model shows would not be optimal even with a very high winter shoots price if the winter shoots biomass is very low in late October. Since it is unlikely that farmers are so completely wrong, we additionally calibrate our winter shoots growth function so that their biomass in late October is higher.

We use the following Chapman-Richards model for winter shoot growth:

$$Y_{s_w} = A_{s_w} \cdot \left(1 - Q_{s_w} e^{-\alpha_{s_w} t_{s_w}}\right)^{1/(1-v_{s_w})},$$

where Y_{s_w} is the total biomass of a winter shoot of age t_{w_x} days. The shoots biomass is basically the dried weight of shoots. The Chapman-Richards model for winter shoot growth yields the following equation of motion for winter shoot biomass:

$$\frac{dY_{s_w}(t_{s_w})}{dt_{s_w}} = \frac{\alpha_{s_w}}{1-v_{s_w}} A_{s_w} Q_{s_w} \left(1 - Q_{s_w} e^{-\alpha_{s_w} t_{s_w}}\right)^{\frac{1}{1-v_{s_w}}-1} e^{-\alpha_{s_w} t_{s_w}}.$$

At the inflection point, where $\frac{d^2 Y_{s_w}(t_{s_w})}{d{t_{s_w}}^2} = 0$, we have:

$$v_{s_w} = 1 - Q_{s_w} e^{-\alpha_{s_w} t_{s_w}}.$$

For the age t_{s_w} of winter shoots, due to its relatively short period of growth, age of bamboo shoots is measured in days rather than years. Winter shooting is from September 1 until February 28. The number of winter shooting days $t_{s_w}^{\max}$ is therefore 181 days.

The parameter A_{s_w} is related to the maximum possible winter shoot biomass for a single winter shoot. According to a video from Zhejiang province of winter shoots in late November 2020 ("Zhejiang Local Winter Shoots Trading on Site", 2020), it is very rare to have winter shoots that is 0.75 kg in Zhejiang province, which is 0.375 kg in dry biomass (using our conversion coefficient that actual weight is $\tau = 2$ times biomass in dry weight). According to Yonghua Qiu, a senior engineer from Suichang Bureau of Forestry (Suichang is a township in Zhejiang province), the maximum possible winter shoots weight could be over 0.5 kg. It is also rare to harvest winter shoots that is more than 1.5 kg (Zeng and Peng, 2013). In our numerical model, we set $Y_{s_w}^{\max}$, the maximum possible winter shoots biomass at the end of winter shooting (day $t_{s_w}^{\max}$), to be 0.75 kg. This is to say, the maximum possible winter shoots weight at the end of winter shooting will be 1.5 kg per shoot in actual weight, and thus 0.75 kg in biomass. We then calibrate A_{s_w}, which is the maximum possible winter shoot biomass as the number of days goes to infinity (which is well past the end of winter shooting) as follows:

$$A_{s_w} = Y_{s_w}^{\max} / \left(1 - Q_{s_w} e^{-\alpha_{s_w} t_{s_w}^{\max}}\right)^{1/(1-v_{s_w})}.$$

For the growth rate α_{s_w} for winter shoots, the growth rate for bamboo shoots is more rapid than that for bamboo stem (Song et al., 2016). To date there have been very few studies on Moso bamboo underground development, winter shoots biomass, and winter shoots growth. Wei et al. (2017) describes underground bamboo shoots development, but only have a time trend of growth of winter shoots in terms of individual height, not biomass. Hu et al. (2020) study gene expression for each month of shoots growth from September to the following year's April. The number of genes expressed in the shoots is a measure of shoots growth activity level, as well as biomass accumulation. Since Hu et al. (2020) find the winter shoots express fewer genes than spring shoots do, we choose a growth rate α_{s_w} for winter shoots that is slightly lower than the growth rate α_{s_s} for spring shoots that we specify below. In particular, since we set the growth rate α_{s_s} for spring shoots to 0.036 below, and winter shoots is expressing less genes compared to spring shoots, we set the growth rate α_{s_w} for winter shoots to 0.016.

For the biological constant Q_{s_w}, which is related to the initial winter shoot biomass at the beginning of winter shooting, we set Q_{s_w} to 1 because we want the biomass of winter shoots to be equal to 0 on day $t_{s_w} = 0$.

The parameter v_{s_w} is related to the inflection point of the Chapman-Richards growth function, where the time rate of change in winter shoot biomass reaches its maximum. This allometric constant lies between zero and one for the Chapman-Richards growth model (Fekedulegn et al., 1999; Liu and Li, 2003). Wei et al. (2017) study the growth of Moso underground shoots by measuring individual shoot diameter from August to February the following year, and find that Moso bamboo shoots grow actively from late August to late November and have the fastest growth from early to late November, during which over half of the underground shoots growth takes place. Bamboo shoots become dormant from December until the following March because of the cold weather (Wei et al., 2017; Hu et al., 2020). Sun et al. (2017) find that underground shoots formed in September; developed into underground shoots in October and November. The winter shoots growth rate slowed down and almost stopped in December until February the following year (Sun et al. 2017). This is to say, the fastest growing time is around day 76 (mid November) of the entire winter shoot growth process. We therefore set the winter day of inflection $t_{s_w}^{\text{infl}}$ to be 76. We calculate v_{s_w} using:

$$v_{s_w} = 1 - Q_{s_w} e^{-\alpha_{s_w} t_{s_w}^{\text{infl}}}$$

and iterating on v_{s_w} until convergence.

A.2. Parameters in Chapman-Richards model of bamboo shoot growth for spring shoots

We use the following Chapman-Richards model for spring shoot growth:

$$Y_{s_s} = A_{s_s} \cdot \left(1 - Q_{s_s} e^{-\alpha_{s_s} t_{s_s}}\right)^{1/(1-v_{s_s})},$$

where Y_{s_s} is the total biomass of a spring shoot of age t_{s_s} days.

For the age t_{s_s} of spring shoots, due to its relatively short period of growth, age of bamboo shoots is measured in spring shooting days rather than years. The spring shooting period starts on March 1 and ends on August 31, the last day of the bamboo growth year. In other words, shoots do not become bamboo stem until the end of the bamboo growth year. This is because, as seen in Song et al. (2016), the bamboo still seems to grow very fast following the spring shoot growth function until the end of the bamboo growth year. Thus, the number of spring shooting days $t_{s_s}^{\max}$ we use in our numerical model is 184 days. Bamboo shoots grow into a bamboo plant after the end of spring shooting (Shi et al., 2013).

The parameter A_{s_w} is related to the maximum possible spring shoot biomass for a single spring shoot. Xu et al. (2011) study the time trend of above ground biomass in Lin'an city, Zhejiang Province, and find that on spring shooting day 88, the spring shoot biomass is approximately 8.25 kg in dry weight. Song et al. (2016) shows shoots biomass at the end of August to be ~8 kg. In our numerical model, we set $Y_{s_s}^{\max}$, the maximum possible spring shoots biomass at the end of spring shooting (day $t_{s_s}^{\max}$), to be 8 kg. We then calibrate A_{s_s}, which is the maximum possible spring shoot biomass as the number of spring shooting days goes to infinity (which is well past the end of spring shooting) as follows:

$$A_{s_s} = Y_{s_s}^{\max} / \left(1 - Q_{s_s} e^{-\alpha_{s_s} t_{s_s}^{\max}}\right)^{1/(1-v_{s_s})}.$$

For the growth rate α_{s_s} for spring shoots, the growth rate for bamboo shoots is more rapid than that for bamboo stem (Song et al., 2016). Based on Song et al. (2016), the growth rate for spring shoots at the end of April is 0.036 per day. We therefore set our spring shoot growth rate α_{s_s} to 0.036.

The biological constant Q_{s_s} is related to the initial spring shoot biomass at the beginning of spring shooting. Since Q_{s_s} is based on the biomass of spring shoots at the beginning of spring shooting, then this should be calculated based on the biomass at the end of winter shooting. In other words, we use the biomass on the last day of winter shooting to calculate Q_{s_s}. The biomass on the last day of winter shooting, $Y_{s_w}^{\max}$, is the Chapman-Richards growth function for winter shoots evaluated on the last day of winter shooting. We then calculate Q_{s_s} as:

$$Q_{s_s} = \frac{1-\left(Y_{s_w}^{\max}/Y_{s_s}^{\max}\right)^{1-v_{s_s}}}{1-\left(Y_{s_w}^{\max}/Y_{s_s}^{\max}\right)^{1-v_{s_s}} e^{-\alpha_{s_s} t_{s_s}^{\max}}}.$$

The parameter v_s is related to the inflection point of the Chapman-Richards growth function, where the time rate of change in spring shoot biomass reaches its maximum. The maximum growth rate occurs at the end of April (Song et al., 2016), which is around 60 days of spring shooting. We therefore set the spring day of inflection $t_{s_s}^{\text{infl}}$ to be 60. We calculate v_{s_s} using:

$$v_{s_s} = 1 - Q_{s_s} e^{-\alpha_{s_s} t_{s_s}^{\text{infl}}}$$

and iterating on v_{s_s} until convergence.

A.3. Parameters in Chapman-Richards model of bamboo stem growth

We use the following Chapman-Richards model for bamboo stem growth:

$$Y_b = A_b \cdot \left(1 - Q_b e^{-\alpha_b t_b}\right)^{1/(1-v_{s_s})},$$

where Y_b is the total biomass of a bamboo stem of age t_b years.

For the age t_b of bamboo forest in years, Moso bamboo stems reach their maximum biomass at age 4-5 years (Zhang et al., 2014; Zhuang et al., 2015), do not increase significantly in biomass after 4.62 years (Zhuang et al., 2015), and mature at age 5-6 years (Yen and Lee, 2011). We assume Moso bamboo stem biomass does not increase after $t_b^{\max}$ years, and set $t_b^{\max}$ to 8 years.

For A_b, which is related to the maximum possible bamboo stem biomass for a single bamboo plant in the specific area, the maximum possible bamboo biomass for a single bamboo plant depends on land quality such as slope, precipitation, soil type, and temperature of the bamboo field we are interested in. Yen (2016) calculate maximize stem biomass for Moso bamboo in central Taiwan in its 5th year growth to be 15.88 kg per plant with standard deviation of 2.51 kg. Zhang et al. (2014) find that the maximum stem biomass for an eight-year-old Moso bamboo has average biomass of 15.06 kg, with a standard deviation of 6.58 kg. Stem biomass accumulation generally slows down when Moso bamboo reaches age 5-6 years (Yen and Lee, 2011). In our numerical model, based on the means in the previous literature, we set $Y_b^{\max}$, the maximum possible bamboo stem biomass at the end of $t_b^{\max}$ years, to be 15.5 kg. We then calibrate A_b, which is the maximum possible bamboo stem biomass as the number of years goes to infinity (which is well past $t_b^{\max}$) as follows:

$$A_b = Y_b^{\max} / \left(1 - Q_b e^{-\alpha_b t_b^{\max}}\right)^{1/(1-v_b)}.$$

For the growth rate α_b for bamboo stem, the growth rate for Moso bamboo differs with studies as well. According to Xu et al. (2011), the major biomass accumulation occurred along with the fast elongation of bamboo stem in the early stage of bamboo growth. In the stage where first shoot shell detached and branch emergence, bamboo biomass tripled. To estimate the biomass accumulation rate for Moso bamboo, we compare bamboo stem biomass in different age groups. According to Zhang et al. (2014), the growth rate for bamboo stem biomass over four 2-year stages is in the range of 0.060 to 0.196 per 2-year stage, or an average of 0.03 to 0.098 per year. Based on Song et al. (2016), the growth rate after 4 months of shooting (in August before the first full bamboo growth year) is 0.75 per year. In our numerical model, we set the growth rate α_b for bamboo stem to 0.75.

The biological constant Q_b, which is related to the initial bamboo stem biomass at the beginning of the first bamboo growth year. For bamboo stem, we model the growth of bamboo stem starting from the end of spring shooting, when bamboo shoots become bamboo stem. At the beginning of its full bamboo growth year (i.e., at the beginning of bamboo growth year age 1), the initial bamboo stem biomass is the maximum bamboo shoot biomass at the end of spring shooting.

The end of spring shooting in years is $t_{b0} = \left(t_{s_w}^{\max} + t_{s_s}^{\max}\right)/365$. The initial bamboo stem biomass at the end of spring shooting (year t_{b0}) is the maximum bamboo shoot biomass $Y_{s_s}^{\max}$ at the end of spring shooting. We then calculate Q_{s_s}as:

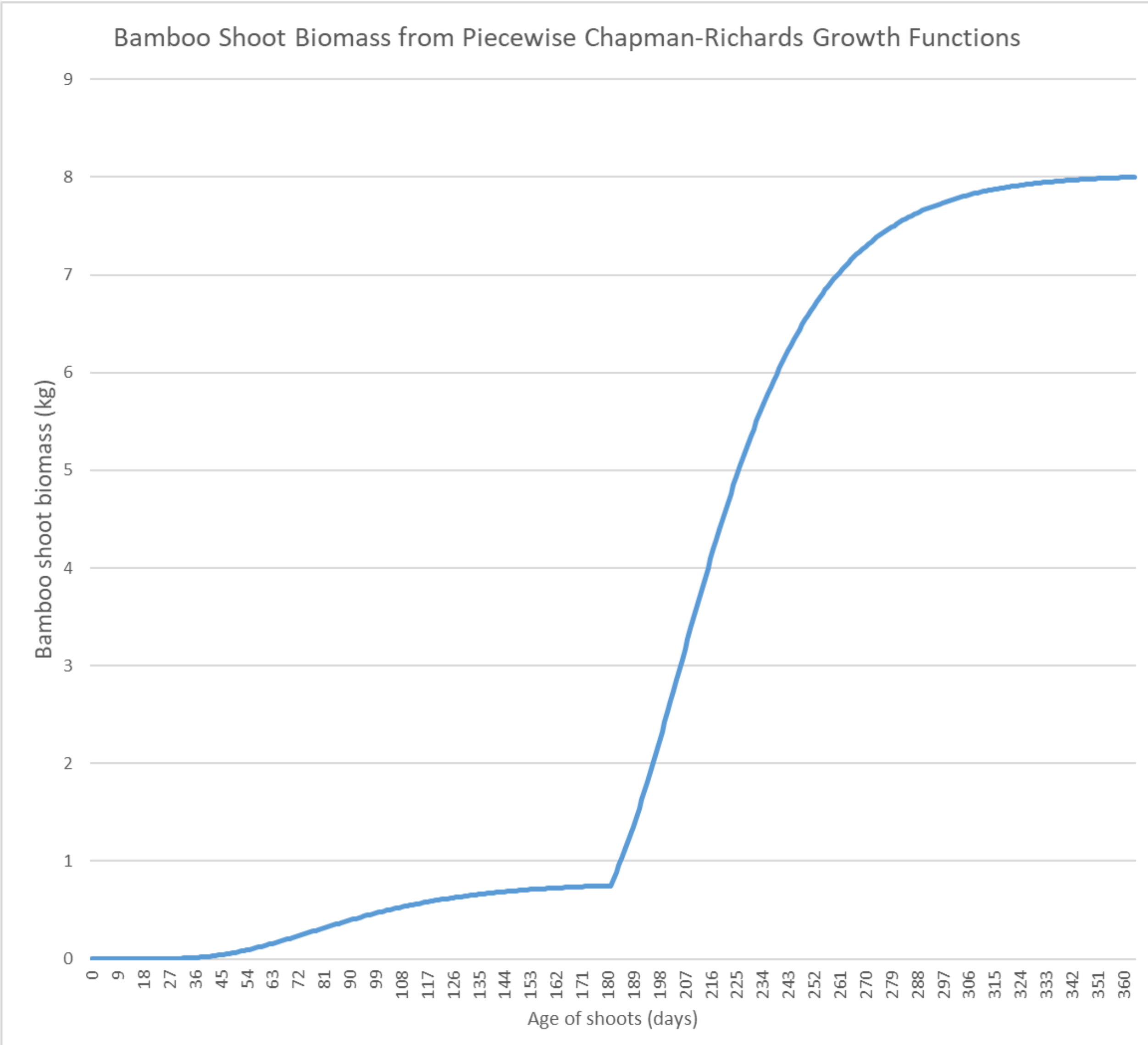
$$Q_b = \frac{1-\left(Y_{s_s}^{\max}/Y_b^{\max}\right)^{1-v_b}}{e^{-\alpha_b t_{b0}}-\left(Y_{s_s}^{\max}/Y_b^{\max}\right)^{1-v_b} e^{-\alpha_b t_b^{\max}}}.$$

The parameter v_b is related to the inflection point of the Chapman-Richards growth function, where the time rate of change in bamboo stem biomass reaches its maximum. In Song et al. (2016), the biomass accumulation is fastest after in September following spring shooting. Since the bamboo growth year starts September 1, this means that the inflection point takes place the first month of the first full bamboo growth year (bamboo growth year age 1). We therefore set the year of inflection t_b^{infl} to be 1. We calculate v_b using:

$$v_b = 1 - Q_b e^{-\alpha_b t_b^{\text{infl}}}$$

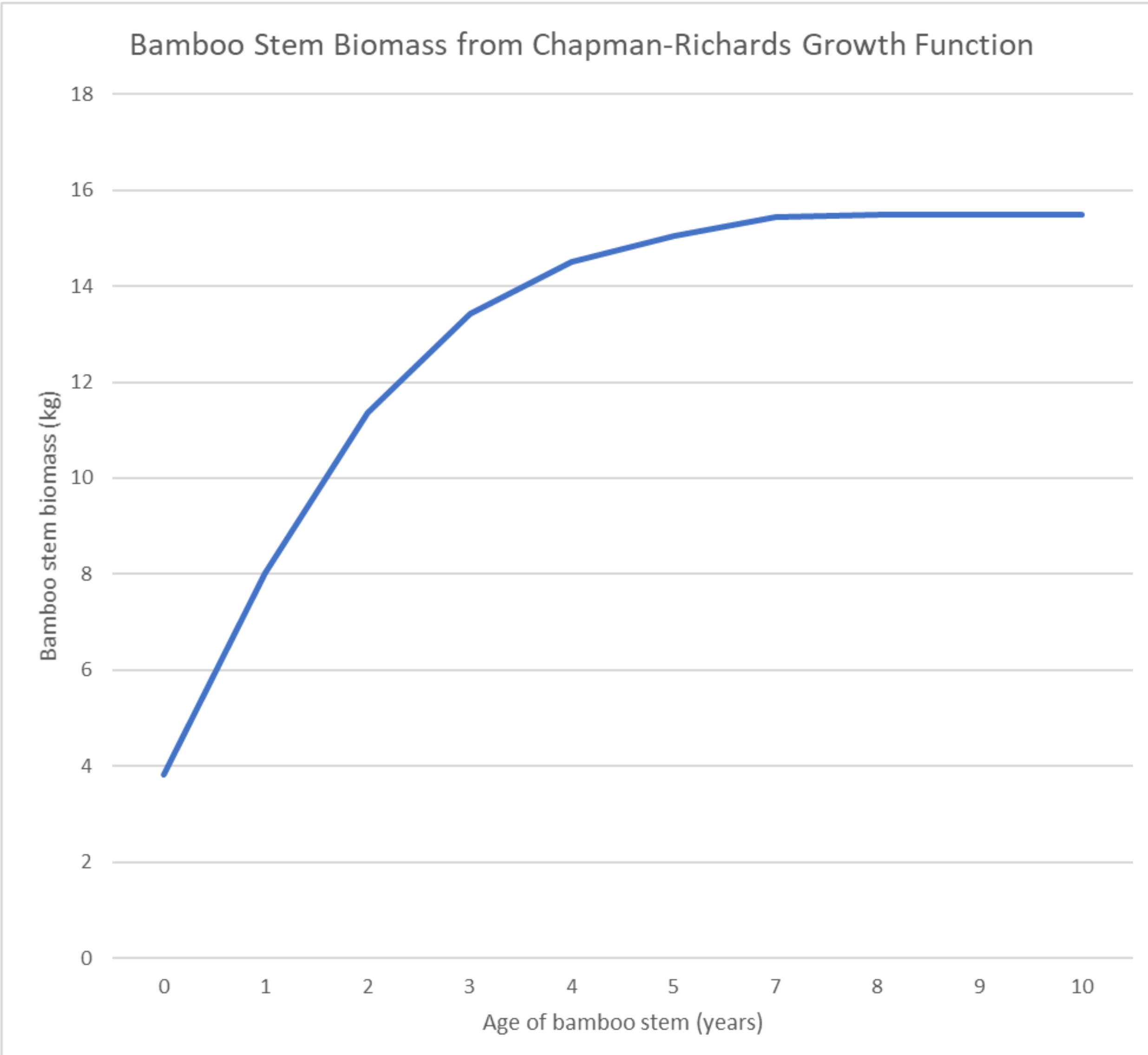
and iterating on v_b until convergence.

Figure A.1. Piecewise Chapman-Richards Growth Function for Bamboo Shoots



Notes: We use separate Chapman-Richards growth functions for winter shooting and spring shooting. The first day of winter shooting is September 1. Winter shooting is from September 1 until February 28. The number of winter shooting days is therefore 181 days. The spring shooting period starts on March 1 and ends on August 31, the last day of the bamboo growth year. The number of spring shooting days is 184 days.

Figure A.2. Chapman-Richards Growth Function for Bamboo Stem



Appendix B. Data and Parameters

B.1 Data on actual bamboo shoot and bamboo stem harvest

We collect, translate, and transcribe individual hard-copy handwritten Chinese records on actual bamboo shoot harvest and bamboo stem harvest decisions on 20 meter by 20 meter bamboo plots in Shanchuan Township and Sian Township in Zhejiang province in China. Our data set includes 35 bamboo plots over 2 bamboo growth years from March 1, 2017 to August 31, 2018: 20 bamboo plots in Sian Township and 15 bamboo plots in Shanchuan Township. For each bamboo plot, we have data on the number of bamboo stem and on the dates, quantity, and price received for each bamboo stem harvest and each bamboo shoots harvest.

B.2. Bamboo shoot price

We use data on daily bamboo shoots prices for Zhejiang province over the period January 1, 2014 to June 30, 2018 from the National Agricultural Products Business Information Public Service Platform operated by China's Ministry of Commerce (National Agricultural Products Business Information Public Service Platform, 2018). We use the shoots prices from the Zhebei Jiashan wholesale market since there are more days available, since their shoots price data tends to be more consistent with the bamboo shoot prices that the farmers in our data set received and recorded in the raw bamboo plot harvest data we collected, and since the data are also more detailed. Generally, there no bamboo shoots are sold in July, August, and September since these months are formation period of shoots underground. From mid June to mid October, there are no shoots on the wholesale market, and thus no price available.

We merge our daily shoots price data with our harvest data as follows. If any bamboo shoots harvest took place during a particular day on a particular bamboo plot, then we use the bamboo shoot price that the farmer received and recorded in the raw bamboo plot harvest data we collected. This means the shoots price are not necessarily the same for the 2 townships due to different shoots harvest activities. This also means that even for the same township, there could be different price for the same day if harvest took place on one bamboo plot but not another. For bamboo plot-days for which no bamboo shoots harvest took place, we use the daily bamboo shoots prices for Zhejiang province from the National Agricultural Products Business Information Public Service Platform (2018).

Figures B.1a and B.1b plot histograms of the daily winter shoots price during winter shooting and the daily spring shoots price during spring shooting, respectively, over the years 2016-2018 for all bamboo plots in our data set.

B.3. Bamboo stem price

There is not much price volatility in bamboo stem price within a year, and there also was not much of a change in bamboo stem price between years during the years of our data set. The bamboo stem prices faced by the bamboo managers in our data set were 0.4 ¥/kg in 2017 and 0.38 ¥/kg in 2018 (personal communication, Mr. Jianping Pan, manager of Fumin Bamboo Shoot Specialized Cooperative, August 2018).

B.4. Harvest costs

According to Mr. Jianping Pan, manager of Fumin Bamboo Shoot Specialized Cooperative, bamboo harvest can be fast: one worker can harvest 1 mu (about 667 square meters) of bamboo per day. For bamboo stem, workers get paid daily with a rate of 300 yuan per day and harvest 1,250 to 2,000 kg of bamboo stem. For spring shoots, workers got paid daily, with a rate of 150 to 180 yuan per day, and can harvest 100 kg of spring shoots per day; the total harvest for each bamboo plot is 200-250 kg per spring shooting period. Winter shoots are more expensive and harder to find than spring shoots, and thus workers get paid for 300 yuan per day and can harvest about 15 to 20 kg per day (personal communication, Mr. Jianping Pan, manager of Fumin Bamboo Shoot Specialized Cooperative, August 2018).

For the harvesting costs in our numerical model, we calculate the unit costs of harvest by dividing estimates of harvest per worker per day by cost per worker per day. We vary the unit cost c_s of bamboo shoot harvest from 300/20 ¥/kg to 300/15 ¥/kg for winter shoots, and from 150/100 ¥/kg to 180/100 ¥/kg for spring shoots. We set the unit cost c_b of bamboo stem harvest from 300/2,000 ¥/kg to 300/1,250 ¥/kg.

B.5. Time

Since the winter shooting period and the corresponding spring shooting period span two consecutive calendar years, we use a bamboo growth year rather than a calendar year for our "year". The first day of each bamboo growth year is the first day of winter shooting on September

1. Each bamboo growth year y starts from September 1 (the first day of winter shooting) of one calendar year and ends on August 31 of the following calendar year. Since bamboo stem harvest is possible during any day throughout the year, we model the decision on each day of the bamboo growth year. Spring shooting begins on March 1 in Zhejiang province. Thus, winter shooting takes place from September 1 until February 28; and spring shooting starts on March 1 and ends on August 31, the last day of the bamboo growth year.

B.6. Finite horizon

Generally, Moso bamboo stems reach their maximum biomass at age 4-5 years (Zhang et al., 2014; Zhuang et al., 2015), do not increase significantly in biomass after 4.62 years (Zhuang et al., 2015), and mature at age 5-6 years (Yen and Lee, 2011). In our numerical dynamic model, we allow bamboo managers the possibility of letting bamboo stem grow to age 11 years, well past their age of maximum biomass, if it is optimal for them to do so. Since it would be very economically inefficient to harvest bamboo stem after 11 years, however, we model bamboo stem growth with a finite horizon of 11 years. We therefore have a finite sequence of 11 one-year finite horizon problems. Thus, the outer dynamic optimization problem is a between-year annual dynamic programming problem with a finite horizon of 11 years.

B.7. Daily probability of high precipitation

The state variable *precip* is a dummy for the cumulative daily precipitation over July and August of that bamboo growth year exceeding a high precipitation threshold that day. We use 400 mm as the cutoff to determine if *precip* is high (*precip* =1) or not (*precip* = 0).

Since cumulative daily precipitation over July and August of a bamboo growth year varies within July and August of a year (and is weakly monotonically increasing), the state variable *precip* is not necessarily constant for all of July and August. For some townships and some years, it is possible that *precip* = 0 at the beginning of July but then becomes 1 closer to the end of August.

The daily probability of high precipitation is the probability that *precip* is equal to 1 (high) that day. The daily probability of high precipitation is weakly monotonically increasing from July 1 to August 31. For each township, for each day in July and August, we calculate the daily empirical probability of high precipitation (*precip* = 1) using the latest daily precipitation data for the township from the National Oceanic and Atmospheric Administration Climate Prediction

Center over the period 2010-2018 (NOAA, 2021). In particular, for each township, for each of the 62 days from July 1 and August 31, the daily empirical probability of high precipitation for that day for that township is calculated as the fraction of years in that township over the period 2010-2018 for which *precip* = 1 on that day.

B.8. Daily probability of shoots decline

More than half of the shoots will degenerate and die naturally before they grow into bamboo plants (Jiang, 2007). In our base case, we set the daily probability of shoots decline during winter shooting to be 1/30, such that the number of shoots is expected to decline by approximately 1 bin per month during winter shooting.

B.9. Discount factor

Since we nest an inner finite-horizon within-year daily dynamic programming problem within an outer finite-horizon between-year annual dynamic programming problem, we use two different discount factors β: a daily discount factor β_d and an annual discount factor β_y. We set the daily discount factor to be $\beta_d = {\beta_y}^{1/365}$, which yields an annual discount factor of β_y over 365 days. In the base case, we set the annual discount factor to be $\beta_y = 0.9$. An annual discount factor of 0.9 is commonly assumed in the literature using dynamic models (see e.g., Ryan (2012); Lin (2013); Sears, Lim and Lin Lawell (2019); Cook and Lin Lawell (2020)).

B.10. Number of bamboo shoots

In our dataset we observe the weight of bamboo shoots harvested (as well as the number of bamboo stem and number of bamboo stem harvested), but do not observe either total number of shoots or the number of shoots harvested. Ideally, we would like to convert the units for the bamboo shoots harvest data and any estimated weight of bamboo shoots into the number of bamboo shoots. Even though we can estimate the total possible weight of bamboo shoots, the actual weight of bamboo shoots would be different if some bamboo shoots were previously harvested that season. In addition, we cannot simply subtract the weight of bamboo shoots harvested earlier in the season from our estimate of the total possible weight of bamboo shoots as a function of bamboo stems, since those bamboo shoots that were harvested earlier in the season would have grown or changed in weight if they had not been harvested. So it would be ideal if we made the harvesting decision in terms of the number of bamboo shoots harvested, so that we can model the weight and change in weight of the remaining bamboo shoots.

We estimate the unobserved bamboo shoot state and control variables as follows. First, for each bamboo plot and each day, we convert the weight of bamboo shoots harvest into the number of bamboo shoots harvested by dividing the weight of bamboo shoots harvest by the bamboo shoot biomass per bamboo shoot that day of the year from Chapman-Richard's model for bamboo shoot growth, assuming that bamboo shoots start growing from the beginning of winter shooting.

We then impute the maximum number of bamboo shoots in the ground in the absence of bamboo shoot harvest for each bamboo plot in each bamboo growth year. To do so, we apply the following model from Zheng, Hong and Zhang (1998) to estimate the weight of bamboo shoots in the ground that remain after all the bamboo shoots have been harvested that season:

$$w_b = 0.0018 * {d_b}^{2.8637},$$

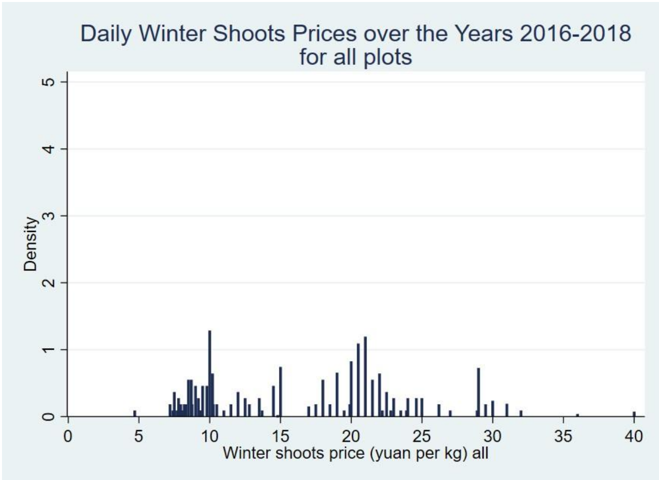
where w_b is weight of an individual bamboo shoot and d_b is its maximum diameter. As we do not have data on the maximum diameter of bamboo shoots, we use data on the diameter at breast height (DBH) of each newly grown bamboo stem that year to represent the diameter at breast height of bamboo shoots if they were to grow until the end of that season. For each bamboo plot and each year in our data set, we use data on the diameter at breast height (DBH) of newly grown bamboo stem, representing the diameter at breast height of bamboo shoots if they were to grow until the end of that season, to estimate the weight of a bamboo shoot if were to grow until the end of the season. Then, for each bamboo plot and each year, to calculate the weight of bamboo shoots on this bamboo plot that are not harvested, we take the sum over all the newly grown bamboo stems of the respective weights of a bamboo shoot if were to grow until the end of the season for that bamboo plot in that year. We convert the weight of bamboo shoots that are not harvested by the end of the season into the number of bamboo shoots that are not harvested by dividing the weight of bamboo shoots not harvested by the bamboo shoot biomass per bamboo shoot from Chapman-Richard's model for bamboo shoot growth, assuming that the unharvested bamboo shoots must have grown from the beginning of winter shooting until the last day of spring shooting.

For each bamboo plot, to calculate the number n_s of bamboo shoots at the beginning of the season, in the absence of any bamboo shoots harvest, we add the total number of bamboo shoots harvested over the season to the total number of bamboo shoots that remain unharvested at the end of the season. For each day on each bamboo plot, we calculate the bamboo shoots harvest action variable a_s as the number of shoots harvested that day on that bamboo plot by the number n_s of bamboo shoots on that bamboo plot at the beginning of the season, in the absence of any bamboo shoots harvest. We then calculate the number n_s of bamboo shoots for each day on each bamboo plot as the number n_s of bamboo shoots on that bamboo plot the previous day that season minus the number of bamboo shoots harvested on that bamboo plot on the previous day that season.

Owing to computational and state space constraints, we discretize the number of bamboo shoots, the number of bamboo shoots harvested, the number of bamboo stem, and the number of stem harvested in our numerical model and our structural model. Although some information in the data is lost by discretizing the state and action variables, one advantage of having to use discretized variables in our numerical model and our structural model is that by discretizing the number of bamboo shoots, the number of bamboo shoots harvested, the number of bamboo stem, and the number of stem harvested, our results are robust to the exact value of the number of bamboo shoots, the number of bamboo shoots harvested, the number of bamboo stem, and the number of stem harvested within our broader size bins. As a consequence, our results are robust to any imprecision and inaccuracy in our conversion of bamboo shoots weight to number of bamboo shoots that still lie within the respective broader size bins. Likewise, our results are robust to any imprecision and inaccuracy in how we model the effects of precipitation and/or the possibility of shoots death that still lie within the respective broader size bins. Thus, the discretization of our state and action variables is not only necessary for our numerical model and dynamic structural econometric model, but also enables us to best model bamboo stem and shoots harvesting decisions given data availability and computational constraints, and in a manner robust to any additional assumptions or imprecision that may be introduced if we were to instead finely model every last detail of every aspect of bamboo management for each and every individual bamboo farmer.

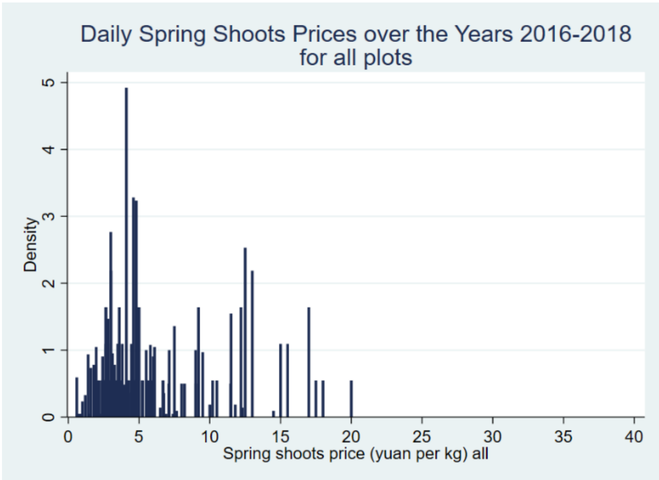
Figure B.1. Bamboo Shoots Prices

(a) Winter Shoots Prices



Notes: Figure plots a histogram of the daily winter shoots price during winter shooting over the years 2016-2018 for all bamboo plots in our data set.

(b) Spring Shoots Prices

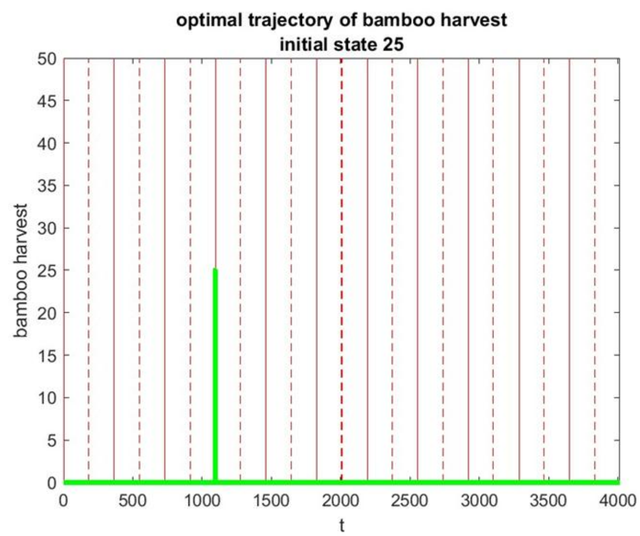


Notes: Figure plots a histogram of the daily winter shoots price during winter shooting over the years 2016-2018 for all bamboo plots in our data set.

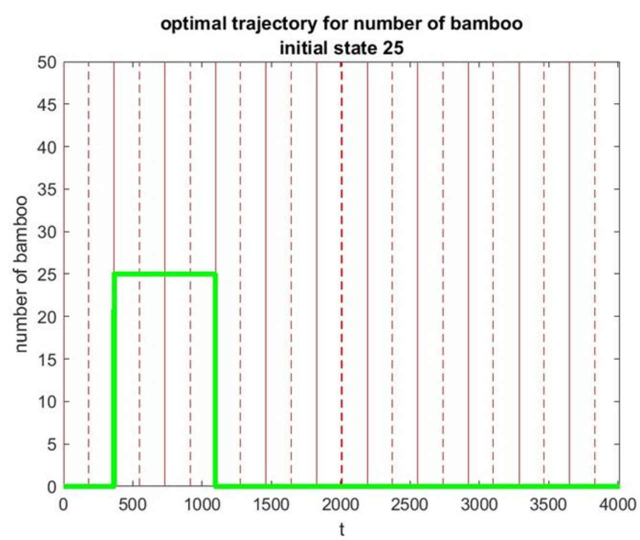
Appendix C. Supplementary Figures and Tables

Figure C.1. Optimal Bamboo Stem Harvest

a) Bamboo Stem Harvest



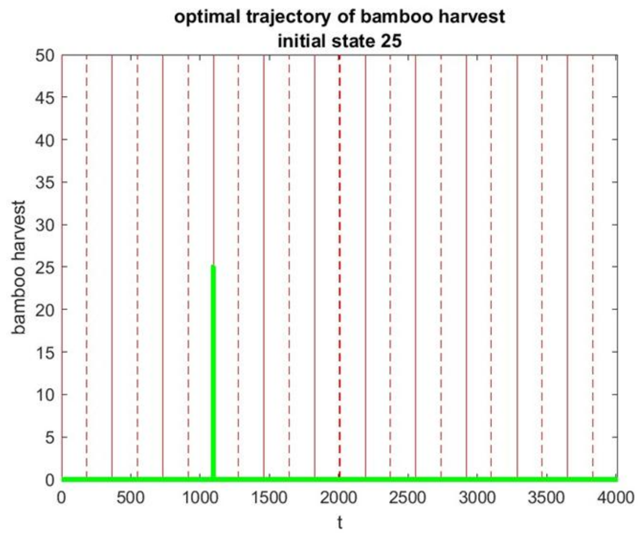
b) Number of Bamboo Stem



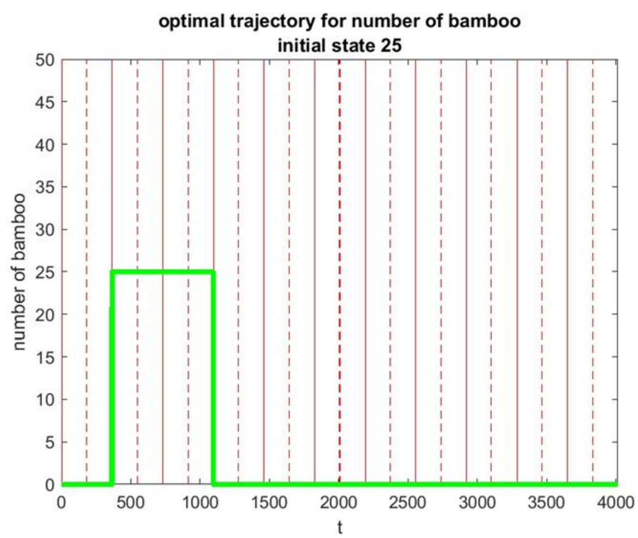
Notes: Figure presents a simulated set of optimal trajectories for bamboo stem harvest and number of bamboo stem, for each day of each year starting from a medium initial number of bamboo shoots ($n_s = 25$) on the first day of the first bamboo growth year, when parameters are set at their base case values. Vertical lines in red that go from the top to the bottom of the graph denote September 1 (first day of winter shooting) of each year. Dashed vertical lines in red that go from the top to the bottom of the graph denote March 1 (first day of spring shooting) of each year.

Figure C.2. Optimal Bamboo Stem Harvest: High Bamboo Stem Price

a) Bamboo Stem Harvest

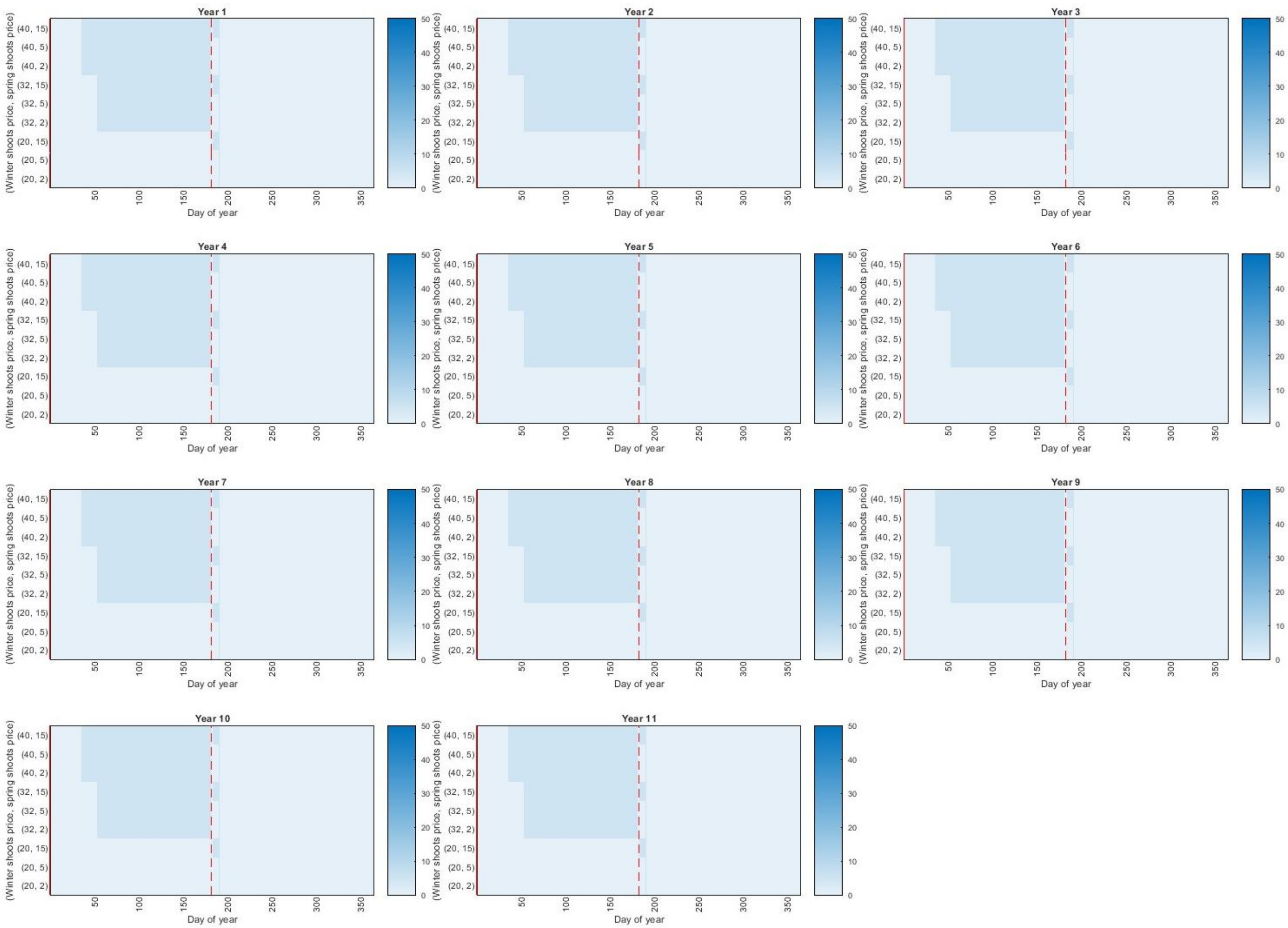


b) Number of Bamboo Stem



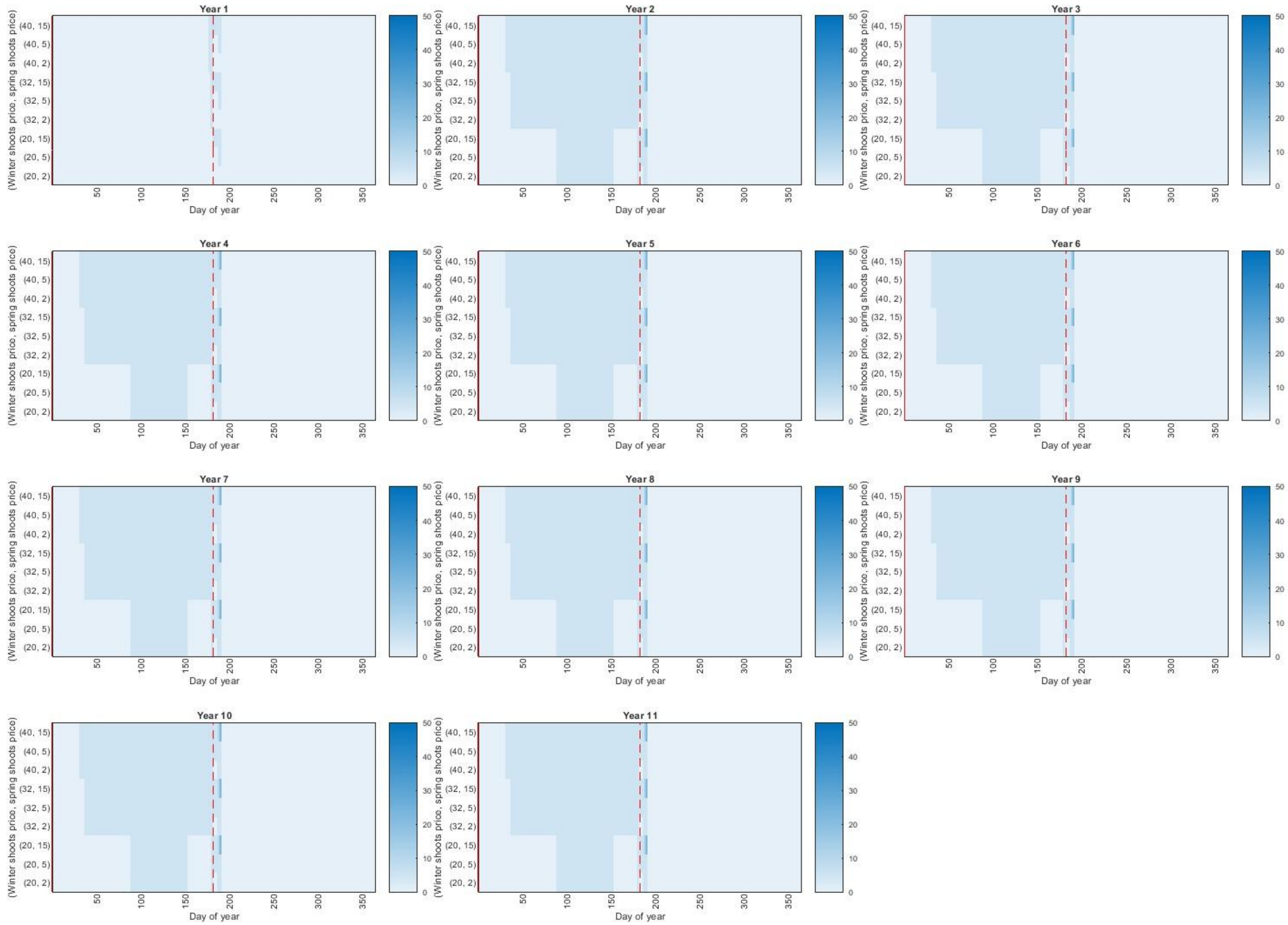
Notes: Figure presents a simulated set of optimal trajectories for bamboo stem harvest and number of bamboo stem, for each day of each year starting from a medium initial number of bamboo shoots ($n_s = 25$) on the first day of the first bamboo growth year, when the bamboo stem price is high, and when all other parameters are set at their base case values. Vertical lines in red that go from the top to the bottom of the graph denote September 1 (first day of winter shooting) of each year. Dashed vertical lines in red that go from the top to the bottom of the graph denote March 1 (first day of spring shooting) of each year.

Figure C.3. Daily Bamboo Shoots Harvest Policy Function When Number of Shoots is Very Low



Notes: Figure presents bamboo shoots harvest policy function for each day for each year as a function of daily shoots price when the number of shoots is very low ($n_s = 5$) and cumulative daily precipitation is low ($precip = 0$), and when parameters are set at their base case values. For each bamboo growth year, dashed vertical lines in red that go from the top to the bottom of the graph denote March 1 (first day of spring shooting) of each year.

Figure C.4. Daily Bamboo Shoots Harvest Policy Function When Risk Averse



Notes: Figure presents bamboo shoots harvest policy function for each day for each year as a function of daily shoots price when the number of shoots is a medium quantity ($n_s = 25$) and cumulative daily precipitation is low ($precip = 0$), when farmers are risk averse (with a coefficient of constant relative risk aversion of $\eta = 0.8$), and when all other parameters are set at their base case values. For each bamboo growth year, dashed vertical lines in red that go from the top to the bottom of the graph denote March 1 (first day of spring shooting) of each year.

Figure C.5. Perceived Chapman-Richards Growth Function for Bamboo Shoots

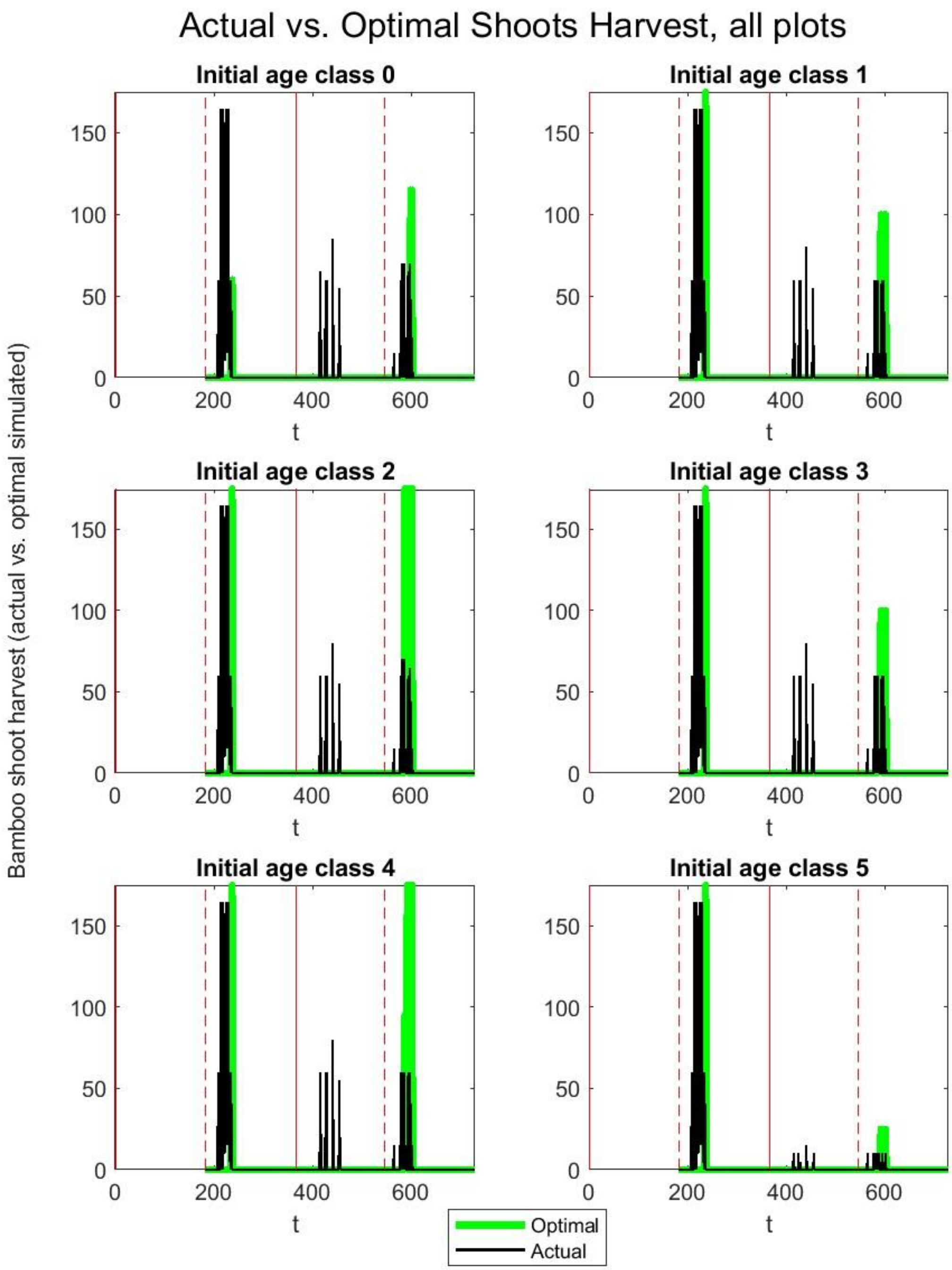
Notes: Figure plots bamboo farmers' perceived Chapman-Richards growth function for winter shooting and spring shooting based on the parameter estimates for winter shoots growth rate α_{s_w} of 0.272 from our dynamic structural model in Table 2. We use separate Chapman-Richards growth functions for winter shooting and spring shooting. The first day of winter shooting is September 1. Winter shooting is from September 1 until February 28. The number of winter shooting days is therefore 181 days. The spring shooting period starts on March 1 and ends on August 31, the last day of the bamboo growth year. The number of spring shooting days is 184 days.

Table C.1. Dynamic Structural Model Results: Shoots Decline Probability

Structural Parameter	Actual (Assumed Value)	All (1)
Daily shoots decline probability during winter shooting	0.0333	0.000*** (0.0000)
# Observations		115,290
# Bamboo plots		35

Notes: The structural parameter estimate is the parameter estimate from our specification of the structural model estimating the shoots decline probability parameter only for the entire sample ("All"). The actual value is the assumed base case parameter value we calibrated based on biological sciences and economic data. Bootstrapped standard errors in parentheses. Significance codes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$

Figure C.6. Optimal vs. Actual Shoots Harvest using structural parameter estimate for winter shoots decline probability



Notes: Time series plots of the perceived optimal vs. actual number of bamboo shoots harvested on each bamboo plot, using the structural parameter estimate for the daily winter shoots decline probability of 0 from Table C.1. Vertical lines in red that go from the top to the bottom of the graph denote September 1 (first day of winter shooting) of each year. Dashed vertical lines in red that go from the top to the bottom of the graph denote March 1 (first day of spring shooting) of each year.

Table C.2. Actual vs. Optimal NPV using structural parameter estimate for winter shoots decline probability

(a)

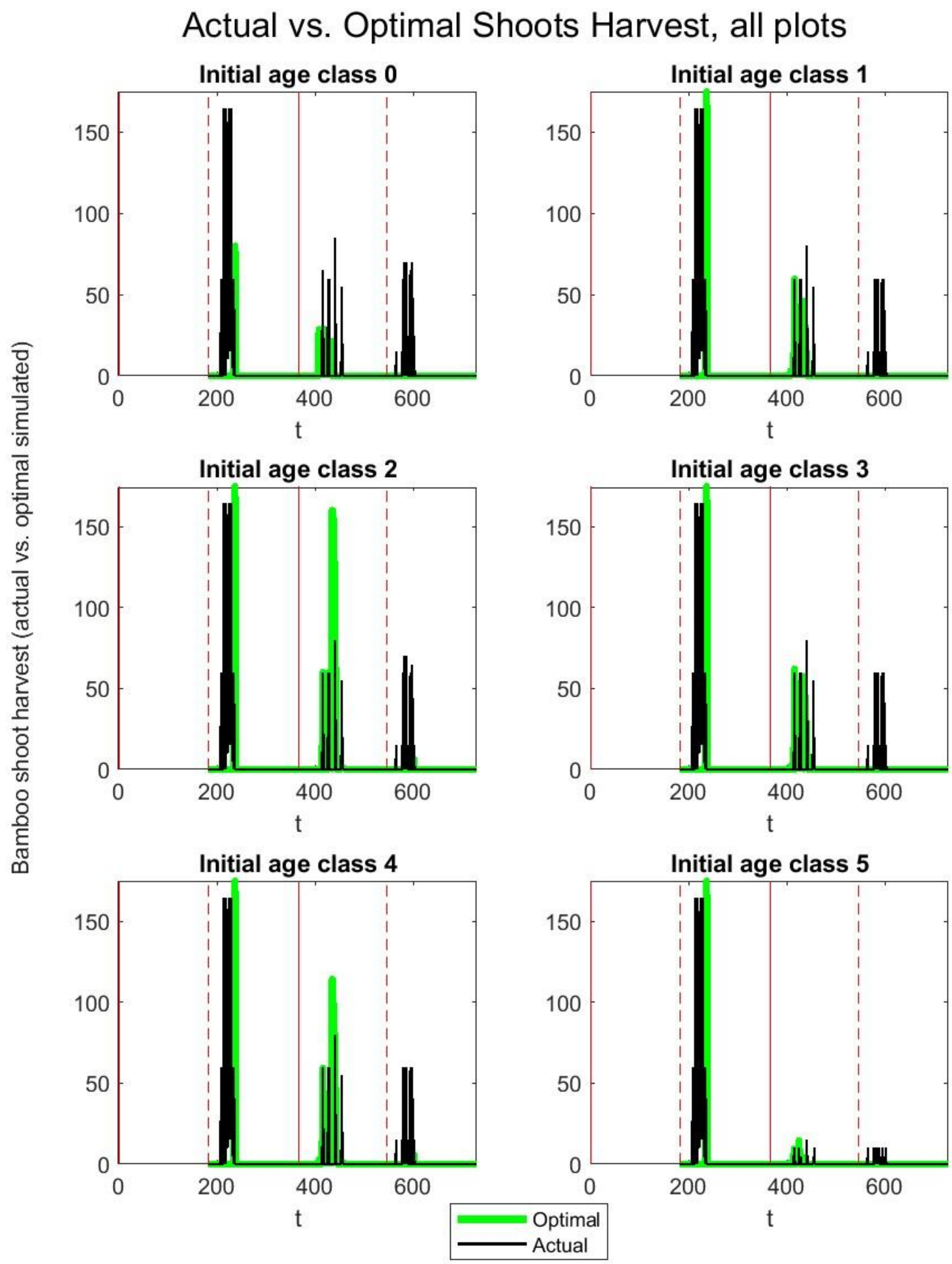
NPV during days with data	Mean (Yuan)
Optimal	722
Actual	127
Optimal minus Actual	595

(b)

Expected NPV over 11-year horizon	Mean (Yuan)
Optimal	12,525
Actual	9,483
Optimal minus Actual	3,042

Notes: Table compares actual and optimal net present value (NPV), where net present value (NPV) is defined as the present discounted value (PDV) of the entire stream of daily profits, using the structural parameter estimate for winter shoots decline probability of 0 from Table C.1. Panel (a) compares actual and optimal NPV during the days with data, where optimal NPV during the days with data is calculated using the actual initial states and actual daily prices and precipitation; and the actual NPV during the days with data is calculated using the actual daily actions, states, prices, and precipitation. Panel (b) compares optimal expected NPV over the entire 11-year horizon, where optimal expected NPV over the entire 11-year horizon is given by the value function evaluated at the initial states, and takes an expectation over stochastic shoots prices and precipitation; and where actual expected NPV over the entire 11-year horizon is the actual NPV during the days with data calculated above plus the discounted continuation value evaluated at the actual state at end of data and assumes optimal behavior after the last day of data.

Figure C.7. Optimal vs. Actual Shoots Harvest using structural parameter estimate for coefficient of constant relative risk aversion



Notes: Time series plots of the perceived optimal vs. actual number of bamboo shoots harvested on each bamboo plot, using the structural parameter estimate for the coefficient of constant relative risk aversion of 0.8 from Table 4. Vertical lines in red that go from the top to the bottom of the graph denote September 1 (first day of winter shooting) of each year. Dashed vertical lines in red that go from the top to the bottom of the graph denote March 1 (first day of spring shooting) of each year.

Table C.3. Actual vs. Optimal Welfare using structural parameter estimate for coefficient of constant relative risk aversion

(a)

PDV payoffs during days with data	Mean (Yuan)
Optimal	58
Actual	-273
Optimal minus Actual	331

(b)

Expected PDV payoffs over 11-year horizon	Mean (Yuan)
Optimal	241
Actual	-98
Optimal minus Actual	339

Notes: Table compares actual and optimal welfare, where welfare is defined as the present discounted value (PDV) of the entire stream of daily payoffs, using the structural parameter estimate for coefficient of constant relative risk aversion of 0.8 from Table 4. Panel (a) compares actual and optimal PDV payoffs during the days with data, where optimal PDV payoffs during the days with data is calculated using the actual initial states and actual daily prices and precipitation; and the actual PDV payoffs during the days with data is calculated using the actual daily actions, states, prices, and precipitation. Panel (b) compares optimal expected PDV payoffs over the entire 11-year horizon, where optimal expected PDV payoffs over the entire 11-year horizon is given by the value function evaluated at the initial states, and takes an expectation over stochastic shoots prices and precipitation; and where actual expected PDV payoffs over the entire 11-year horizon is the actual PDV payoffs during the days with data calculated above plus the discounted continuation value evaluated at the actual state at end of data and assumes optimal behavior after the last day of data.

Table C.4. Dynamic Structural Model Results: Annual Discount Factor

Structural Parameter	Actual (Assumed Value)	All
		(1)
Annual discount factor β_y	0.9	1.000 ***
		(0.000)
# Observations		115,290
# Bamboo plots		35

Notes: The structural parameter estimate is the parameter estimate from our specification of the structural model estimating the annual discount factor parameter only for the entire sample ("All"). The actual value is the assumed base case parameter value. Bootstrapped standard errors in parentheses. Significance codes: *** p<0.001, ** p<0.01, * p<0.0