

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

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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.

Keywords: forest management, dynamic model, interdependent products, tree crops, bamboo

JEL codes: Q23, L73, C61, Q57

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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.³

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

³ 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).

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 National Forestry and Grassland Administration, 2018), as well as the third most important source of timber in China. Bamboo is also an interesting case study owing to anecdotal evidence that bamboo farmers in China may be making harvest decisions that are unsustainable, leading to profit loss and a deterioration of the forest resource (Wu et al., 2026a), and therefore may possibly benefit from a better understanding of the optimal harvesting strategy.

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 stems 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 shoot 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 stems.

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 shoot 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 our model comes close to approximating the actual bamboo stem and bamboo shoot harvests in the data, but provides suggestive evidence that bamboo farmers may be overharvesting winter shoots, revealing a possible channel for improving farmer profits and sustainability at the margin. Our results have important implications for bamboo forest management and, to the extent that some of the differences between actual harvests and the optimal harvest strategy 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 stems 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. (2026b), 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 (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, 2026; Sears et al., 2026a; Sears et al., 2026b), 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, 2026; Kheiravar, Lin Lawell and Jaffe, 2026), agriculture (Carroll et al., 2019; Meneses et al., 2026a; Gómez and Lin Lawell, 2026; Meneses et al., 2026b; Carroll et al., 2026a; Sambucci, Lin Lawell and Lybbert, 2026), health (Iskhakov, 2010; Agarwal et al., 2021), development (Duflo, Hanna and Ryan, 2012; Rojas Valdés, Lin Lawell and Taylor, 2026), and consumer behavior (Gowrisankaran and Rysman, 2012; Ching and Osborne, 2020). Sant'Anna (2024) estimates a dynamic structural harvesting model applied to sugarcane in Brazil; we build on this work by considering multiple interdependent products and applying our model to bamboo forests in China.

Dynamic structural models capture important decision-making margins and responses that are overlooked by static models (Ryan, 2012; Yi, Lin Lawell and Thome, 2026). For example, Scott (2013) and Araujo, Costa, and Sant'Anna (2026) argue that price elasticities estimated from static models can be severely understated, and that incorporating dynamic decision-making is essential to recover economically meaningful responses. Dynamic structural models can also inform policies and outcomes that are more efficient and sustainable over the long run than those resulting from more myopic behavior (Timmins, 2022; Carroll et al., 2026b). 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 stems 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 National 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 stems: the more bamboo stems, 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 shoot 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 newly grown bamboo stems (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 stems (Jiang, 2007).

Bamboo shoots grow into bamboo stems after the end of spring shooting (Shi et al., 2013). The number of newly grown bamboo stems 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 shoot 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 the difficulty of locating and harvesting underground winter bamboo shoots, as well as popular preference for their more tender taste, winter bamboo

shoots command a higher market price than spring bamboo shoots. Both winter shoots and spring shoots are more expensive than bamboo stems (Wu et al., 2026a).

The harvest costs for bamboo shoots and bamboo stems are 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. (2026a).

4. Dynamic Model of Moso Bamboo Management

4.1. Numerical model

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 shoot price, the daily number of shoots, daily shoot death, and daily precipitation. The outer finite-horizon between-year annual dynamic programming problem captures annual bamboo stem growth from year to year.

We model the harvesting of bamboo that was all planted at the same time (and therefore of the same age class). Each day $d \in \{0, 1, 2, \dots, D\}$ of each year $y \in \{1, 2, \dots, Y\}$, the bamboo farmer chooses an action $a \in A$. The daily control (action) variables $a = (a_s, a_b)$ are the bamboo shoot harvest a_s (in units of number of bamboo shoots) and bamboo stem harvest a_b (in units of number of bamboo stems); actions are discrete. The daily state variables x include the number of bamboo stems n_b ; the number of bamboo shoots n_s ; our precipitation state r , 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 shoot 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 shoot 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 shoot price from the empirical distribution of daily winter shoot price, we draw the daily spring price from the empirical distribution of daily spring shoot price, and we draw the daily high precipitation dummy r from the daily empirical probability of high precipitation ($r = 1$) for each township. For the possibility of bamboo shoot 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 stems b . The Chapman-Richards model is given by:

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

where $Y_j(\cdot)$ 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 stems); 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 stems, respectively.

The per-period profit function is:

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

$$\pi(a, x, d, y) = \pi_b(a_b, x, y) + \pi_s(a_s, x, d),$$

where $\pi_b(a_b, x, y)$ is the profit from harvesting bamboo stems and $\pi_s(a_s, x, d)$ is profit from harvesting bamboo shoots. 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. (2026a), we assume that the bamboo market is perfectly competitive and that bamboo farmers are therefore price takers.

The profit $\pi_b(a_b, x, y)$ from bamboo stem harvest is given by:

$$\pi_b(a_b, x, y) = (p_b - c_b)\tau a_b Y_b(y),$$

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 $a_b Y_b(\cdot)$ to comparable units.⁵

The profit $\pi_s(a_s, x, d)$ from bamboo shoot harvest is given by:

$$\pi_s(a_s, x, d) = (p_s - c_s)\tau a_s Y_s(d),$$

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

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

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

⁵ The Chapman-Richard's model predicts biomass $Y_f(\cdot)$ for bamboo stems and bamboo shoots 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).

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 $\pi(a, x, d, y)$:

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

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 expected present discounted value (PDV) of the entire stream of per-period payoffs. The value function, which is the expected PDV 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:

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

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 shoot 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 stems 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 stems at the beginning of the year (remaining after bamboo stems are harvested the previous year): the more bamboo stems, 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, r , 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 ($r = 1$) for that township.⁶ The number of bamboo shoots n_s is bounded below by 0 and bounded above by an upper bound $\bar{n}_s$ that reflects in part the carrying capacity for bamboo plants.

We nest an inner finite-horizon within-year daily dynamic programming problem within an outer finite-horizon between-year annual dynamic programming problem. The terminal condition for the outer annual backwards iteration is that there is no continuation value after the last day of the last year.⁷ 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. The nested nature of our Bellman equation is summarized in Section 4.2; the derivation and intuition are presented in detail in Appendix C.

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 stems n_b , number of bamboo shoots n_s , high precipitation dummy r , and shoot 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.

4.2. Nested nature of Bellman equation

For the base case specification of risk neutrality, the nested nature of our nested stochastic dynamic bioeconomic model is as follows.⁸ Let $v_{1,d}(x)$ denote the value function for bamboo plants in year 1, which is the expected present discounted value (PDV) of the entire stream of bamboo shoot harvest profits $\pi_s(a_s, x, d)$ and bamboo stem harvest profits $\pi_b(a_b, x, y)$ from day d in year 1 onwards when harvests are chosen optimally. Since in the first bamboo growth year

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.

⁷ As explained in more detail in Appendix B, we set the finite horizon for the outer between-year annual dynamic programming problem to $Y = 11$ 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).

⁸ A more detailed description, derivation, and intuition for our nested stochastic dynamic bioeconomic model, including an analysis of how uncertainty and the interdependence between shoots and stems affect the optimal solution, is provided in Appendix C.

bamboo plants are exclusively bamboo shoots, the value function $v_{1,d}(x)$ for bamboo plants in year 1 is given by:

$$v_{1,d}(x) = \max_{a_s \leq n_s} \pi_s(a_s, x, d) + \beta E[v_{1,d+1}^s(x') | a_s, x]$$

before the last day of spring shooting in bamboo growth year 1 ($d < D$), and by:

$$v_{1,D}(x) = \max_{a_s \leq n_s} \pi_s(a_s, x, D) + \beta E[v_{2,0}^b(x'; n_{b20}, r_{1,D}) | a_s, x]$$

on the last day of spring shooting in bamboo growth year 1 ($d = D$), where $v_{2,0}^b(\cdot)$ is the value function for bamboo stems from the first day ($d = 0$) of bamboo growth year 2 ($y = 2$) onwards, and gives the expected PDV of the entire stream of bamboo stem harvest profits $\pi_b(\cdot)$ and bamboo shoot profits $\pi_s(\cdot)$ from year 2 onwards when harvests are chosen optimally.

The bamboo stem value function $v_{y,d}^b(\cdot)$ for each day d of each year y from year 2 onwards is given by:

$$v_{y,d}^b(x; n_{b20}, r_{y-1,D}) = \max_{a_b \leq n_b} I\{d = 0\} \cdot \tilde{v}_0^s(x; n_{by0}, r_{y-1,D}) + \pi_b(a_b, x, y) + \beta E[v_{y',d'}^b(x'; n_{b20}, r_{y'-1,D}) | a_b, x; n_{b20}, r_{y-1,D}],$$

where $\tilde{v}_0^s(\cdot)$ is the within-year bamboo shoots value function on the first day ($d = 0$) of year y , which is the expected PDV of the entire stream of bamboo shoot harvest profits $\pi_s(\cdot)$ for year y when bamboo shoot harvests are chosen optimally for year y , and which depends on the number of bamboo stems n_{by0} at the beginning of bamboo growth year, but not on any bamboo stem harvesting decision that takes place during the bamboo growth year, and which without loss of generality we can therefore assume is received as a lump sum on the first day ($d = 0$) of year y .

For each bamboo growth year y from year 2 until the year the bamboo stems are all harvested, the within-year value function for bamboo shoots $\tilde{v}_d^s(\cdot)$ is given by:

$$\tilde{v}_d^s(x; n_{by0}, r_{y-1,D}) = \max_{a_s \leq n_s} \pi_s(a_s, x, d) + \beta E[\tilde{v}_{d+1}^s(x'; n_{by0}, r_{y-1,D}) | a_s, x; n_{by0}, r_{y-1,D}]$$

for each day $d < D$ before last day of the bamboo growth year, and by:

$$\tilde{v}_D^s(x; n_{by0}, r_{y-1,D}) = \max_{a_s \leq n_s} \pi_s(a_s, x, D)$$

for the last day $d = D$ of the bamboo growth year.

We describe our nested stochastic dynamic bioeconomic model in more detail in Appendix C.

5. Results of Numerical Model

5.1. Optimal harvest policy

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 stems until the fourth bamboo growth year or later, after their growth has begun to slow down, and to harvest bamboo stems at the beginning of the year (Figure 2 and Figure C.1 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; Zhuang et al., 2015), and since the number of bamboo shoots at the beginning of each year depends on the number of bamboo stems 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 stems in order to allow bamboo stem biomass to accumulate, and to make bamboo shoot 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 stems remaining at the beginning of that year; it is therefore optimal to harvest bamboo stems at the beginning of the bamboo growth year it is being harvested.

For the optimal bamboo shoot harvest (Figure 3), 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 stems 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 stems at the end of the first year, which would then result in there being both bamboo shoots and bamboo stems 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 stems remaining at the beginning of each year.

In terms of within-year timing for any winter shoot harvest, we find that even if there is a possibility of shoot death, it is generally optimal to wait at least until the end of October and when

the winter shoot price is high to do any winter shoot harvest. This is because over 50% of winter shoot 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 shoot price is high, and there is a possibility of shoot death, it may be optimal to harvest some winter shoots earlier, including in the first bamboo growth year (Figure C.5 in Appendix C). The intuition is that with very few winter shoots and the possibility of shoot death, it may be worthwhile to harvest earlier if the winter shoot 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 shoot death, it may be optimal to harvest some winter shoots earlier (Figure C.8 in Appendix C). With the possibility of shoot death, it may be worthwhile for a risk averse farmer to harvest earlier even though the shoots have less biomass 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 shoot harvest, we find that, unless the spring shoot price is high, it is optimal to wait until the last days of spring shooting for which spring shoots are marketable to do any spring shoot harvest. The intuition is that the more time the spring shoots are given to grow during spring shooting, the more biomass there is.

Figure 4 presents a sample set of optimal trajectories for bamboo stem harvest, shoot harvest, number of bamboo stems, 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.

5.2. Interdependence and uncertainty

When there is both uncertainty and interdependent forest products, the interaction between these two phenomena leads to a complicated set of trade-offs. We conduct an analysis of how

uncertainty and the interdependence between shoots and stems affect the optimal solution in Appendix C. Some of the key takeaways are as follows.

First, for bamboo stems, when there is no interdependence with bamboo shoots, and therefore no value to waiting longer before harvesting bamboo stems in order to allow for more years of bamboo shoot harvests, the bamboo farmer will harvest bamboo stems in an earlier year (Figure C.2. in Appendix C), compared to the case when there is interdependence with shoots (Figure 2). Furthermore, when there is no interdependence with bamboo shoots, uncertainty (in precipitation, shoot price, and shoot death) does not matter for the bamboo stem harvesting problem. Thus, when there is no interdependence with bamboo shoots, the primary trade-off the bamboo farmer considers is that between waiting for bamboo stems to grow biomass and the time cost of delay; the optimal bamboo stem harvest timing is the age at which the growth rate of the bamboo stem equals the rate of interest.

Second, for bamboo stems, owing to the interdependence between bamboo stems and bamboo shoots, bamboo farmers may wish to delay harvesting bamboo stems in order to allow shoots to grow annually from the bamboo plant. Uncertainty in shoot prices and uncertainty in shoot death both enter in the bamboo stem harvest problem through their effect on the within-year value for bamboo shoots $\tilde{v}_0^s(\cdot)$ for that year. When there is uncertainty in precipitation, it may be optimal to harvest some bamboo stems earlier when the number of bamboo stems is very high, since with the possibility of high precipitation and a high remaining number of bamboo stems, the number of bamboo shoots at the beginning of subsequent bamboo growth years can still be high.

Third, for bamboo shoots, if there is no interdependence between shoots and stems, there is no value to having any bamboo shoots remaining at the end of the first bamboo growth year.

Fourth, for bamboo shoots, uncertainty in precipitation affects the bamboo shoot harvesting problem in the first bamboo growth year, and enters the bamboo shoot harvesting problem in year 1 through its effect on the value function for bamboo stems from year 2 onwards. The number of bamboo shoots $n_{s1D'}$ remaining at end of spring shooting in bamboo growth year 1 determines the number of bamboo stems n_{b20} at the beginning of bamboo growth year 2, which, along with the precipitation state $r_{1,D}$ at the end of year 1, together determine the number of bamboo shoots n_{s20} at the beginning of bamboo growth year 2.

Fifth, for bamboo shoots, uncertainty in shoot death and uncertainty in shoot prices affect the within-year bamboo shoot harvest decision each year. Uncertainty in shoot death leads a

farmer to harvest winter shoots earlier (Figure 3), since in the absence of the possibility of shoot death a bamboo farmer can afford to wait for a better price and to allow the shoots to grow in biomass without any risk that some shoots may die (Figure C.4 in Appendix C). When shoot prices are low, a bamboo farmer who faces uncertainty over shoot prices (and therefore the possibility that shoot prices might be higher in the future) will wait to harvest bamboo shoots (Figure C.9 in Appendix C), and will therefore harvest bamboo shoots later than a bamboo farmer who does not face price uncertainty and therefore knows that the shoot price will always be low (Figure C.10 in Appendix C).

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. Since some differences between actual and optimal values may reflect the discretized values of actions and states in our numerical model, we base our comparison on qualitative differences, trends, and patterns rather than on precise quantitative values.

Figure 5 presents time series plots of the optimal vs. actual number of bamboo stems 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.⁹

Figure 6 presents time series plots of the optimal vs. actual number of bamboo shoots harvested on each bamboo plot. Actual shoot harvests also tend to be close to what our model deems to be optimal: bamboo shoot harvest take place when shoot prices are high; and if the number of shoots is very low and there is a possibility of winter shoot death, winter shoots are harvested earlier when the shoot price is high. Nevertheless, bamboo farmers may be harvesting more winter shoots than is optimal. Previous anecdotal evidence suggests that winter shoots have sometimes been overharvested for high profit, leaving too few shoots for future bamboo forest development (Wu et al., 2026a).

⁹ Bamboo stems in initial age class 2 turn age 3 at the beginning of the second year of data (as delineated by the solid red vertical line in Figure 5) and are therefore in their fourth bamboo growth year during the latter half of the time series in our data set.

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 shoot 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. Since some differences between actual and optimal values may reflect the discretized values of actions and states in our numerical model, we once again base our comparison on relative differences rather than on precise quantitative values. 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.

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 expand the per-period payoff to each discrete choice a to include both a deterministic component $U_0(\pi(a, x, d, y); \theta)$ and a stochastic component $\varepsilon(a)$. The deterministic component $U_0(\pi(a, x, d, y); \theta)$ of the per-period payoff in our structural model is equal to the bamboo farmer's per-period payoff $U(\pi(a, x, d, y))$ 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. For each possible discrete action choice $a \in A$, the stochastic component to the per-period payoff is an unobserved shock $\varepsilon(a)$ associated with that discrete action choice a that is assumed to be distributed i.i.d. extreme value across days d , years y , farmers i , and actions a . There is a choice-specific shock $\varepsilon(a)$ associated with each possible discrete choice $a \in A$. The vector of choice-specific shocks $\varepsilon \equiv \{\varepsilon(a) | a \in A\}$ is observed by the bamboo farmer at day d in year y , before he makes his action choice for day d in year y , but is never observed by the econometrician. The value function incorporating these unobserved shocks $\varepsilon(a)$ is now given by:

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

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

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

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

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

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 $\Pr(a|x, d, y; \theta)$:

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

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_{sw} for winter shoots. In a second specification, the structural parameters θ we estimate are parameters in the shoot harvesting cost, namely the winter shoot harvest cost parameter c_{sw} , the spring shoot harvest cost parameter c_{ss} , and the shoot harvest cost convex cost parameter c_{s2} . In a third specification, the structural parameter θ we estimate is the daily shoot 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 $U_0(\pi(a, x, d, y); \theta)$ 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 shoot harvest cost parameter c_{sw} 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.¹⁰ 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. Discussion of results and policy implications

Table 2 presents the results of the different specifications of our dynamic structural econometric model. We discuss our structural econometric results in detail in Appendix D. Appendix E introduces and analyzes heterogeneity by township.

Results from the specification of our dynamic structural model in which we estimate the growth rate α_{s_w} for winter shoots show that bamboo farmers may perceive or believe the growth rate for winter shoots to be different from what it might actually be based on research and information on Moso bamboo from biological science (Table 2a), and moreover that the perceived winter shoot growth rate differs by township (Table E.2a in Appendix E). It is possible that our structural parameter estimates reflect local growth conditions and heterogeneity in winter shoot growth. Since winter shoots are underground and difficult to observe (Tang and Dong, 2024),

¹⁰ When bootstrapping the standard errors, we use 100 bootstrap samples for all specifications except the specification of our structural model in which the structural parameters θ we estimate are parameters in the shoot harvesting cost. Owing to constraints on computational time, for the shoot harvest cost parameters specification, which involves estimating multiple parameters simultaneously, we were only able to run 50 bootstrap samples.

however, and since farmers therefore may not know how large a winter shoot is before digging to harvest winter shoots, these results may also suggest that bamboo farmers may lack full information about winter shoot growth. If bamboo farmers do not know what the winter shoot growth rate actually is, this lack of information may contribute 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.

Results of the specification of the dynamic structural model in which we estimate parameters in the shoot harvesting cost show that the shoot harvest costs that rationalize the decisions in the data are similar to the monetary costs we calibrate, albeit slightly higher (Table 2b). Since we have less information on costs and since costs can vary by farmer, we therefore feel less confident that the harvest cost parameters we use for our model reflect the true harvest costs for all bamboo farmers; it is therefore very possible that the structural estimates for the shoot harvest costs may better reflect the shoot harvesting costs, monetary and otherwise, that farmers face. Nevertheless, if the slightly higher costs lead to a loss in farmer NPV, there may be scope for improving bamboo farmer profits and sustainability through initiatives that address the reason shoot harvest costs are high. For example, if the slightly higher costs arise due to labor shortages or labor constraints, then policies that alleviate the labor market frictions might be beneficial.

When we allow for risk aversion and estimate the coefficient of constant relative risk aversion η , results show that bamboo farmers may be risk averse (Table 2d), especially in Sian Township (Table E.2c in Appendix E). 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. Households with greater savings, more stable wage income, better access to credit, or more diversified assets may be better able to smooth consumption when the profits from bamboo stem and shoot harvests are low. This may be the case in Shanchuan Township, which our structural results found to have bamboo farmers who are risk neutral, and where tourism employment, homestay income, and other local business activities may provide households with income sources outside bamboo production that may increase their capacity to absorb bamboo-income shocks, and therefore make them less risk averse.

It is possible that our structural parameter estimates reflect the true values of the respective parameters. Nevertheless, for each parameter (or, in the case of harvest costs, set of parameters) θ we estimate, when we rerun our numerical nested stochastic dynamic bioeconomic model using

the structural parameter estimate, we find that differences between the structural parameter estimates and our calibrated values do not fully explain the discrepancy between actual and optimal decisions. Even under the structural parameter estimate for winter shoot growth rate (Figure D.2 in Appendix D) or those for the shoot harvest costs (Figure D.3 in Appendix D), the optimal strategy still involves less winter shoot harvesting than takes place in the actual data. Moreover, actual harvests still yield lower NPV than the optimal strategy under the structural parameter estimates for winter shoot growth rate (Table D.1 in Appendix D) or shoot harvest costs (Table D.2 in Appendix D). Thus, even if the structural parameter estimates were the true values of the respective parameters, there is still scope for farmers to improve their harvesting strategies and increase their farmer NPV.

Likewise, the optimal shoot harvest strategy under risk aversion involves relatively more winter shoot harvests, which may better match the actual winter shoot harvests, but also involves harvesting some winter shoots at the end of winter shooting, which does not take place in the actual data (Figure D.5 in Appendix D). In addition, the optimal bamboo stem harvest strategy under risk aversion involves harvesting some bamboo stems earlier than actually takes place in the data. Actual harvests yield lower welfare (PDV of the entire stream of daily payoffs) and lower NPV (PDV of the entire stream of daily profits) than does the optimal strategy under risk aversion (Table D.4 in Appendix D). Thus, even if farmers were risk averse, there is still scope for risk averse farmers to improve their harvesting strategies and increase their farmer NPV.

For many bamboo farmers in China, profits from bamboo harvests may not necessarily be their sole source of annual income (Wu et al., 2026a). As a consequence, bamboo farmers might not be fully optimizing because they might not need to do so, or because the computational or cognitive costs to doing so when they have multiple competing demands for their time and attention are too high. If bamboo farmers are unable to determine the optimal strategy or find it too costly to do so, their satisficing contributes to a loss in farmer NPV (as seen in Table 1) and can be addressed via programs and policies that better inform farmers about the optimal bamboo harvest strategy.

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. 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 bamboo farmers may be harvesting more winter shoots than is optimal. Our optimal strategy is consistent with traditional bamboo management guidance to avoid harvesting too many winter shoots (Forestry Department of Hunan Province, 2008), and our results are consistent with anecdotal evidence that winter shoots have sometimes been overharvested for high profit, leaving too few shoots for future bamboo forest development (Wu et al., 2026a). Our model provides suggestive evidence that by reducing their winter shoot harvest, it might be possible for a bamboo farmer to improve their NPV at the margin.

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 point to risk aversion and different perceptions about winter shoot growth as possible sources of differences between actual behavior and the optimal strategy. To the extent that the overharvesting of winter shoots and its resulting loss in farmer NPV is due to farmers' lack of full information about winter shoot growth – which is very possible since winter shoots are underground and difficult to observe (Tang and Dong, 2024), and since farmers therefore may not know how large a winter shoot is before digging to harvest winter shoots – this inefficiency can be addressed via programs and policies that better inform farmers about winter shoot growth. 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.

Some of the differences between actual harvests and optimal harvests may arise because bamboo farmers are satisficing and find it too costly to determine the optimal strategy, for example owing to computational costs, cognitive costs, or opportunity costs of time. In this case, their overharvesting of winter shoots and resulting loss in farmer NPV can be addressed via programs and policies that better inform farmers about the optimal bamboo harvest strategy.

There are several important features of bamboo forest management that are at least partially captured by our model. These include winter shoot 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 shoot 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; and where the interaction between uncertainty and interdependent forest products leads to a complicated set of trade-offs that might be difficult to assess and quantify analytically. 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., 2026b). 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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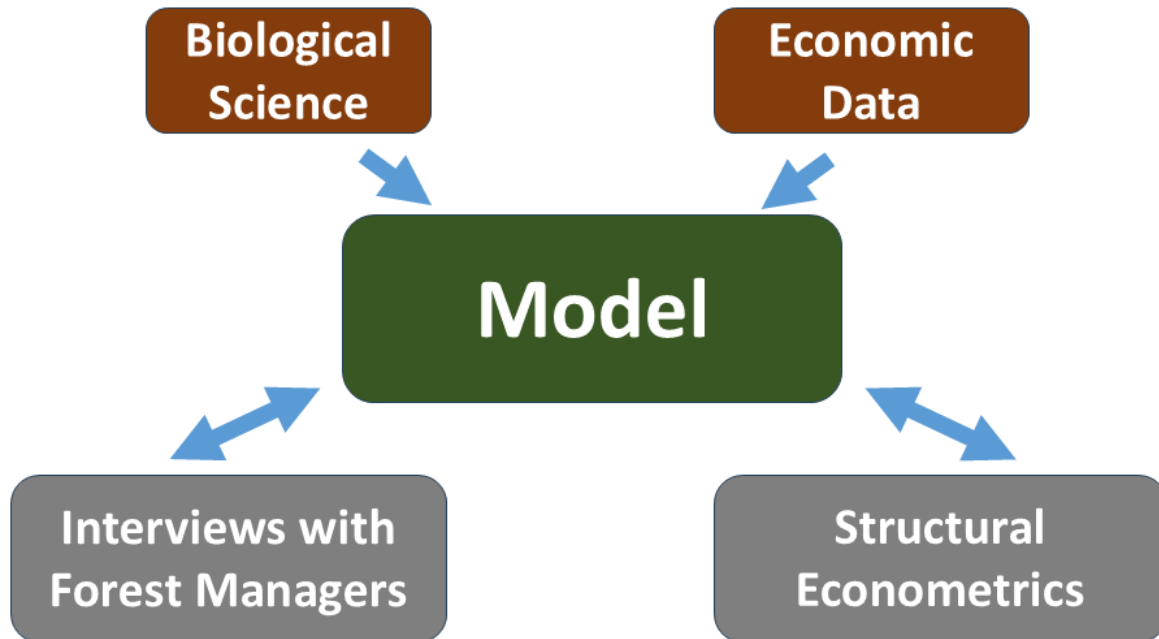
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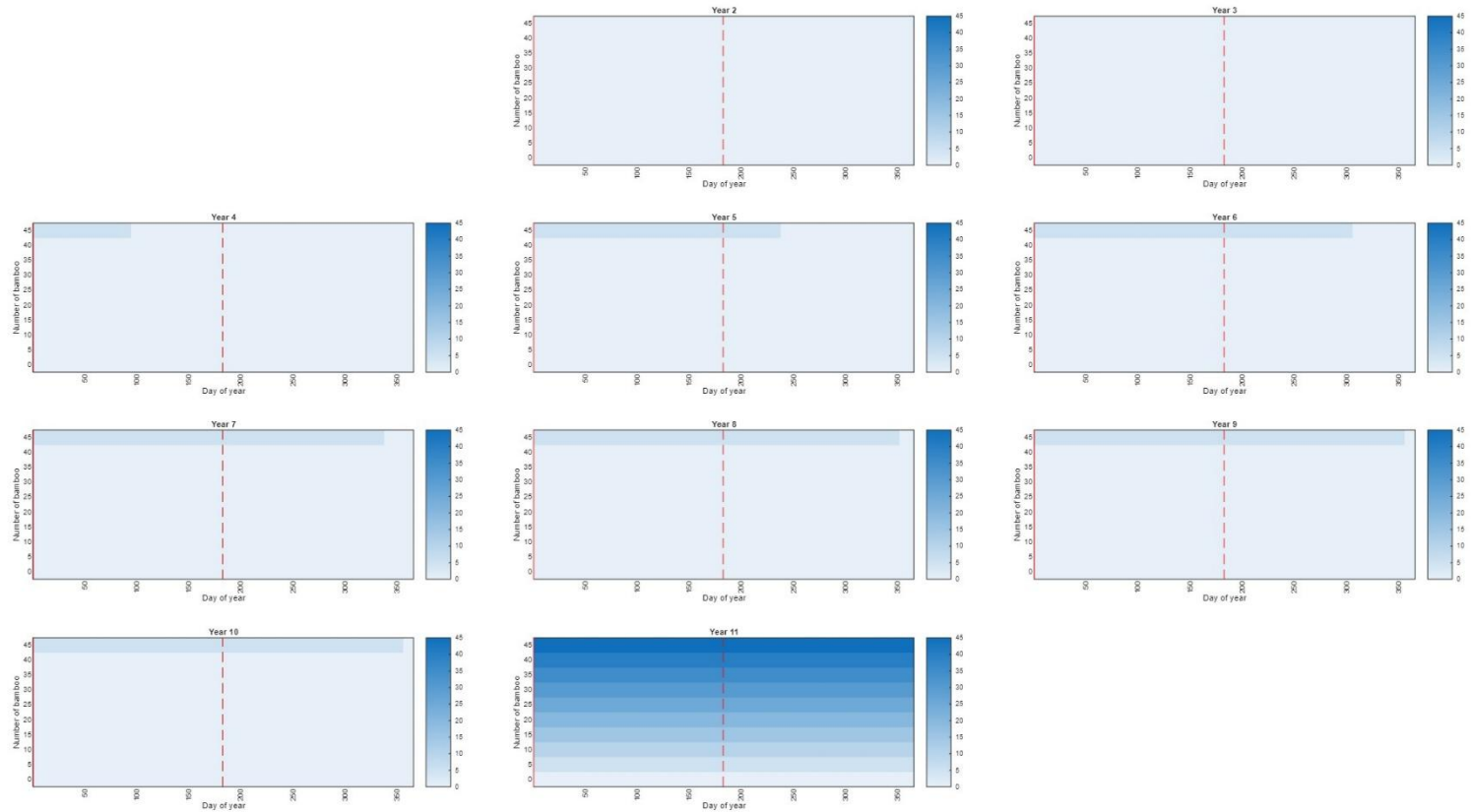
Figure 1. Iterative Approach to Model Development and Refinement

Iterative Approach



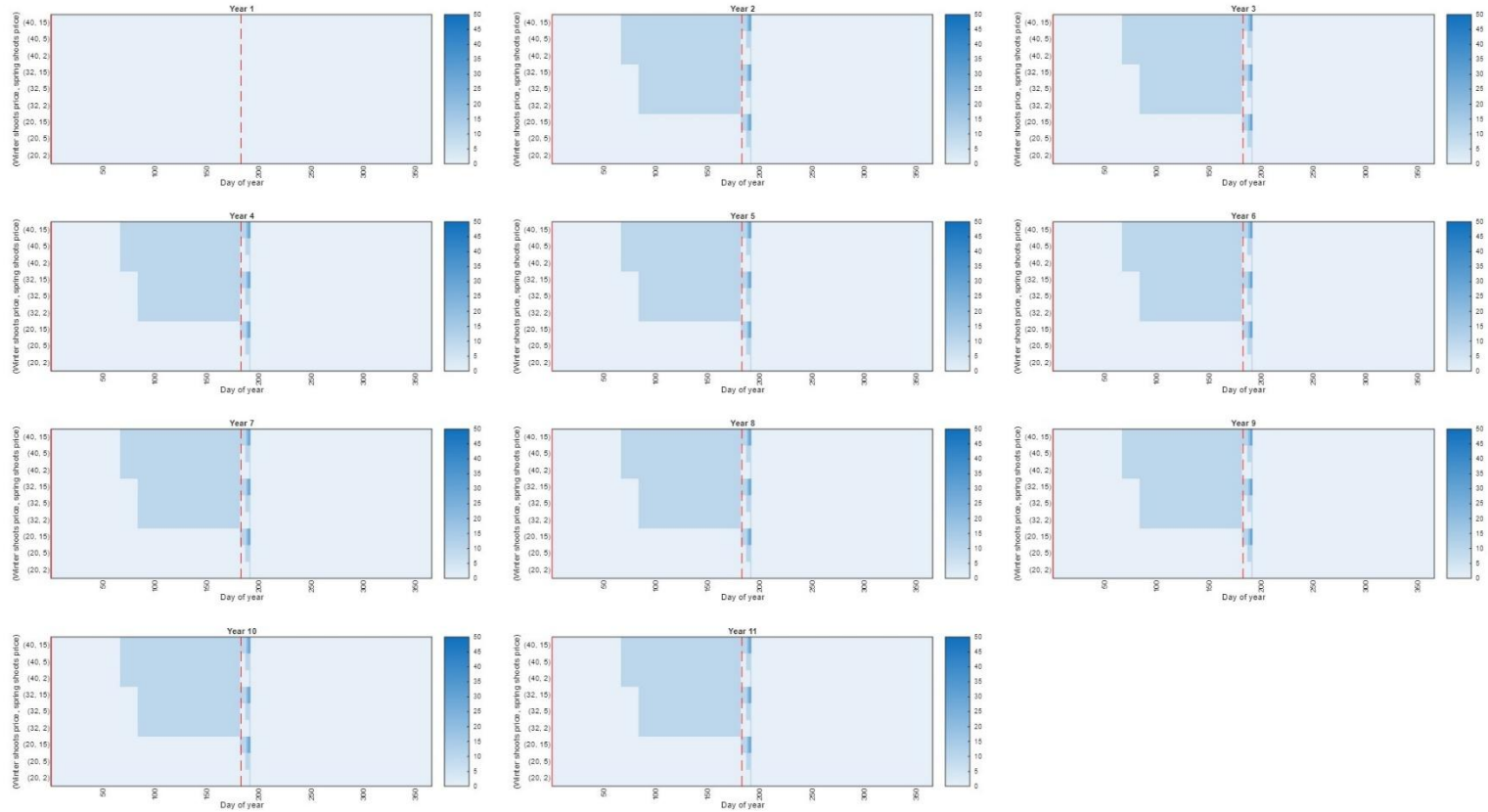
Notes: We use an iterative approach to developing and refining the model to ensure that it best reflects reality. We use research and information on Moso bamboo from the biological sciences, economic data, and interviews we conducted with bamboo forest managers to develop our model and calibrate the 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. Bamboo Stem Harvest Policy Function



Notes: Figure presents the bamboo stem harvest policy function for each day for each year as a function of the number of bamboo stems, 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.

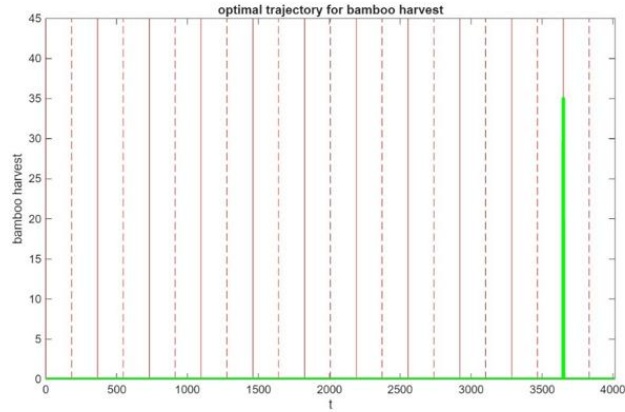
Figure 3. Bamboo Shoot Harvest Policy Function



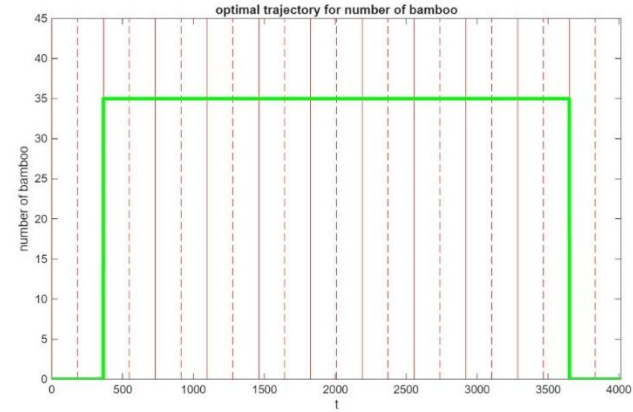
Notes: Figure presents the bamboo shoot harvest policy function for each day for each year as a function of the daily shoot price when the number of shoots is a medium quantity ($n_s = 30$) and cumulative daily precipitation is low ($r = 0$), and when parameters are set at their base case values. For 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 4. Example of Optimal Trajectories

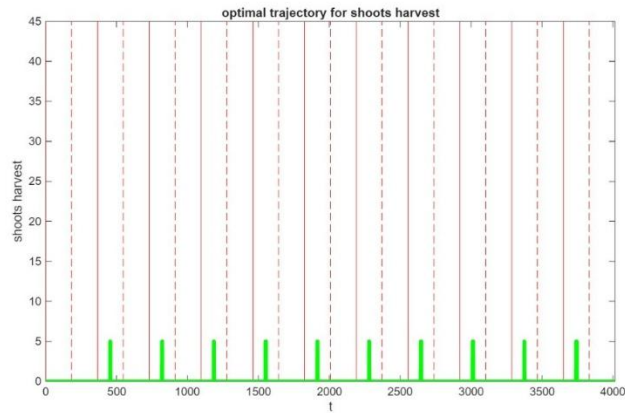
a) Bamboo Stem Harvest



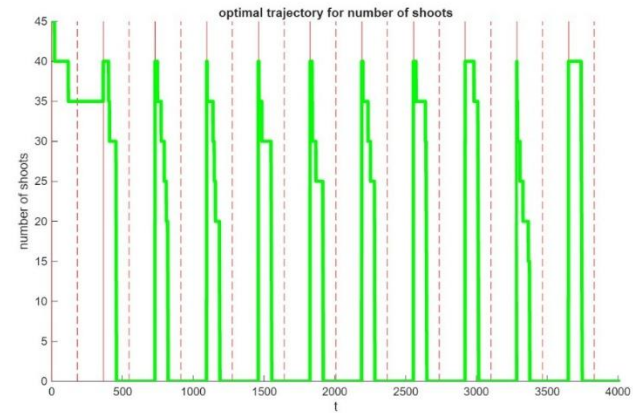
c) Number of Bamboo Stems



b) Shoot Harvest

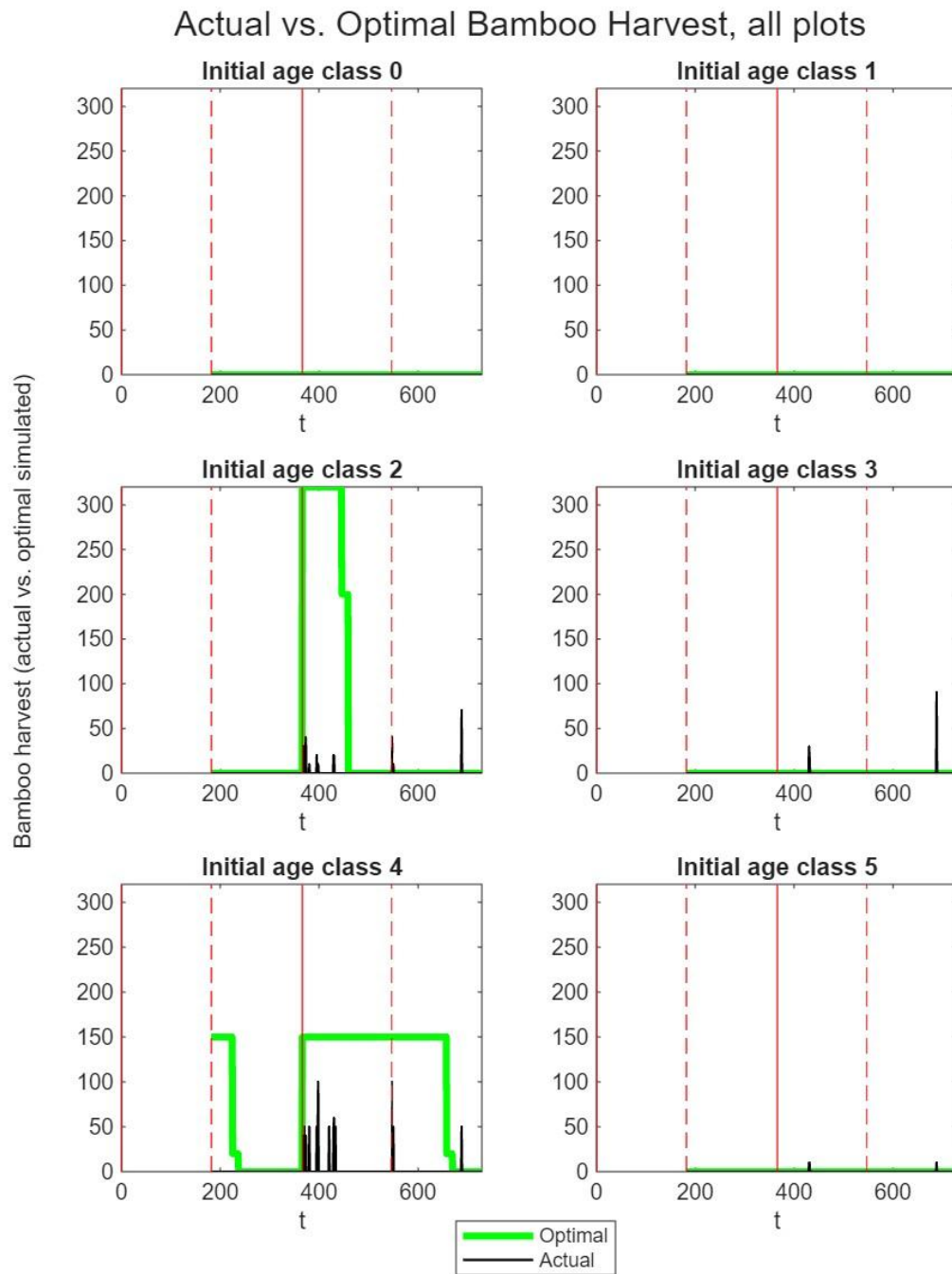


d) Number of Shoots



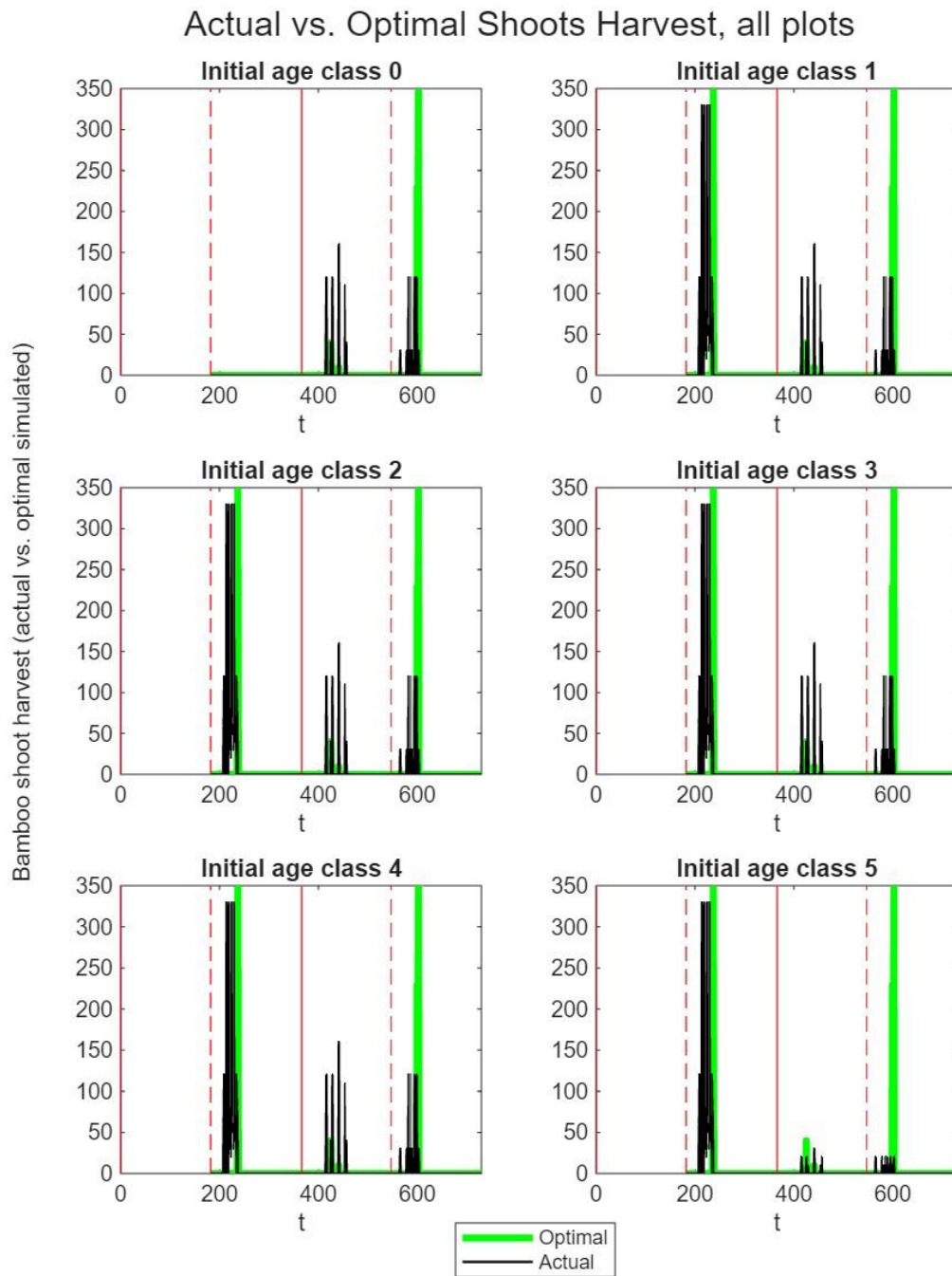
Notes: Figure presents a simulated set of optimal trajectories for bamboo stem harvest, bamboo shoot harvest, number of bamboo stems, and number of bamboo shoots for each day of each year starting from a large initial number of bamboo shoots ($n_s = 45$) on the first day of the first bamboo growth year. Solid 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 Bamboo Stem Harvest



Notes: Time series plots of the optimal and actual number of bamboo stems harvested by initial age class. Solid 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 6. Optimal vs. Actual Shoot Harvest



Notes: Time series plots of the optimal vs. actual number of bamboo shoots harvested on each bamboo plot. Solid 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	3,013
Actual	827
Optimal minus Actual	2,185

(b)

Expected NPV over 11-year horizon	Mean (Yuan)
Optimal	6,943
Actual	5,479
Optimal minus Actual	1,464

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. There are 35 bamboo plots in the data set, each with 6 initial age classes; table reports means over all bamboo plot – initial age classes. 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 shoot 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

Structural Parameter	Actual (Assumed Value)	All
<i>(a) Winter shoot growth only</i>		
Winter shoot growth rate α_{sw}	0.016	0.012 ** (0.004)
# Observations		115,290
# Bamboo plots		35
<i>(b) Shoot cost parameters only</i>		
Winter shoot harvest cost parameter c_{sw}	15	16.43 *** (0.155)
Spring shoot harvest cost parameter c_{ss}	1.5	1.69 *** (0.017)
Shoot harvest cost convex cost parameter c_{s2}	50	50.0 *** (0.000)
# Observations		115,290
# Bamboo plots		35
<i>(c) Shoot decline probability parameter only</i>		
Daily winter shoot decline probability d_w	0.0164	0.00000 (0.00001)
# Observations		115,290
# Bamboo plots		35
<i>(d) Coefficient of relative risk aversion only</i>		
Coefficient of constant relative risk aversion η	0 (risk neutral)	0.837 * (0.342)
# Observations		115,290
# Bamboo plots		35
<i>(e) Annual discount factor only</i>		
Annual discount factor β_y	0.9	1.000 *** (0.000)
# Observations		115,290
# Bamboo plots		35

Notes: The structural parameter estimates are the parameter estimates from separate specifications of the structural model estimating (a) the winter shoot growth parameter only, (b) the shoot cost parameters only, (c) the shoot decline probability parameter only, (d) the coefficient of relative risk aversion only, and (e) the annual discount factor only, respectively, 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 are in parentheses. Specifications (a), (c), (d), and (e) use 100 bootstrap samples each; owing to constraints on computational time, specification (b), which involves estimating multiple parameters simultaneously, uses 50 bootstrap samples. 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 stems b . The Chapman-Richards model is given by:

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

where $Y_j(\cdot)$ 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 stems); 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 shoot growth. We calibrate our model for winter shoot growth to capture what previous research has found about winter shoots, and also to better match the actual winter shoot 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 shoot 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 shoot price is very high, which our dynamic model shows would not be optimal even with a very high winter shoot 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 shoot growth function so that their biomass in late October is higher.

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

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

where Y_{s_w} is the total biomass of a winter shoot of age t_{s_w} 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:

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

At the inflection point, where $\frac{d^2 Y_{s_w}(t_{s_w})}{dt_{s_w}^2} = 0$, 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 $Y_{sw}^{\max}$, the maximum possible winter shoots biomass at the end of winter shooting (day $t_{sw}^{\max}$), 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_{sw} , 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:

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

For the growth rate α_{sw} for winter shoots, the growth rate for bamboo shoots is more rapid than that for bamboo stems (Song et al., 2016). To date there have been very few studies on Moso bamboo underground development, winter shoots biomass, and winter shoot growth. Wei et al. (2017) describe underground bamboo shoot 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 shoot growth from September to the following year's April. The number of genes expressed in the shoots is a measure of shoot 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_{sw} for winter shoots that is slightly lower than the growth rate α_{ss} for spring shoots that we specify below. In particular, since we set the growth rate α_{ss} for spring shoots to 0.036 below, and winter shoots is expressing less genes compared to spring shoots, we set the growth rate α_{sw} for winter shoots to 0.016.

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

The parameter v_{sw} 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 shoot 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 shoot 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_{sw}^{infl} to be 76. We calculate v_{sw} using:

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

and iterating on v_{sw} 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:

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

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 stems 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 $t_{s_s}^{\text{max}}$ 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_s} 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 $Y_{ss}^{\max}$, the maximum possible spring shoots biomass at the end of spring shooting (day $t_{ss}^{\max}$), to be 8 kg. We then calibrate A_{ss} , 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:

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

For the growth rate α_{ss} for spring shoots, the growth rate for bamboo shoots is more rapid than that for bamboo stems (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_{ss} to 0.036.

The biological constant Q_{ss} is related to the initial spring shoot biomass at the beginning of spring shooting. Since Q_{ss} 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_{ss} . The biomass on the last day of winter shooting, $Y_{sw}^{\max}$, is the Chapman-Richards growth function for winter shoots evaluated on the last day of winter shooting. We then calculate Q_{ss} as:

$$Q_{ss} = \frac{1 - (Y_{sw}^{\max} / Y_{ss}^{\max})^{1-v_{ss}}}{1 - (Y_{sw}^{\max} / Y_{ss}^{\max})^{1-v_{ss}} e^{-\alpha_{ss} t_{ss}^{\max}}}.$$

The parameter v_{ss} 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_{ss}^{infl} to be 60. We calculate v_{ss} using:

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

and iterating on v_{ss} until convergence.

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

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

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

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:

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

For the growth rate α_b for bamboo stems, 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 stems 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 stems 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 stems, we model the growth of bamboo stems starting from the end of spring shooting, when bamboo shoots become bamboo stems. 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 $t_{b0} = (t_{sw}^{\max} + t_{ss}^{\max})/365$. The initial bamboo stem biomass at the end of spring shooting (year t_{b0}) is the maximum bamboo shoot biomass $Y_{ss}^{\max}$ at the end of spring shooting. We then calculate Q_{ss} as:

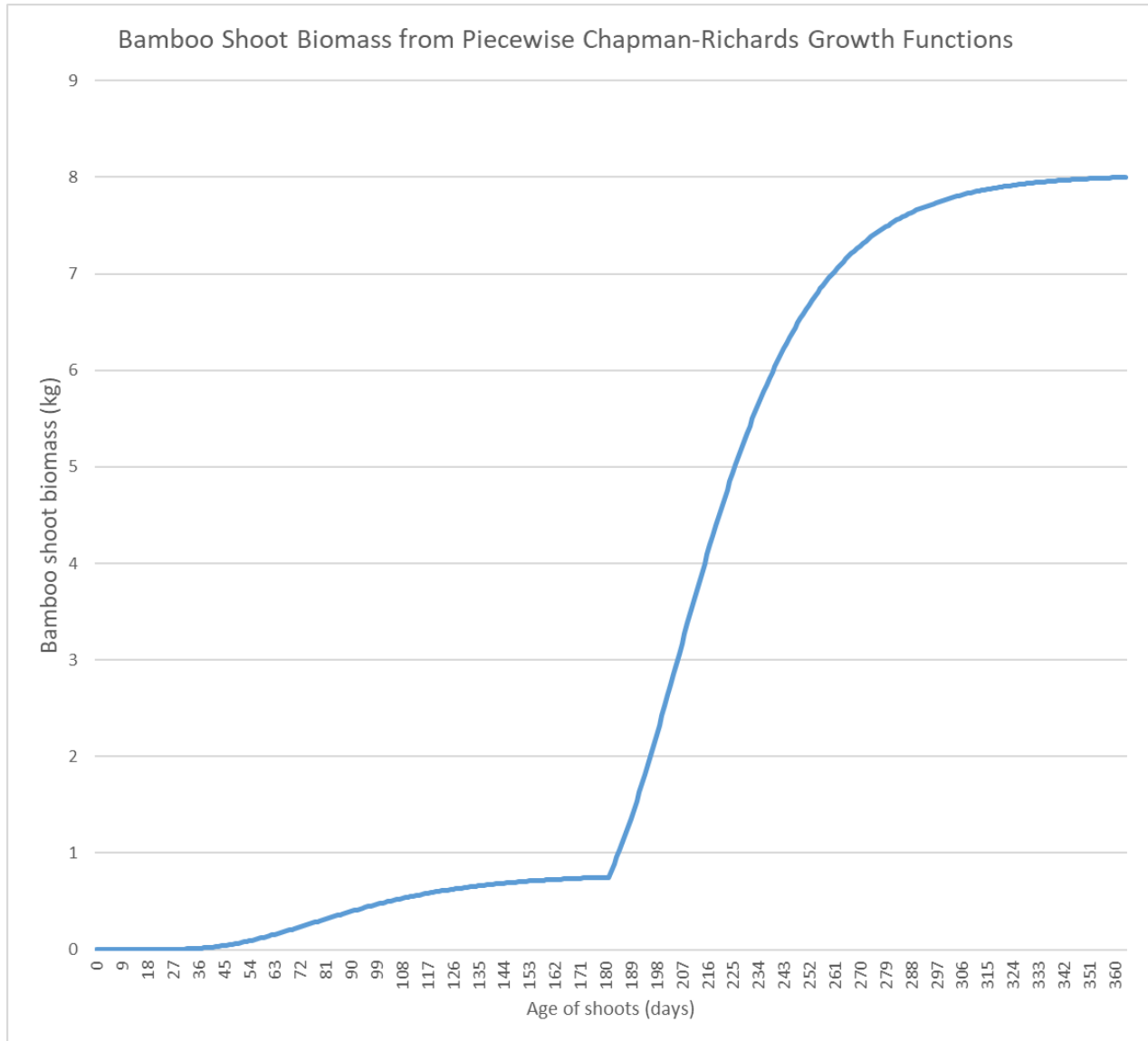
$$Q_b = \frac{1 - (Y_{ss}^{\max}/Y_b^{\max})^{1-v_b}}{e^{-\alpha_b t_{b0}} - (Y_{ss}^{\max}/Y_b^{\max})^{1-v_b} e^{-\alpha_b t_b^{\max}}}.$$

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:

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

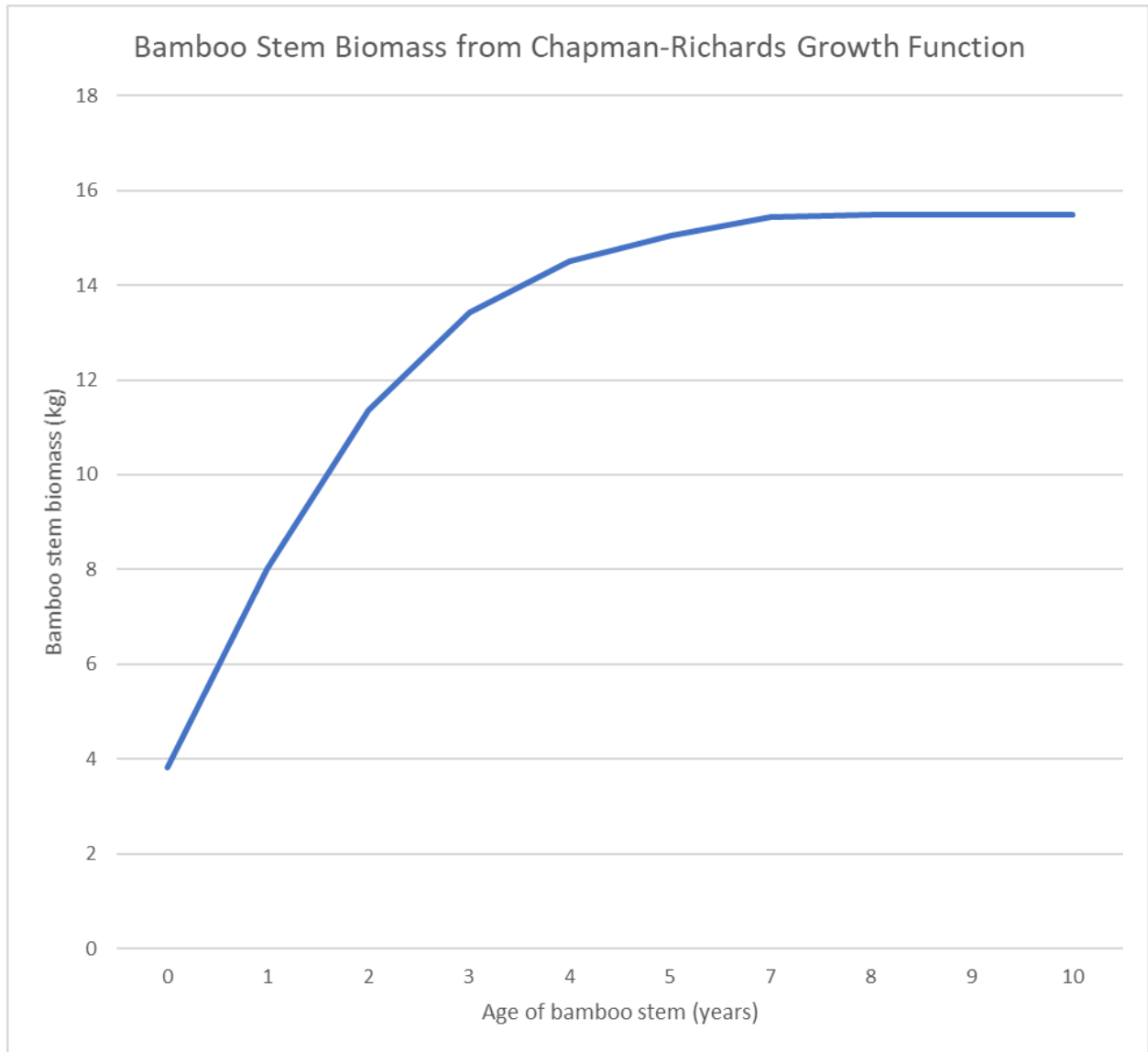
and iterating on v_b until convergence.

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 Stems



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 stems and on the dates, quantity, and price received for each bamboo stem harvest and each bamboo shoot harvest.

B.2. Bamboo shoot price

We use data on daily bamboo shoot 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 shoot prices from the Zhebei Jiashan wholesale market since there are more days available, since their shoot 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, 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 shoot price data with our harvest data as follows. If any bamboo shoot 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 shoot price is not necessarily the same for the 2 townships due to different shoot 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 shoot harvest took place, we use the daily bamboo shoot 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 shoot price during winter shooting and the daily spring shoot 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 stems, workers get paid daily with a rate of 300 yuan per day and harvest 1,250 to 2,000 kg of bamboo stems. 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 stems 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 stems 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 r 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 r is high ($r = 1$) or not ($r = 0$).

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 r is not necessarily constant for all of July and August. For some townships and some years, it is possible that $r = 0$ 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 r 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 ($r = 1$) 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 $r = 1$ on that day.

B.8. Daily probability of shoot 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 shoot decline during winter shooting to be $1/61$, such that the number of shoots is expected to decline by approximately 1 bin every 2 months 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 stems and number of bamboo stems 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 shoot 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 harvested into the number of bamboo shoots harvested by dividing the weight of bamboo shoots harvested 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 stems, 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.

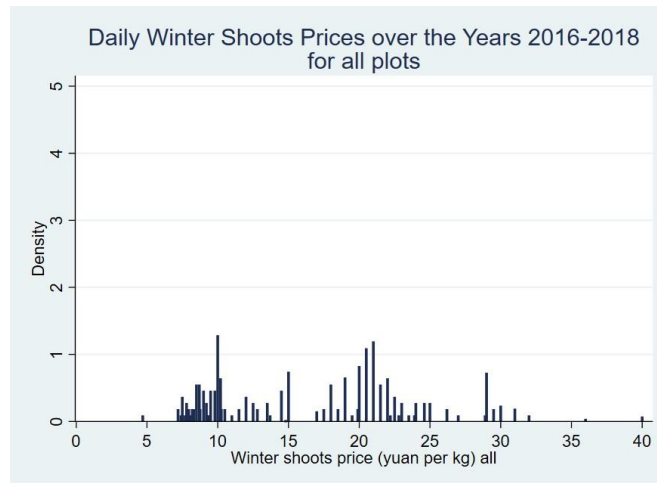
For each bamboo plot, to calculate the number n_s of bamboo shoots at the beginning of the season, in the absence of any bamboo shoot harvest, we add the total number of bamboo shoots harvested over the season to the total number of bamboo shoots that remain unharvested at the end

of the season. For each day on each bamboo plot, we calculate the bamboo shoot 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 shoot 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 stems, and the number of stems 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 stems, and the number of stems 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 stems, and the number of stems 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 shoot 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 shoot 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.

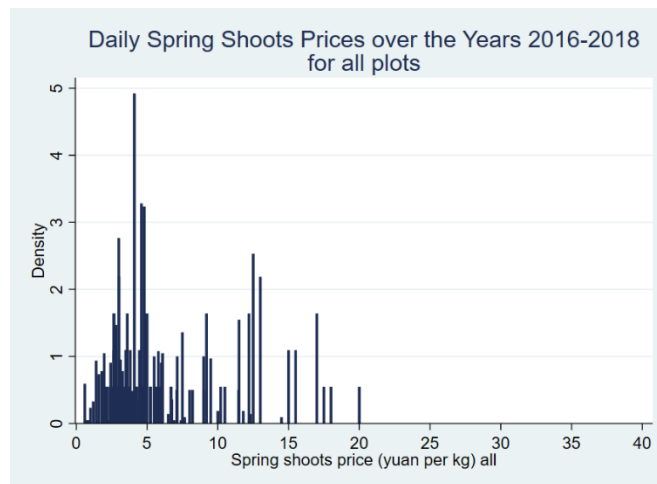
Figure B.1. Bamboo Shoot Prices

(a) Winter Shoot Prices



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

(b) Spring Shoot Prices



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

Appendix C. Nested Stochastic Dynamic Bioeconomic Model

C.1. Bamboo stem harvest benchmark: No uncertainty, no interdependence

We first solve for the bamboo stem harvest policy under the benchmark case of no uncertainty and no interdependence between bamboo stems and bamboo shoots, for the base case specification of risk neutrality. Since the bamboo stem harvest profit $\pi_b(a_b, x, y)$ is linear in the number of bamboo stems harvested a_b , the bamboo stem harvest problem reduces to an optimal bamboo stem harvest timing problem wherein the bamboo farmer chooses the optimal age t_b at which to harvest bamboo stems that were planted at the same time (and therefore of the same age).

When there is neither uncertainty nor interdependence between bamboo stems and bamboo shoots, the optimal bamboo stem harvest timing problem is given by:

$$\max_{t_b} \beta^{t_b} \pi_b(a_b, x, t_b) = \beta^{t_b} (p_b - c_b) a_b \cdot \tau Y_b(t_b), \quad (\text{C.1})$$

where $Y_b(t_b)$ is the Chapman-Richards model for bamboo stem growth, and gives the biomass of a bamboo stem as a function of its age t_b (in years).

The first-order condition for the optimal bamboo stem harvest timing age t_b^* at which to harvest bamboo stems when there is neither uncertainty nor interdependence between bamboo stems and bamboo shoots is given by:

$$\frac{Y_b'(t_b^*)}{Y_b(t_b^*)} = -\ln(\beta) \geq 0. \quad (\text{C.2})$$

If the discount factor β reflects interest that is continuously compounded at an interest rate ρ so that $\beta = e^{-\rho}$, then the first-order condition (C.2) is equivalent to:

$$\frac{Y_b'(t_b^*)}{Y_b(t_b^*)} = \rho. \quad (\text{C.3})$$

At the optimal age t_b^* of bamboo stem harvest, the growth rate $\frac{Y_b'(t_b^*)}{Y_b(t_b^*)}$ of the bamboo stem equals the interest rate ρ . In other words, it is optimal to harvest bamboo stems at the age t_b^* when the bamboo stem biomass is growing at the same rate that money is growing in the bank. If the bamboo farmer discounts the future ($\beta < 1$), then the growth rate $\frac{Y_b'(t_b^*)}{Y_b(t_b^*)}$ of the bamboo stem is still positive at the optimal bamboo stem harvest timing age t_b^* , and hence the optimal bamboo stem harvest timing age t_b^* is less than the age $t_b^{\max}$ at which the bamboo stem achieves its maximum biomass. Thus, when there is neither uncertainty nor interdependence between bamboo stems and bamboo

shoots, a bamboo farmer who discounts the future should harvest the bamboo stem before it stops growing.

C.2. Bamboo shoot harvest benchmark: No uncertainty, no interdependence

Also as part of establishing the no uncertainty, no interdependence benchmark, we solve for the bamboo shoot harvest policy under the benchmark case of no uncertainty and no interdependence between bamboo stems and bamboo shoots, for the base case specification of risk neutrality. Since bamboo shoots grow annually from bamboo stems and only grow within a year, in the absence of any interdependence with bamboo stems, the bamboo shoot harvesting problem is a within-year problem. Furthermore, if the bamboo shoot harvest profit $\pi_s(a_s, x, d)$ is linear in the number of bamboo shoots harvested a_s , the bamboo shoot harvest problem reduces to an optimal bamboo shoot harvest timing problem wherein the bamboo farmer chooses the optimal age t_s at which to harvest bamboo shoots that began growing at the same time. To further build intuition, we also assume here for the simple theory model under the no uncertainty case that while winter shoot prices may differ from spring shoot prices, there is no uncertainty and no variation in winter shoot prices, and no uncertainty and no variation in spring shoot prices.

When there is neither uncertainty nor interdependence between bamboo stems and bamboo shoots, and when the bamboo shoot harvest profit $\pi_s(a_s, x, d)$ is linear in the number of bamboo shoots harvested a_s , the optimal bamboo shoot harvest timing problem is given by:

$$\max_{t_s} \beta^{t_s} \pi_s(a_s, x, t_s) = \beta^{t_s} (p_s - c_s) a_s \cdot \tau Y_s(t_s), \quad (\text{C.4})$$

where $Y_s(t_s)$ is the Chapman-Richards model for bamboo shoot growth, and gives the biomass of a bamboo shoot as a function of its age t_s (in days).

Since winter shoots reach their maximum biomass at the end of winter shooting, if winter shoot prices are constant, the maximum profit from winter shoot harvest occurs at the end of winter shooting on day $t_{sw}^{\max}$. Similarly, since spring shoots reach their maximum biomass at the end of spring shooting, if spring shoot prices are constant, the maximum profit from spring shoot harvest occurs at the end of spring shooting on day $t_{ss}^{\max}$.

When there is no uncertainty and no interdependence between bamboo shoots and bamboo stems, and if the bamboo shoot harvest profit $\pi_s(a_s, x, d)$ is linear in the number of bamboo shoots

harvested a_s , the bamboo farmer will weakly choose to harvest the bamboo shoots as winter shoots at the end of winter shooting (rather than as spring shoots at the end of spring shooting) if:

$$\beta^{t_{s_w}^{\max}} (p_{s_w} - c_{s_w}) a_s \cdot \tau Y_{s_w}(t_{s_w}^{\max}) \geq \beta^{t_{s_s}^{\max}} (p_{s_s} - c_{s_s}) a_s \cdot \tau Y_{s_s}(t_{s_s}^{\max}), \quad (C.5)$$

which yields the condition:

$$\frac{p_{s_w} - c_{s_w}}{p_{s_s} - c_{s_s}} \geq \beta^{t_{s_s}^{\max} - t_{s_w}^{\max}} \frac{Y_{s_s}(t_{s_s}^{\max})}{Y_{s_w}(t_{s_w}^{\max})}. \quad (C.6)$$

As seen in condition (C.6), when there is no uncertainty and no interdependence with bamboo stems, and if the bamboo shoot harvest profit $\pi_s(a_s, x, d)$ is linear in the number of bamboo shoots harvested a_s , whether it is optimal for the bamboo farmer to harvest bamboo shoots as winter shoots or spring shoots depends on: (i) the relative net prices between winter and spring shoots $\frac{p_{s_w} - c_{s_w}}{p_{s_s} - c_{s_s}}$, (ii) the relative biomass of winter shoots and spring shoots $\frac{Y_{s_s}(t_{s_s}^{\max})}{Y_{s_w}(t_{s_w}^{\max})}$ at the end of winter shooting and spring shooting, respectively, which depends on the winter shoot growth rate α_{s_w} , and (iii) the discount factor β .

C.3. Optimal bamboo shoot harvest policy from year 2 onwards

We now add in uncertainty and interdependence between bamboo stems and bamboo shoots, and solve for the optimal bamboo shoot harvest policy for the second bamboo growth year onwards, after the bamboo shoots remaining at the end of the first bamboo growth year have become bamboo stems from which bamboo shoots can grow year after year, until the year the bamboo stems are harvested, under uncertainty and interdependence between bamboo stems and bamboo shoots, for the base case specification of risk neutrality. For each bamboo growth year y from year 2 until the year the bamboo stems are all harvested, the number of shoots at the beginning of the year depends on the number of bamboo stems, and the number of bamboo stems is independent of any bamboo shoot harvesting decision. Since for each year from year 2 onwards the bamboo shoot harvest decisions that year do not affect the number of bamboo shoots the following year, and since for each year from year 2 onwards the continuation value for bamboo shoots on the last day of the bamboo growth year (which is the expected value of the value function for bamboo shoots the following year conditional on action and state) is therefore the same regardless of the bamboo shoot harvest decisions that year, we can reduce the multi-year problem for bamboo shoots from year 2 until the year the bamboo stems are all harvested into a repeated

series of independent finite-horizon within-year dynamic programs, one for each bamboo growth year from year 2 until the year the bamboo stems are all harvested.¹¹

Let $\tilde{v}_d^s(x; n_{by0}, r_{y-1,D})$ denote the within-year value function for bamboo shoots for each year y from year 2 until the year the bamboo stems are all harvested, given the number of bamboo stems n_{by0} at the beginning of the bamboo growth year and the precipitation state $r_{y-1,D}$ on the last day of the previous bamboo growth year, which together determine the number of bamboo shoots n_{sy0} on the first day of bamboo growth year y . For each day d in a given year y from year 2 until the year the bamboo stems are all harvested, the within-year value function for bamboo shoots $\tilde{v}_d^s(\cdot)$ is the expected present discounted value (PDV) of the entire stream of daily bamboo shoot harvest profits $\pi_s(a_s, x, d)$ from day d until the last day D of that year when bamboo shoot harvests are chosen optimally.

For each day $d < D$ before the last day of the bamboo growth year, the within-year value function for bamboo shoots $\tilde{v}_d^s(\cdot)$ is given by:

$$\tilde{v}_d^s(x; n_{by0}, r_{y-1,D}) = \max_{a_s \leq n_s} \pi_s(a_s, x, d) + \beta E[\tilde{v}_{d+1}^s(x'; n_{by0}, r_{y-1,D}) | a_s, x; n_{by0}, r_{y-1,D}]. \quad (C.7)$$

The bamboo farmer will weakly choose to harvest bamboo shoots on day $d < D$ before the last day of the bamboo growth year if the profit from harvesting bamboo shoots that day exceed the discounted continuation value from waiting before harvesting:

$$\pi_s(a_s, x, d) \geq \beta E[\tilde{v}_{d+1}^s(x'; n_{by0}, r_{y-1,D}) | a_s, x; n_{by0}, r_{y-1,D}]. \quad (C.8)$$

On the last day $d = D$ of the bamboo growth year, the within-year value function for bamboo shoots $\tilde{v}_D^s(\cdot)$ is given by:

$$\tilde{v}_D^s(x; n_{by0}, r_{y-1,D}) = \max_{a_s \leq n_s} \pi_s(a_s, x, D). \quad (C.9)$$

In the absence of the possibility of shoot death, a bamboo farmer can afford to wait for a better shoot price and to allow the shoots to grow in biomass before harvesting without any risk that some shoots may die. As a consequence, all else equal the bamboo farmer who faces no possibility of shoot death will harvest winter shoots later (Figure C.4) than a bamboo farmer who faces the possibility of shoot death (Figure 3).

¹¹ In their analysis of the effects of monitoring and financial incentives on labor supply in rural India, Duflo, Hanna and Ryan (2012) use similar logic to reduce their infinite horizon model of a teacher's daily attendance decisions into a repeated series of independent finite horizon programs, one for each month.

When there is a possibility of shoot death and the winter shoot price is high, a bamboo farmer who has very few shoots may harvest winter shoots earlier (Figure C.5) compared to a farmer with more shoots (Figure 3), even though the shoots have less biomass, because there is a chance that if the bamboo farmer waits all the very few shoots may die before they are harvested. Nevertheless, even if the number of shoots n_s is very low and the winter shoot price is high, the bamboo farmer who faces no possibility of shoot death will harvest winter shoots later (Figure C.7) compared to a bamboo farmer who faces the possibility of shoot death (Figure C.5).

Likewise, when there is a possibility of shoot death, a bamboo farmer who is risk averse may harvest some winter shoots earlier (Figure C.8) compared a bamboo farmer who is not (Figure 3). With the possibility of shoot death, it may be worthwhile for a risk averse farmer to harvest earlier even though the shoots have less biomass 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.

When there is uncertainty in shoot prices, there is an option value to waiting for a higher price, compared to when there is no uncertainty in shoot price and no possibility of waiting for a higher shoot price. As a consequence, all else equal when shoot prices are low, a bamboo farmer who faces uncertainty over shoot prices (and therefore the possibility that shoot prices might be higher in the future) will wait to harvest bamboo shoots (Figure C.9) and will therefore harvest bamboo shoots later than a bamboo farmer who does not face price uncertainty and therefore knows that the shoot price will always be low (Figure C.10).

Since the within-year bamboo shoot harvesting problem and the within-year value function for bamboo shoots $\tilde{v}_d^s(\cdot)$ from year 2 onwards only depend on the precipitation state $r_{y-1,D}$ at the end of the previous bamboo growth year (and in particular on whether the cumulative daily precipitation over July and August of the previous bamboo growth year exceeds a high precipitation threshold), and since for each year $y \geq 2$ the previous year's precipitation state $r_{y-1,D}$ is known and constant throughout year y , whether there is uncertainty in precipitation does not matter for the within-year bamboo shoot harvesting dynamic optimization problem from year 2 onwards.

C.4. Optimal bamboo stem harvest policy from year 2 onwards

We now solve for the optimal bamboo stem harvest policy from the second bamboo growth year onwards, after the bamboo shoots remaining at the end of the first bamboo growth year have become bamboo stems, under uncertainty and interdependence between bamboo stems and bamboo shoots, for the base case specification of risk neutrality.

Let $v_{y,d}^b(x; n_{b20}, r_{y-1,D})$ denote the value function for bamboo stems for each day d of each year $y \geq 2$ from year 2 onwards, which is the expected PDV of the entire stream of bamboo stem harvest profits $\pi_b(x, a, y)$ from day d of year $y \geq 2$ onwards when harvests are chosen optimally, given the number of bamboo stems n_{b20} at the beginning of the second bamboo growth year and the precipitation state $r_{y-1,D}$ on the last day of the previous bamboo growth year, considering interdependence with bamboo shoots and the value of bamboo shoots.

For each bamboo growth year y from year 2 until the year the bamboo stems are all harvested, the within-year bamboo shoot harvesting problem and the within-year value function for bamboo shoots $\tilde{v}_d^s(x; n_{by0}, r_{y-1,D})$ only depend on the number of bamboo stems n_{by0} at the beginning of bamboo growth year, and not on any bamboo stem harvesting decision that takes place during the bamboo growth year. Thus, for the bamboo stem harvesting problem and bamboo stem value function from year 2 until the year the bamboo stems are all harvested, without loss of generality we can assume that for each year y from year 2 onwards, the within-year bamboo shoots value $\tilde{v}_0^s(\cdot)$ for that year, which is the expected PDV of the bamboo shoot harvests for that year when bamboo shoot harvests are chosen optimally for that year, is received as a lump sum on the first day ($d = 0$) of year y . The bamboo stem value function $v_{y,d}^b(\cdot)$ for year 2 onwards is therefore given by:

$$v_{y,d}^b(x; n_{b20}, r_{y-1,D}) = \max_{a_b \leq n_b} I\{d = 0\} \cdot \tilde{v}_0^s(x; n_{by0}, r_{y-1,D}) + \pi_b(a_b, x, y) + \beta E[v_{y',d'}^b(x'; n_{b20}, r_{y'-1,D}) | a_b, x; n_{b20}, r_{y-1,D}]. \quad (C.10)$$

Owing to the interdependence between bamboo shoots and bamboo stems, a bamboo farmer may find it optimal to wait before harvesting bamboo stems (Figure 2), since each additional year with bamboo stem yields an additional year of bamboo shoot harvests. The desire to wait for additional years of bamboo shoot harvest may be attenuated, however, if the bamboo stem price is relatively high; and a bamboo farmer facing a relatively high bamboo stem price therefore may not wait as long to harvest bamboo stems (Figure C.1).

Uncertainty in shoot prices and uncertainty in shoot death both enter in the bamboo stem harvest problem through their effect on the within-year value for bamboo shoots $\tilde{v}_0^s(\cdot)$ for that year.

When there is uncertainty in precipitation and therefore a possibility of high precipitation, it may be optimal to harvest some bamboo stems earlier when the number of bamboo stems is very high (Figure 2), since with the possibility of high precipitation and a high remaining number of bamboo stems, the number of bamboo shoots at the beginning of subsequent bamboo growth years can still be high. When there is no possibility of high precipitation, however, it is no longer optimal to harvest any bamboo stems earlier since any bamboo stem harvest would decrease the bamboo shoot harvests in subsequent years without any possibility for high precipitation to make up for it; as a consequence, it is optimal to wait to harvest all the bamboo stems at the same time (Figure C.3).

When there is no interdependence with bamboo shoots, the value function for bamboo stems from year 2 onwards would instead be:

$$v_{y,d}^b(x; n_{b20}, r_{y-1,D}) = \max_{a_b \leq n_b} \pi_b(a_b, x, y) + \beta E[v_{y',d'}^b(x'; n_{b20}, r_{y'-1,D}) | a_b, x; n_{b20}, r_{y-1,D}]. \quad (C.11)$$

Since the bamboo stem profit is linear in harvest, without interdependence with shoots, the bamboo farmer will harvest all stems at same time, so the bamboo stem problem without interdependence with shoots reduces to:

$$v_{y,d}^b(x; n_{b20}, r_{y-1,D}) = \max\{\pi_b(a_b, x, y), \beta E[v_{y',d'}^b(x'; n_{b20}, r_{y'-1,D}) | a_b, x; n_{b20}, r_{y-1,D}]\}. \quad (C.12)$$

Furthermore, when there is no interdependence with bamboo shoots, uncertainty (in precipitation, shoot price, and shoot death) does not matter for the bamboo stem harvesting problem, and the bamboo stem harvesting problem reduces to the benchmark bamboo stem harvest problem (C.1) of no uncertainty and no interdependence between bamboo stems and bamboo shoots, whose solution is given by the first-order condition in equation (C.2). When there is no interdependence with bamboo shoots, and therefore no value to waiting longer before harvesting bamboo stems in order to allow for more years of bamboo shoot harvests, the bamboo farmer will harvest bamboo stems in an earlier year (Figure C.2), compared to the case when there is interdependence with shoots (Figure 2).

C.5. Optimal bamboo shoot harvest policy in year 1

Last, we solve for the optimal bamboo shoot harvest policy for the first bamboo growth year under uncertainty and interdependence between bamboo stems and bamboo shoots, for the base case specification of risk neutrality.

Let $v_{1,d}^s(x)$ denote the value function for bamboo shoots in year 1, which is the expected PDV of the entire stream of bamboo shoot harvest profits $\pi_s(\cdot)$ and bamboo stem harvest profits $\pi_b(\cdot)$ from day d in year 1 onwards when harvests are chosen optimally, considering interdependence with bamboo stems and the value of bamboo stems and bamboo shoots.¹²

The value function $v_{1,d}^s(\cdot)$ for bamboo shoots in year 1 is given by:

$$v_{1,d}^s(x) = \max_{a_s \leq n_s} \pi_s(a_s, x, d) + \beta E[v_{1,d+1}^s(x') | a_s, x] \quad (\text{C.13})$$

for each day $d < D$ before the last day of spring shooting in bamboo growth year 1, and by:

$$v_{1,D}^s(x) = \max_{a_s \leq n_s} \pi_s(a_s, x, D) + \beta E[v_{2,0}^b(x'; n_{b20}, r_{1,D}) | a_s, x] \quad (\text{C.14})$$

on the last day $d = D$ of spring shooting in bamboo growth year 1, where $v_{2,0}^b(\cdot)$ is the value function for bamboo stems from the first day ($d = 0$) of bamboo growth year 2 ($y = 2$) onwards, and gives the expected PDV of the entire stream of daily bamboo stem harvest profits $\pi_b(\cdot)$ and daily bamboo shoot profits $\pi_s(\cdot)$ from year 2 onwards when harvests are chosen optimally; and where the number of bamboo stems n_{b20} at the beginning of bamboo growth year 2 is the number of bamboo shoots n_{s1D} remaining at end of spring shooting in bamboo growth year 1:

$$n_{b20} = n_{s1D} - a_{s1D}. \quad (\text{C.15})$$

Uncertainty in precipitation affects the bamboo shoot harvesting problem in year 1 through the effect of the precipitation state $r_{1,D}$ at the end of year 1 (and in particular on whether the cumulative daily precipitation over July and August of the previous bamboo growth year exceeds a high precipitation threshold) on the value function for bamboo stems $v_{2,0}^b(\cdot)$ from the first day ($d = 0$) of bamboo growth year 2 ($y = 2$) onwards. The precipitation state $r_{1,D}$ at the end of year

¹² Let $v_{1,d}(x)$ denote the value function for bamboo plants in year 1, which is the expected PDV of the entire stream of bamboo shoots harvest profits $\pi_s(\cdot)$ and bamboo stem harvest profits $\pi_b(\cdot)$ from day d in year 1 onwards. Because the value function for bamboo shoots in year 1, $v_{1,d}^s(x)$, considers the value of harvest profits from both bamboo stems and bamboo shoots, the value function for bamboo plants in year 1 is equal to the value function for bamboo shoots in year 1: $v_{1,d}(x) = v_{1,d}^s(x)$.

1, along with the number of bamboo stems n_{b20} at the beginning of bamboo growth year 2, together determine the number of bamboo shoots n_{sy0} at the beginning of bamboo growth year 2.

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 stems at the end of the first year, which would then result in there being both bamboo shoots and bamboo stems at the beginning of the second year, and annual bamboo shoot harvests each future year until the year bamboo stems are harvested (Figure 3).

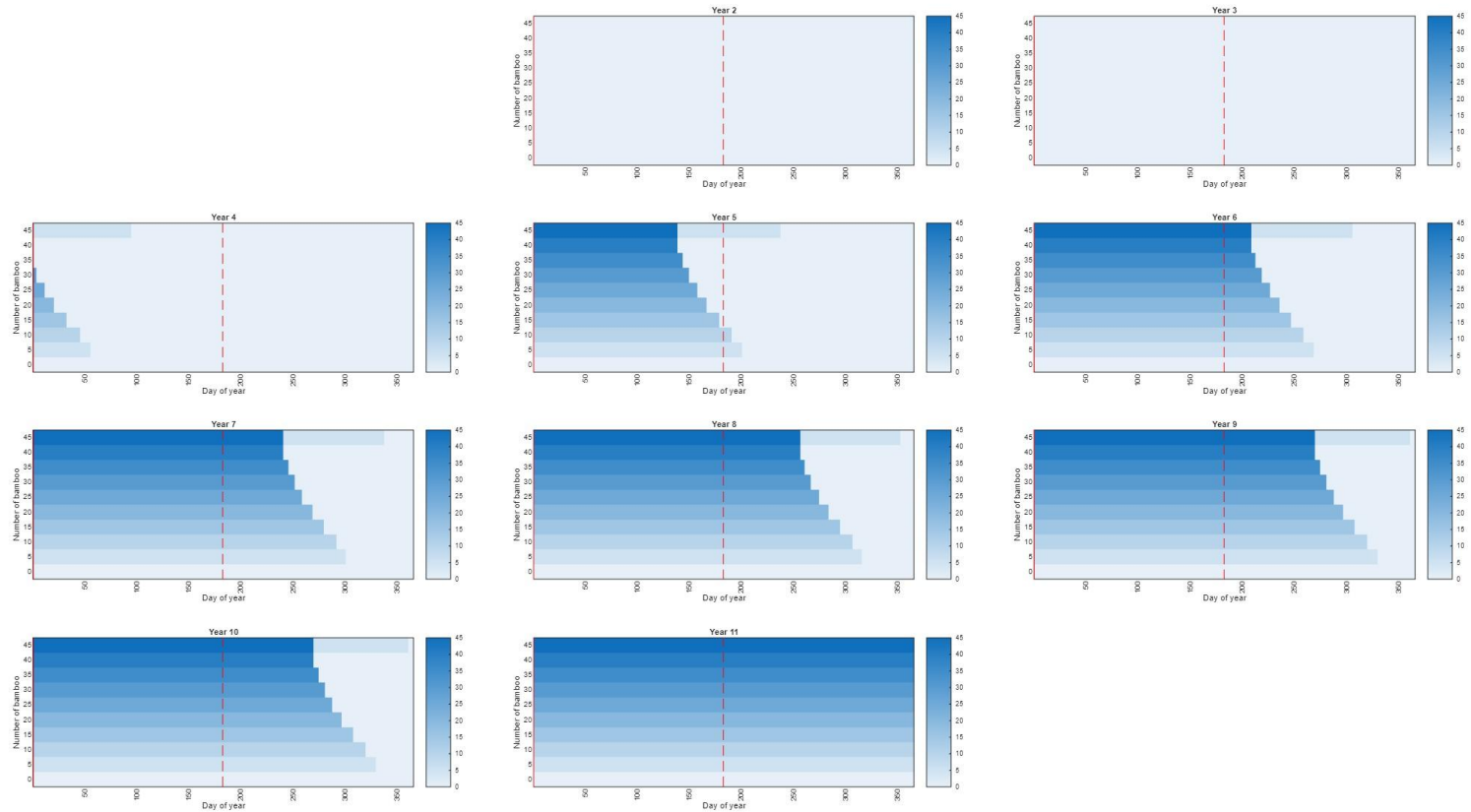
When the number of shoots n_s is very low and there is a possibility of shoot death, however, it may be worthwhile to harvest some winter shoots in the first bamboo growth year if the winter shoot price is high, even though any bamboo shoot harvest in the first bamboo growth would mean foregoing future bamboo shoot harvests profits and bamboo stem harvests profits in future years, because there is a chance that if the bamboo farmer waits all the very few shoots may die before they are harvested (Figure C.5). If, in addition, there is no possibility of high precipitation that would lead to more shoots and therefore more stems at the beginning of the second bamboo growth year, then it may be worthwhile to harvest some winter shoots in the first bamboo growth year if the winter shoot price is medium or high when the number of shoots n_s is very low and there is a possibility of shoot death (Figure C.6). But if there is no possibility of shoot death, it is not optimal to harvest bamboo shoots in the first bamboo growth year even if the number of shoots n_s is very low and the winter shoot price is high (Figure C.7).

Without interdependence between shoots and stems, the value function for spring shoots on the last day $d = D$ of spring shooting in bamboo growth year 1 would instead be:

$$v_{1,D}^s(x) = \max_{a_s \leq n_s} \pi_s(a_s, x, D). \quad (C.16)$$

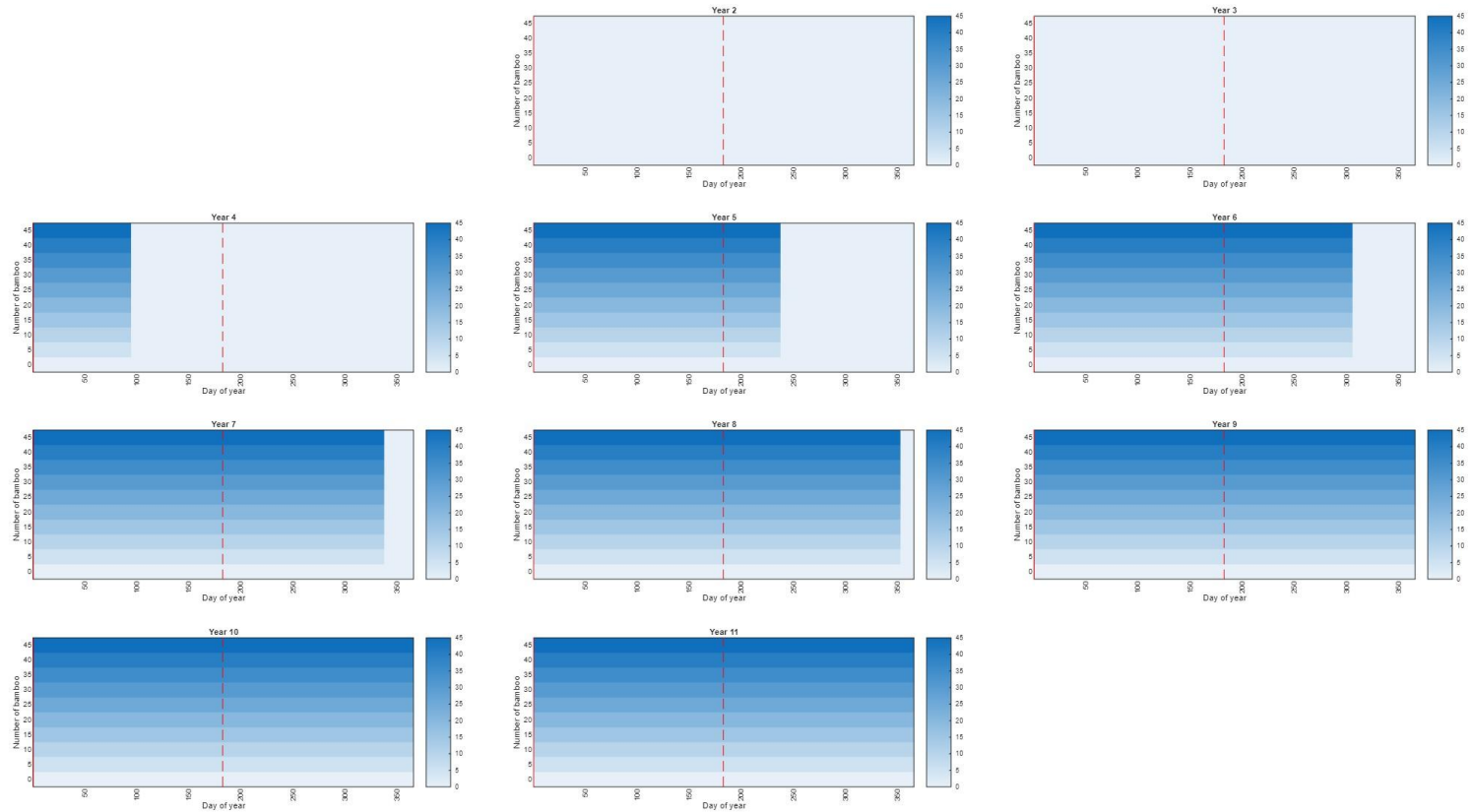
When there is no interdependence between shoots and stems, and therefore no possibility for shoots to grow into stems at the end of the bamboo growth year, there is no continuation value after the last day of the first bamboo growth year, and there is therefore no longer any value to having any bamboo shoots remaining at the end of the first bamboo growth year. Thus, in the absence of any interdependence between shoots and stems, the bamboo shoot harvesting problem in the first bamboo growth year reduces to the within-year bamboo shoot harvesting problem given the number of bamboo shoots $n_{s,1,0}$ on the first day ($d = 0$) of the first bamboo growth year ($y = 1$).

Figure C.1. Bamboo Stem Harvest Policy Function: Relatively High Bamboo Stem Price



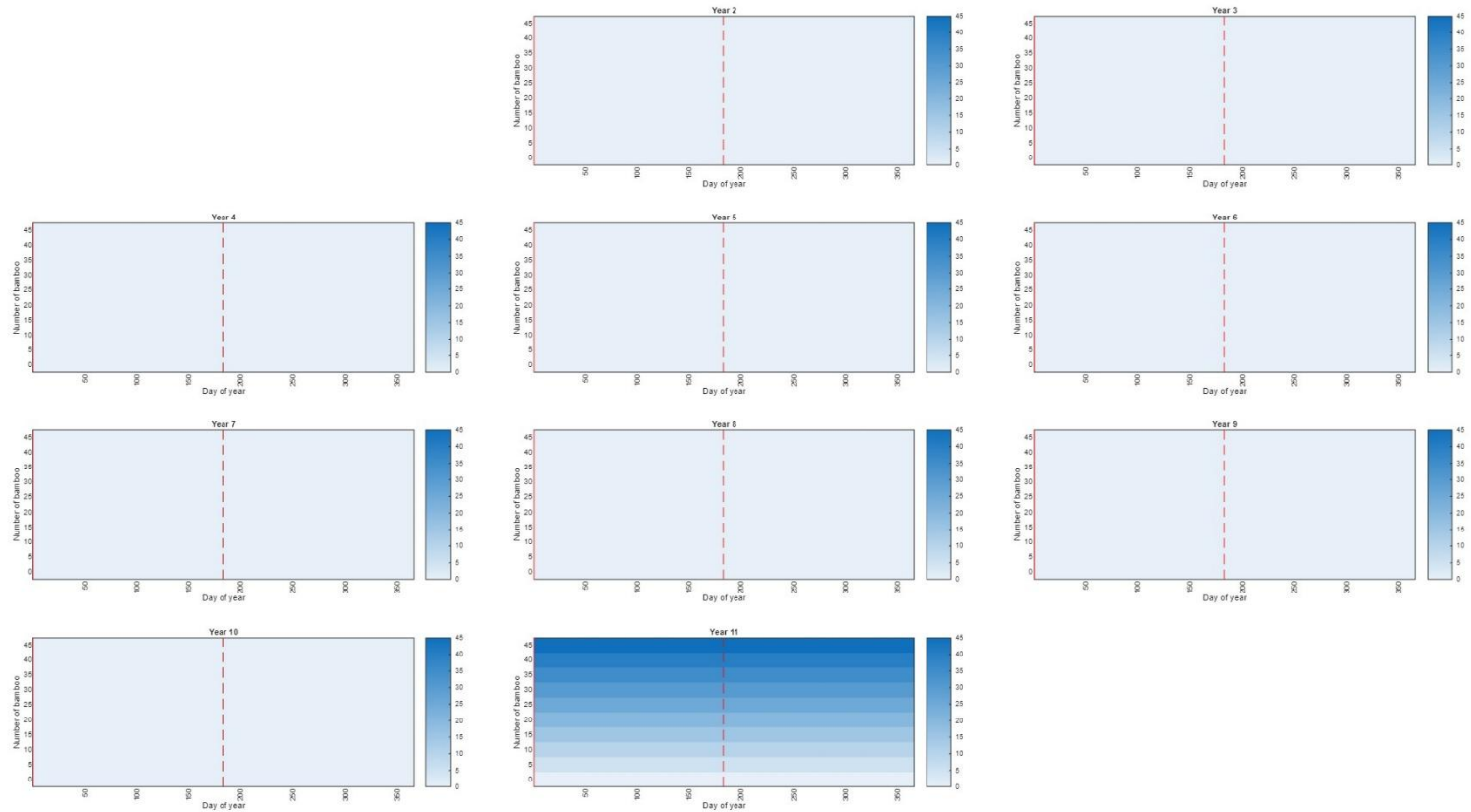
Notes: Figure presents the bamboo stem harvest policy function for each day for each year as a function of the number of bamboo stems, when the bamboo stem price is high and the bamboo shoot price is low, and when all other parameters are set at their base case values. For each bamboo growth year, dashed 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.2. Bamboo Stem Harvest Policy Function: Zero Bamboo Shoot Price



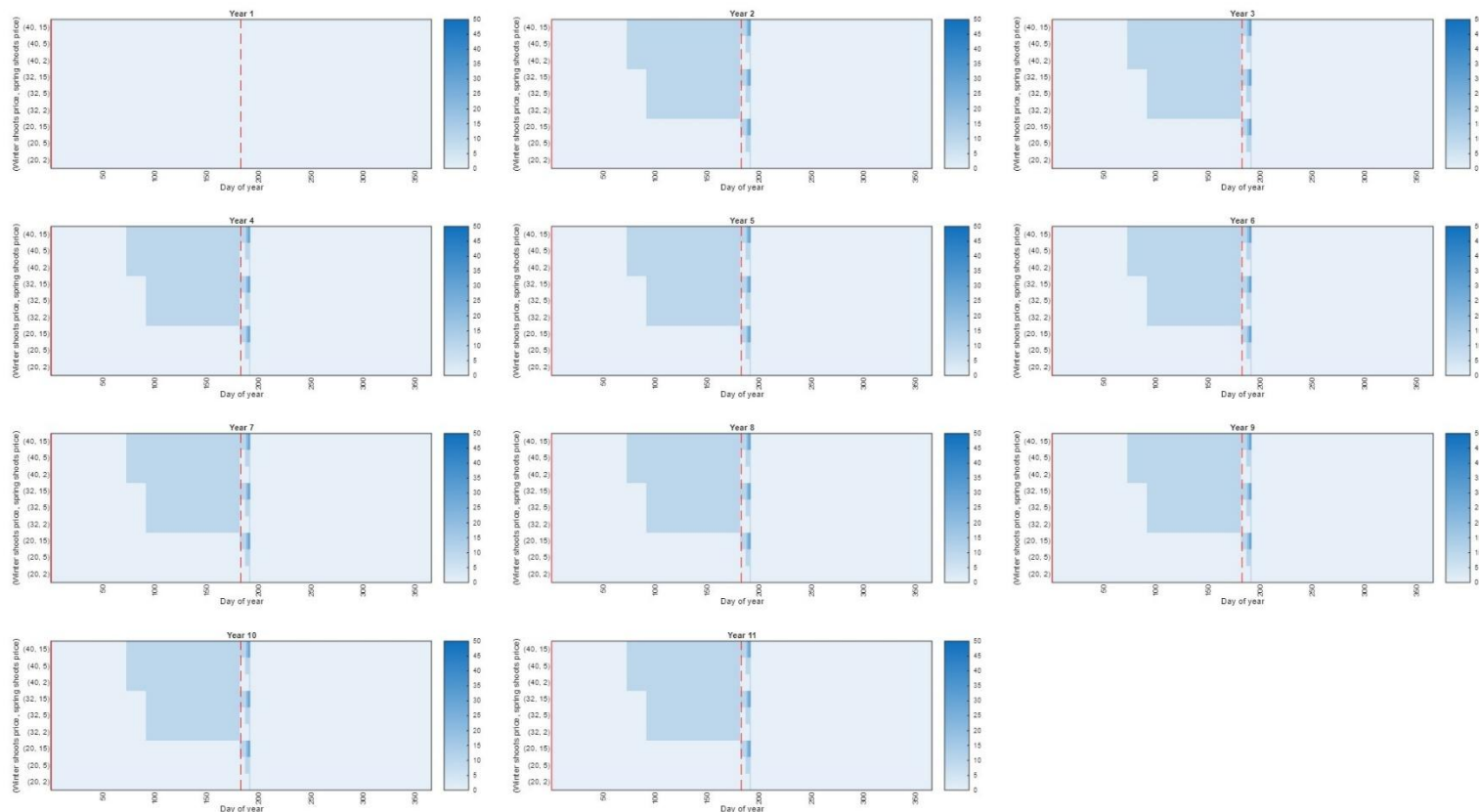
Notes: Figure presents the bamboo stem harvest policy function for each day for each year as a function of the number of bamboo stems, when the bamboo shoot price is zero, and when all other parameters are set at their base case values. For each bamboo growth year, dashed vertical lines in red that go from the top to the bottom of the graph denote March 1 (first day of spring shooting) of each year.

Figure C.3. Bamboo Stem Harvest Policy Function: No Possibility of High Precipitation



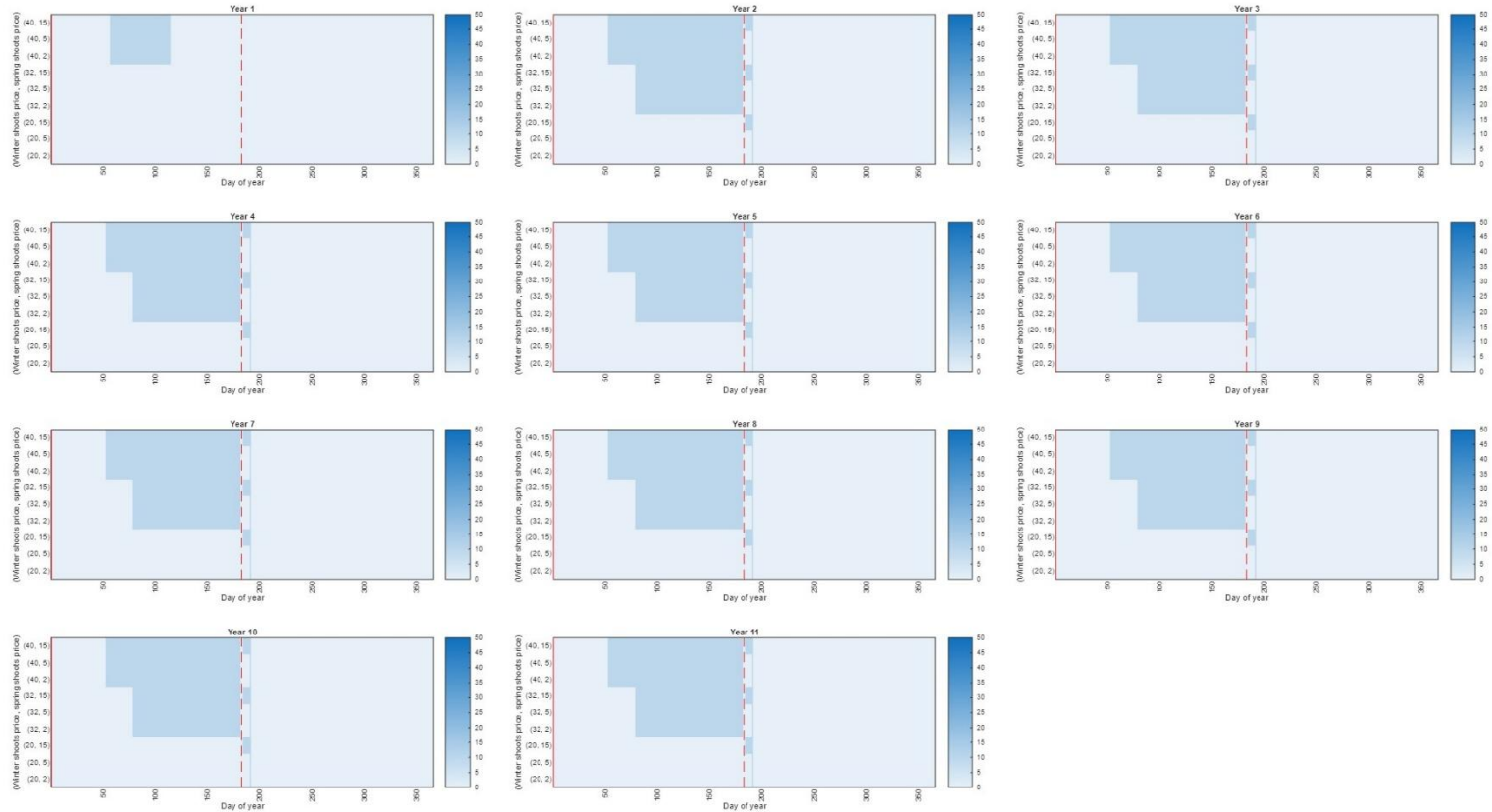
Notes: Figure presents the bamboo stem harvest policy function for each day for each year as a function of the number of bamboo stems, when there is no possibility of high precipitation, and when all other parameters are set at their base case values. For each bamboo growth year, dashed vertical lines 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.4. Bamboo Shoot Harvest Policy Function: No Possibility of Shoot Death



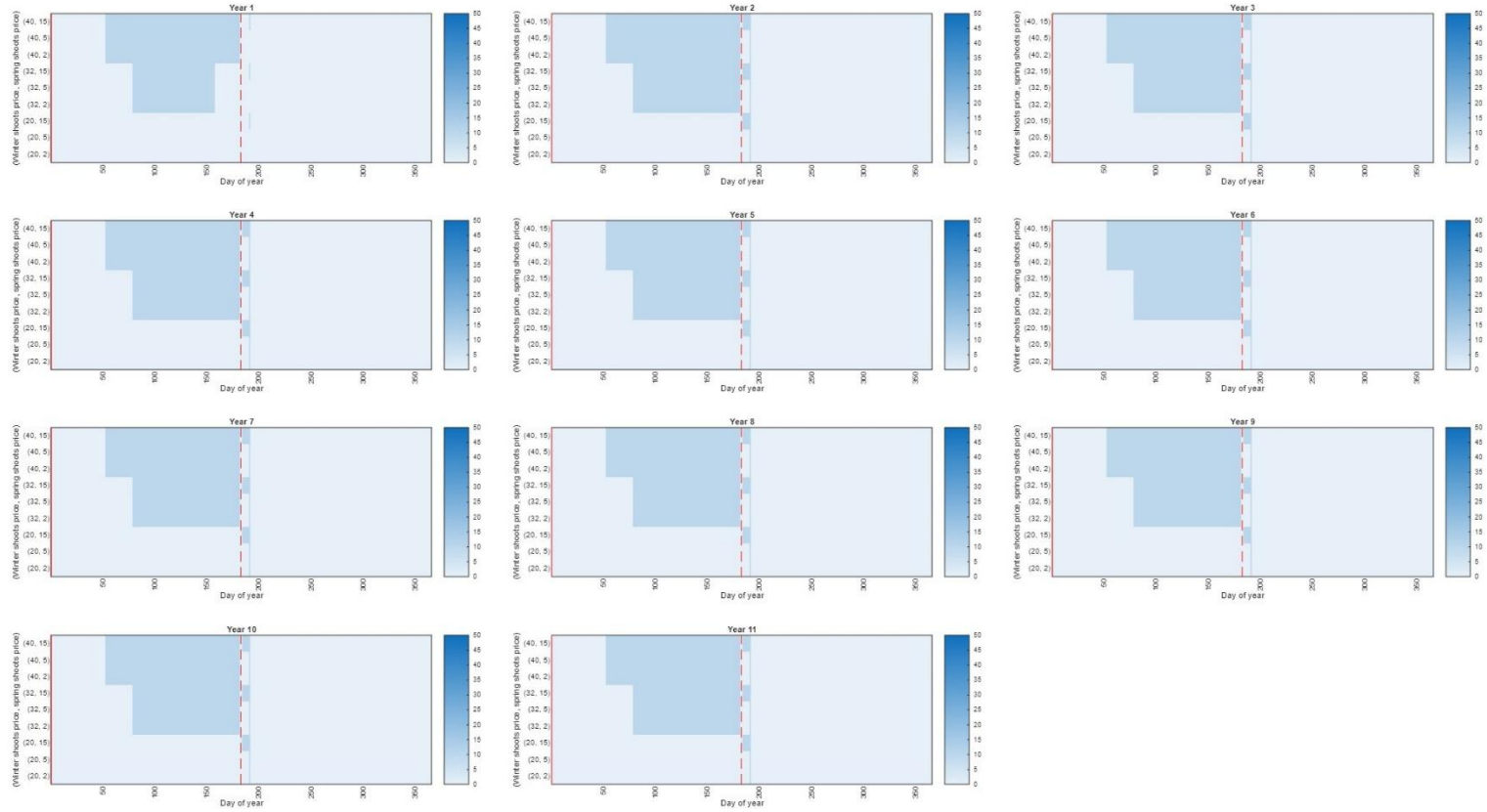
Notes: Figure presents the bamboo shoot harvest policy function for each day for each year as a function of the daily shoot price when the number of shoots is a medium quantity ($n_s = 30$) and cumulative daily precipitation is low ($r = 0$), when there is no possibility of shoot death, and when all 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. Bamboo Shoot Harvest Policy Function: Number of Shoots is Very Low



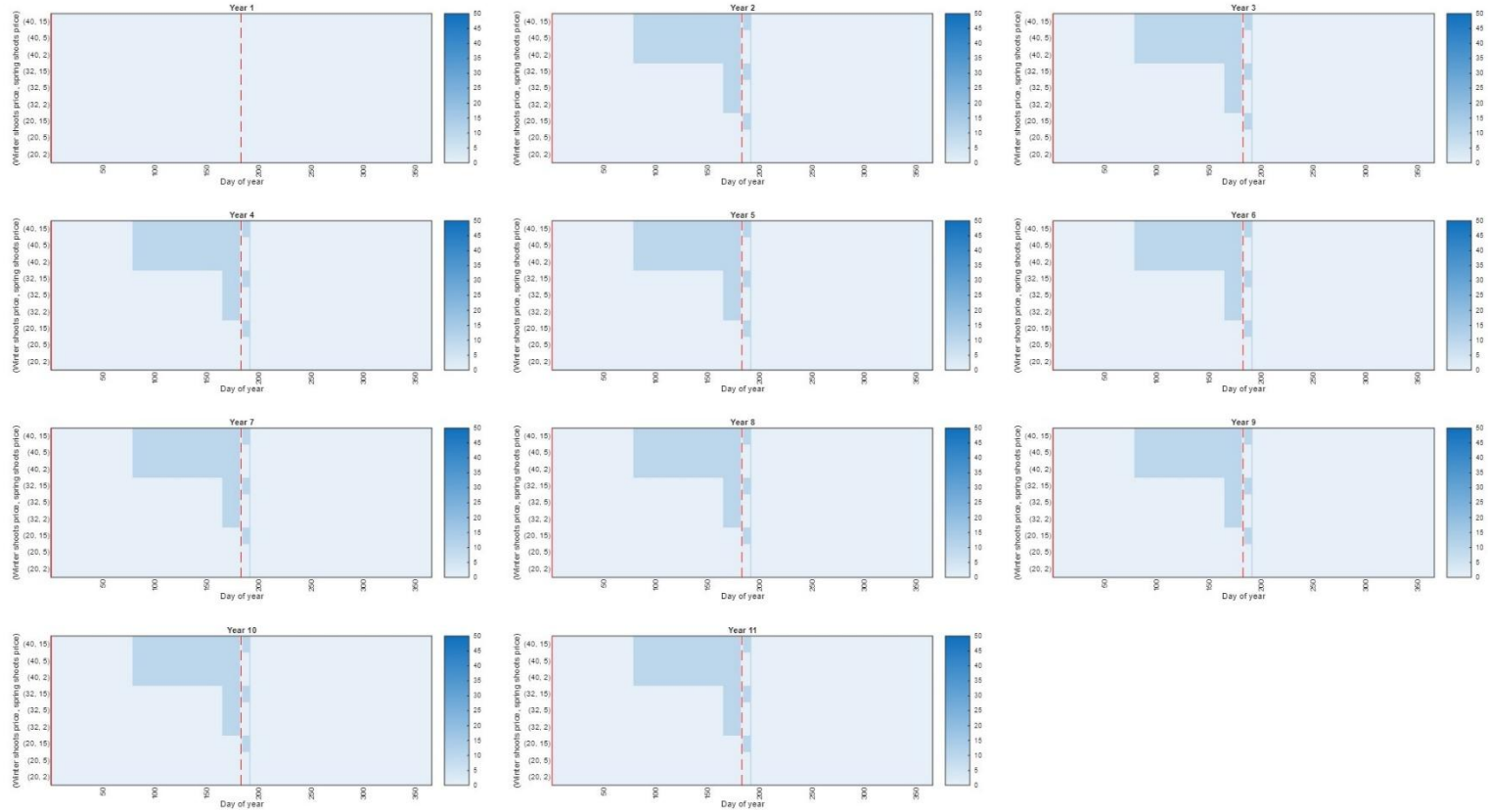
Notes: Figure presents the bamboo shoot harvest policy function for each day for each year as a function of the daily shoot price when the number of shoots is very low ($n_s = 10$) and cumulative daily precipitation is low ($r = 0$), and when parameters are set at their base case values. For each bamboo 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.6. Bamboo Shoot Harvest Policy Function: Number of Shoots is Very Low and No Possibility of High Precipitation



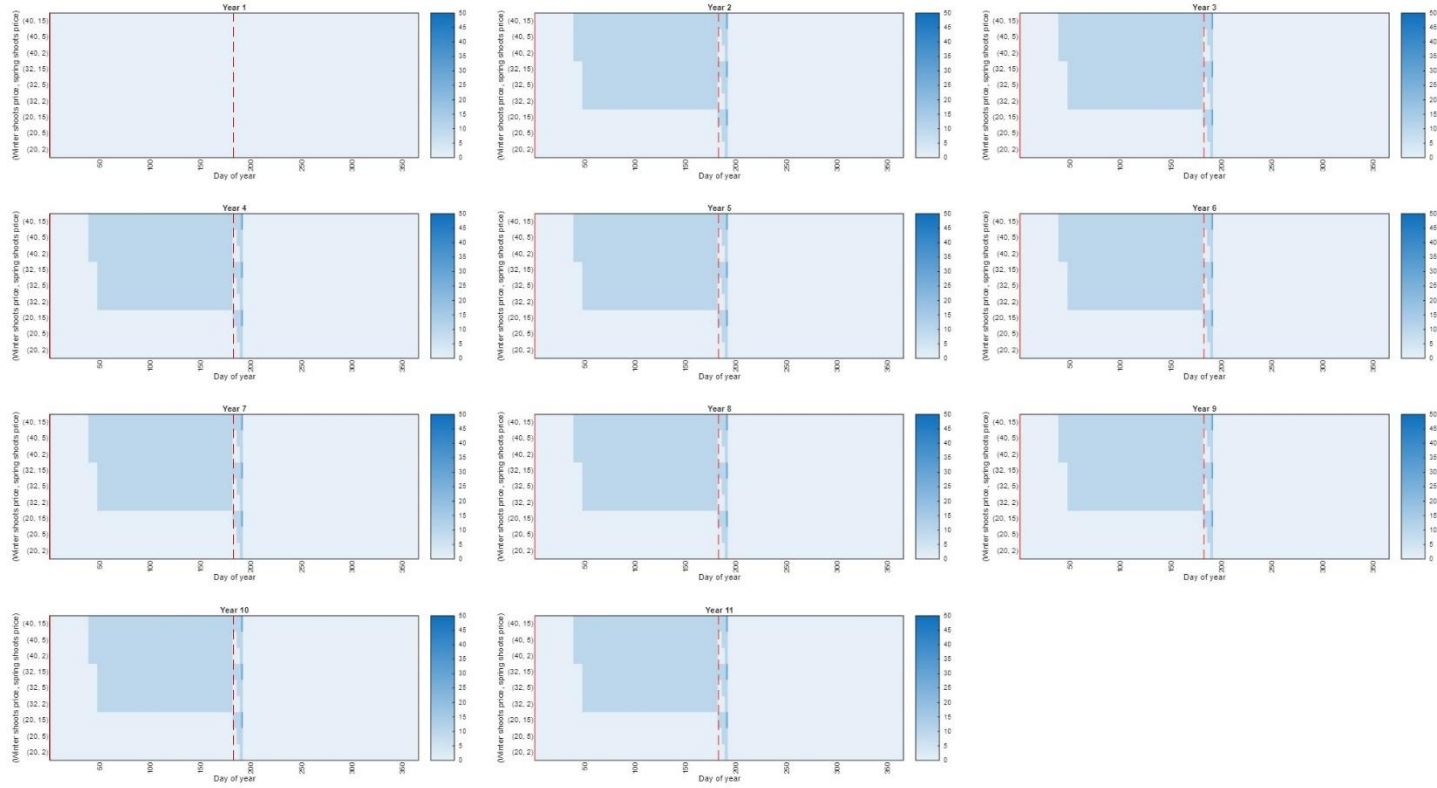
Notes: Figure presents the bamboo shoot harvest policy function for each day for each year as a function of the daily shoot price when the number of shoots is very low ($n_s = 10$) and cumulative daily precipitation is low ($r = 0$), when there is no possibility of high precipitation, and when all other 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.7. Bamboo Shoot Harvest Policy Function: Number of Shoots is Very Low and No Possibility of Shoot Death



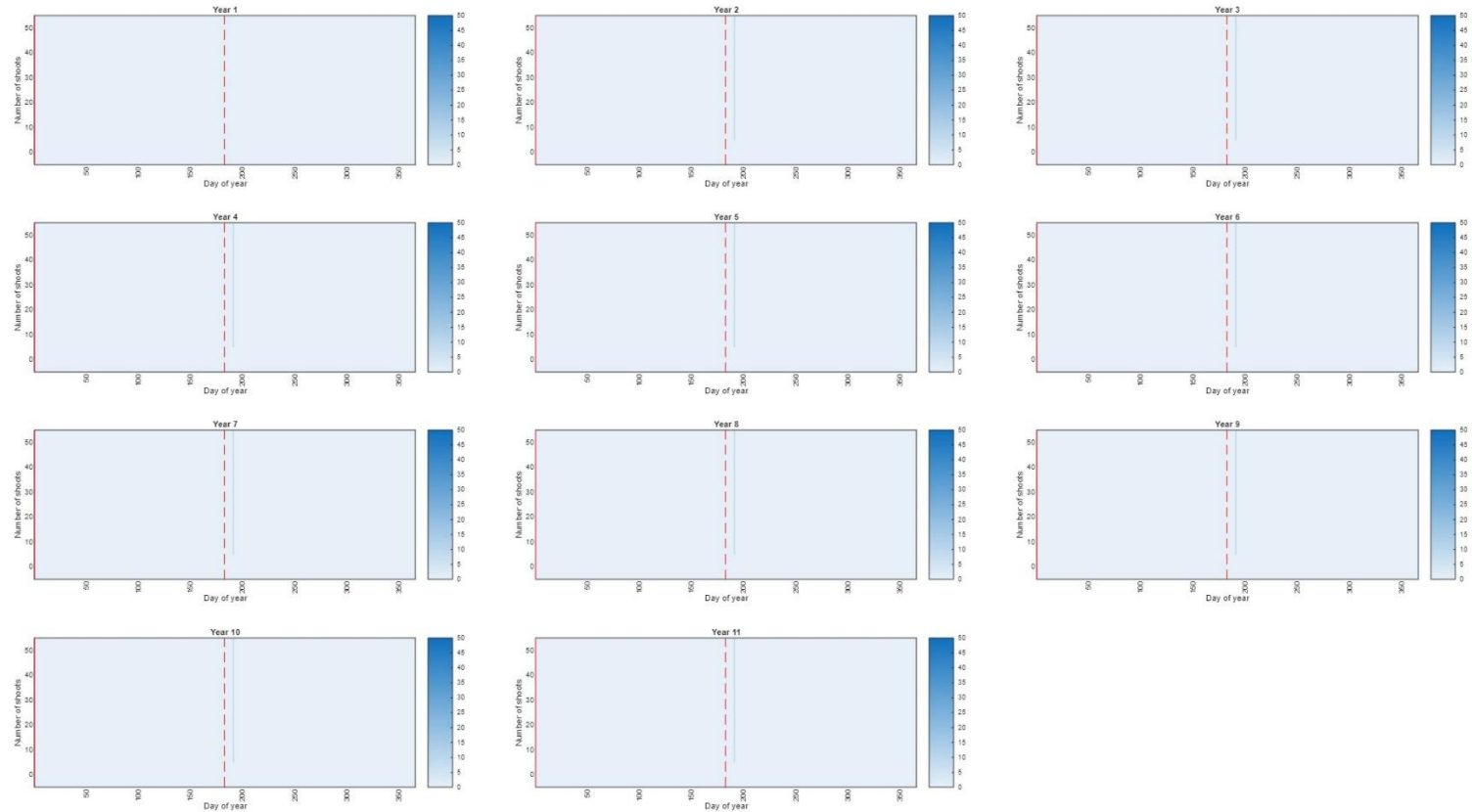
Notes: Figure presents the bamboo shoot harvest policy function for each day for each year as a function of the daily shoot price when the number of shoots is very low ($n_s = 10$), there is no possibility of shoot death, and cumulative daily precipitation is low ($r = 0$), and when parameters are set 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.8. Bamboo Shoot Harvest Policy Function: Risk Averse



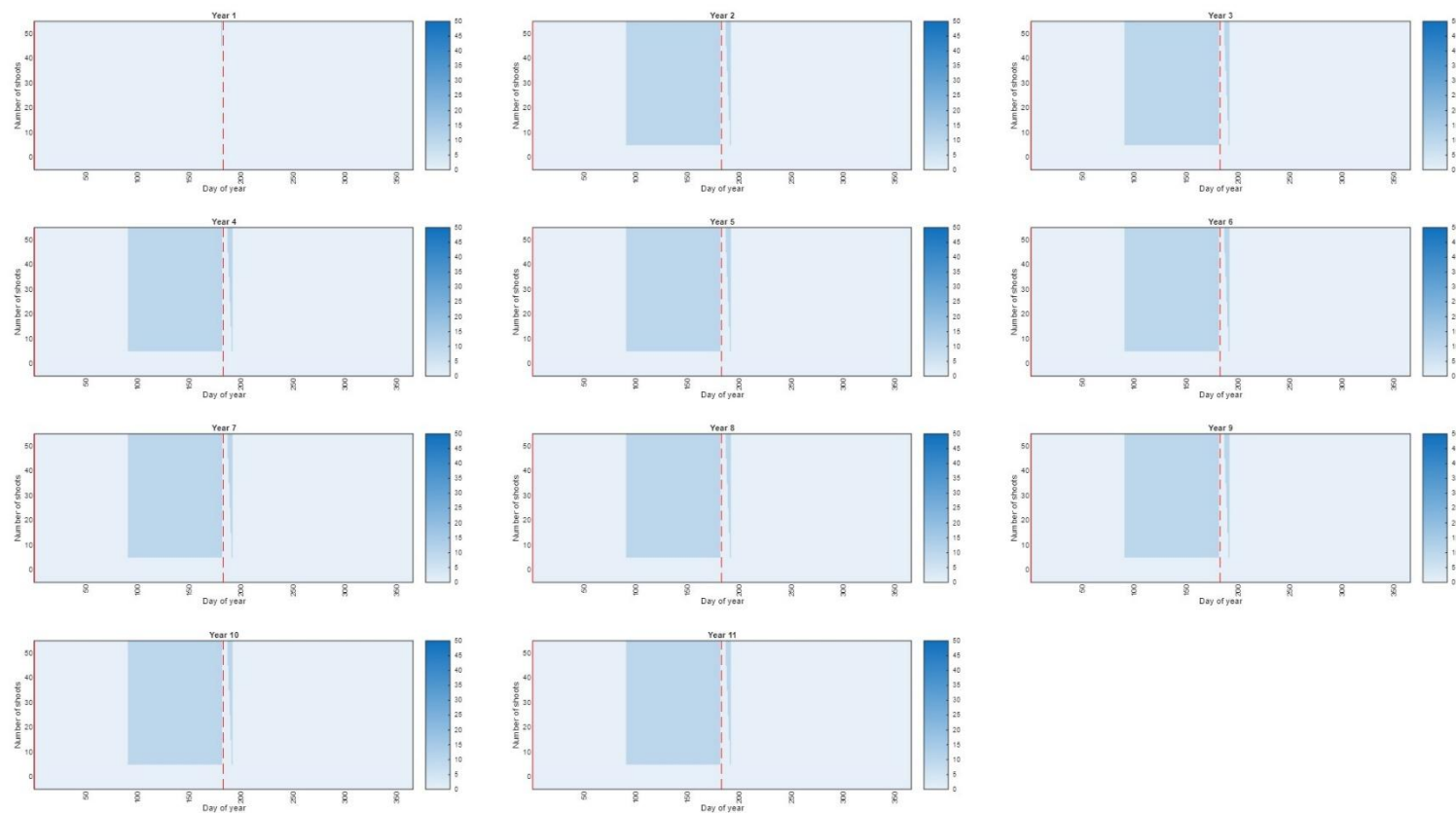
Notes: Figure presents the bamboo shoot harvest policy function for each day for each year as a function of the daily shoot price when the number of shoots is a medium quantity ($n_s = 30$) and cumulative daily precipitation is low ($r = 0$), when farmers are risk averse (with a coefficient of constant 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.9. Bamboo Shoot Harvest Policy Function: Shoot Price is Low



Notes: Figure presents the bamboo shoot harvest policy function for each day for each year as a function of the number of bamboo shoots when cumulative daily precipitation is low ($r = 0$), winter shoot price is low, and spring shoot price is low; 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.10. Bamboo Shoot Harvest Policy Function: Shoot Price is Low and No Shoot Price Uncertainty



Notes: Figure presents the bamboo shoot harvest policy function for each day for each year as a function of the number of bamboo shoots when cumulative daily precipitation is low ($r = 0$); when there is no shoot price uncertainty, winter shoot price is (always) low, and spring shoot price is (always) low; 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.

Appendix D. Results from Dynamic Structural Model

Table 2a presents the results of the specification of our dynamic structural model in which the structural parameter θ we estimate is the growth rate α_{sw} for winter shoots. Our structural parameter estimate for the winter shoot growth rate α_{sw} of 0.012 is lower than the winter shoot growth rate α_{sw} of 0.016 we calibrated based on biological research and information on winter shoots. Thus, the harvesting behavior of the bamboo farmers in our data can be rationalized by low 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 lower than may actually be the case based on data and information on winter shoots from plant scientists. Figure D.1 plots the bamboo farmers' perceived Chapman-Richards growth function for winter shooting and spring shooting based on our structural parameter estimate for the winter shoot growth rate. We rerun our numerical nested stochastic dynamic bioeconomic model using the structural parameter estimate for winter shoot growth rate α_{sw} of 0.012. Actual winter shoot harvests are still higher than the optimal strategy under the structural parameter estimate for winter shoot growth rate α_{sw} of 0.012 (Figure D.2), and actual harvests still yield a lower NPV than the optimal strategy (Table D.1). Thus, while results suggest that farmers may lack full information about winter shoot growth, this lack of information may only partially explain the discrepancy between actual and optimal strategies.

Table 2b presents the results of the specification of the dynamic structural model in which the structural parameters θ we estimate are parameters in the shoot harvesting cost. The structural parameter estimates for the winter shoot harvest cost parameter c_{sw} and the spring shoot harvest cost parameter c_{ss} of $c_{sw} = 16.43$ and $c_{ss} = 1.69$ from our dynamic structural model are similar to the respective calibrated values of $c_{sw} = 15$ and $c_{ss} = 1.5$, albeit slightly higher. This suggests that the bamboo farmers in our data are acting as if they perceive or believe winter shoot harvest costs and spring shoot harvest costs to be somewhat higher than their respective actual monetary cost. Since we have less information on costs and since costs can vary by farmer, we therefore feel less confident that the harvest cost parameters we use for our model reflect the true harvest costs for all bamboo farmers; it is therefore very possible that the structural estimates for the shoot harvest costs may better reflect the shoot harvesting costs, monetary and otherwise, that farmers

face. The differences between our calibrated cost parameters and our structural estimates are small, however. Moreover, even when our numerical nested stochastic dynamic bioeconomic model is rerun using the structural parameter estimates for the shoot harvest cost, actual winter shoot harvests might still be higher than optimal (Figure D.3), and actual harvests still yield a lower NPV than the optimal strategy (Table D.2). Thus, while farmers' perceived shoot harvesting costs, monetary and otherwise, might be slightly higher than our calibrated values, these slightly higher costs may only partially explain the discrepancy between actual and optimal decisions.

Table 2c presents the results of the specification of the dynamic structural model in which the structural parameter θ we estimate is the daily shoot decline probability during winter shooting. Our structural parameter estimate for the daily winter shoot decline probability is statistically insignificant and zero. When we rerun our numerical nested stochastic dynamic bioeconomic model using a daily winter shoot decline probability of zero, the optimal strategy when there is no possibility of shoot death no longer involves any winter shoot harvest (Figure D.4), and the calibrated parameter better explains the actual winter shoot harvest (Figure 6). In addition, the difference between optimal expected NPV and actual NPV over the entire 11-year horizon is higher under the structural parameter point estimate (Table D.3) 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., 2026a). For these reasons, it is unlikely that the discrepancy between actual and optimal decisions is due to bamboo farmers misperceiving the daily winter shoot decline probability to be zero.

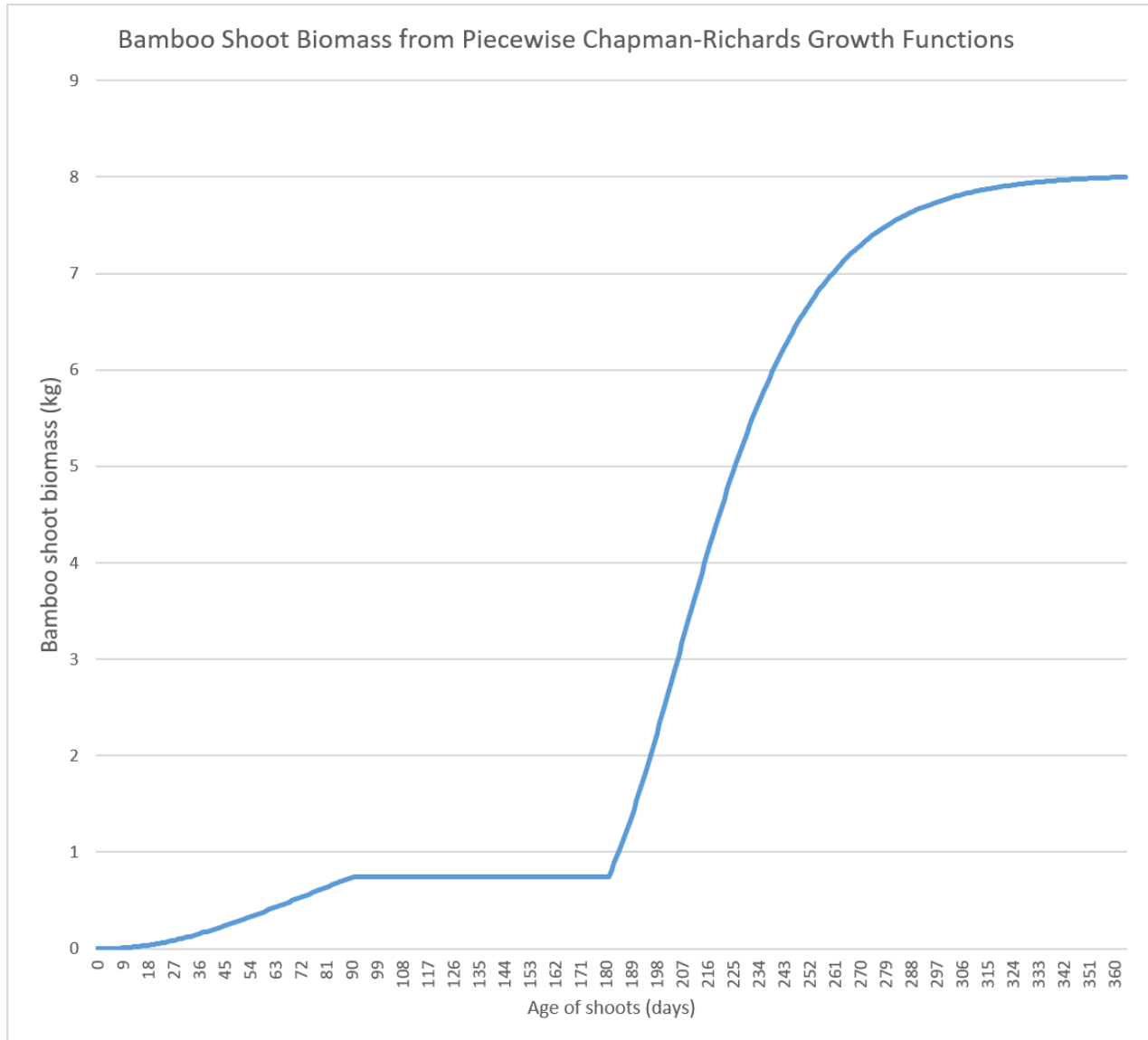
Table 2d presents the results of the specification of the dynamic structural model in which we allow for risk aversion and the structural parameter θ we estimate is the coefficient of constant relative risk aversion η . We find that the harvesting behavior of the bamboo farmers in our data can be rationalized by a coefficient of constant relative risk aversion of $\eta = 0.84$. We rerun our numerical nested stochastic dynamic bioeconomic model using a coefficient of constant relative risk aversion of $\eta = 0.84$. When farmers are risk averse (with $\eta = 0.84$), the optimal shoot harvest strategy involves relatively more winter shoot harvests, which may better match the actual winter shoot harvests, but also involves harvesting some winter shoots at the end of winter shooting (as seen in the second year of data before the second dashed red vertical line), which does not take place in the actual data (Figure D.5). The optimal bamboo stem harvest strategy under risk

aversion (with $\eta = 0.84$) also involves harvesting some bamboo stems in their third bamboo growth year (as seen in the first half of the graph for initial age class 2 during the first year of data before the solid red vertical line),¹³ which also does not take place in the actual data (Figure D.6). Table D.4 compares resulting optimal welfare with actual welfare, where welfare is defined as the present discounted value (PDV) of the entire stream of daily payoffs. Even if farmers are risk averse, their actual harvests still yield lower welfare as well as lower NPV on average than does the optimal strategy under risk aversion.

Table 2e 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.

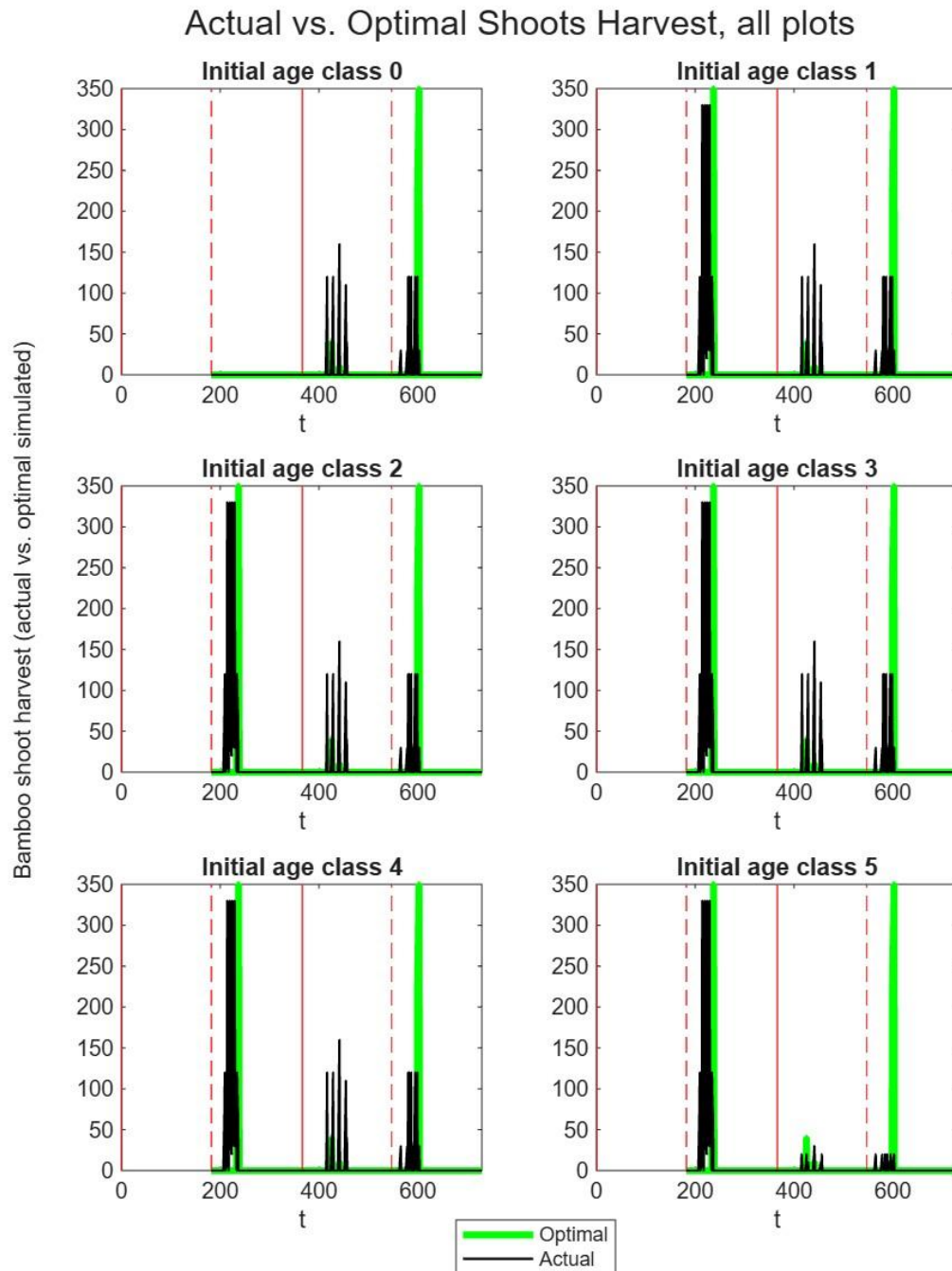
¹³ Bamboo stems in initial age class 2 are of age 2 during the first year of data (prior to the solid red vertical line in Figure D.6) and are therefore in their third bamboo growth year during the first half of the time series in our data set.

Figure D.1. 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 structural parameter estimate for winter shoot growth rate α_{sw} of 0.012 from our dynamic structural model in Table 2a. 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 D.2. Optimal vs. Actual Shoot Harvest: Perceived Winter Shoot Growth Rate



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 winter shoot growth rate α_{sw} of 0.012 from our dynamic structural model in Table 2a. Solid 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 D.1. Actual vs. Optimal NPV: Perceived Winter Shoot Growth Rate**(a)**

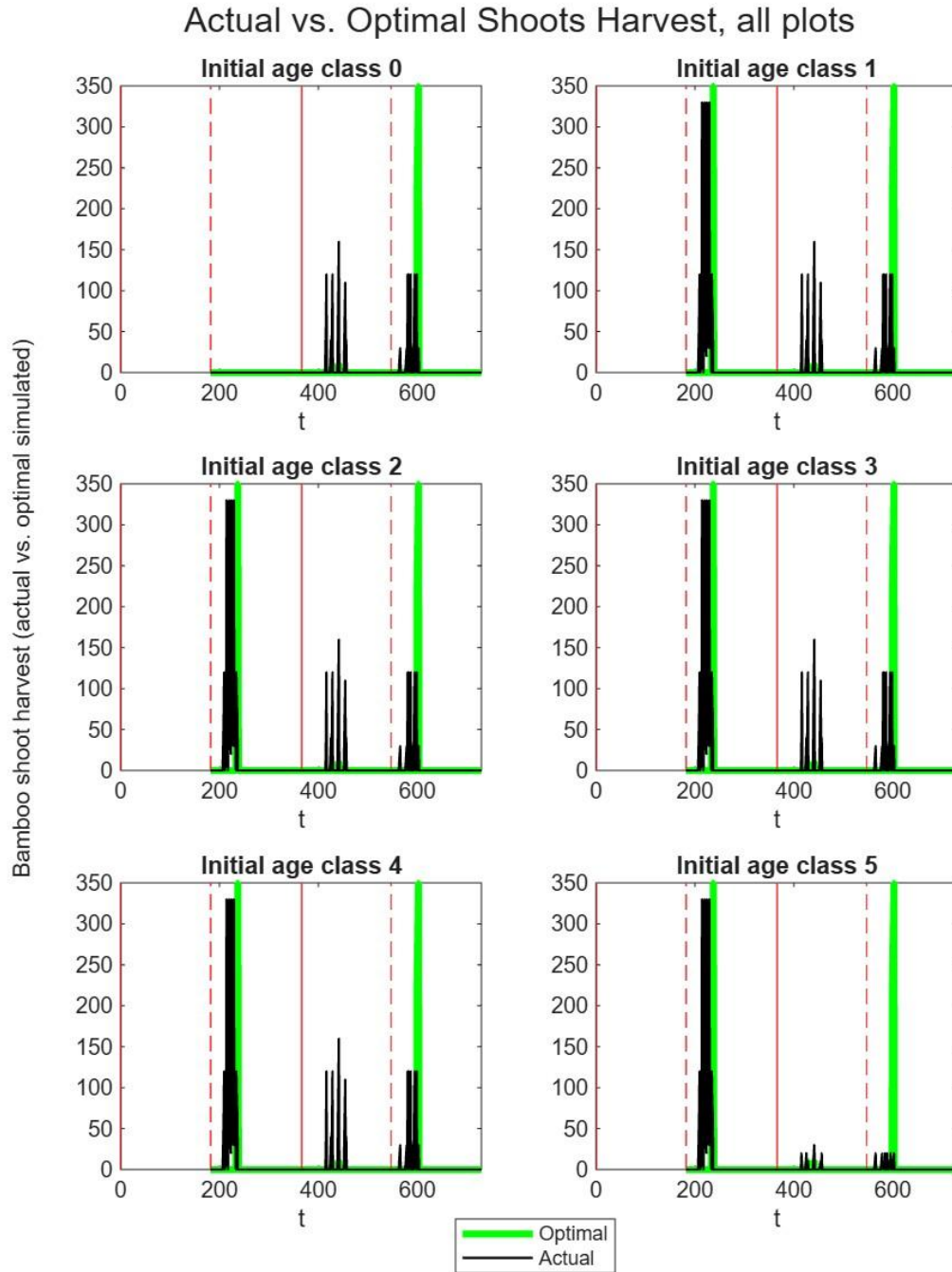
NPV during days with data	Mean (Yuan)
Optimal	3,013
Actual	827
Optimal minus Actual	2,185

(b)

Expected NPV over 11-year horizon	Mean (Yuan)
Optimal	6,943
Actual	5,479
Optimal minus Actual	1,464

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 shoot growth rate α_{sw} of 0.012 from our dynamic structural model in Table 2a. There are 35 bamboo plots in the data set, each with 6 initial age classes; table reports means over all bamboo plot – initial age classes. 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 shoot 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 D.3. Optimal vs. Actual Shoot Harvest: Perceived Shoot Harvest Costs



Notes: Time series plots of the perceived optimal vs. actual number of bamboo shoots harvested on each bamboo plot, using the structural parameter estimates for the shoot harvest cost of $c_{sw} = 16.43$ and $c_{ss} = 1.69$ from our dynamic structural model in Table 2b. Solid 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 D.2. Actual vs. Optimal NPV: Perceived Shoot Harvest Costs**(a)**

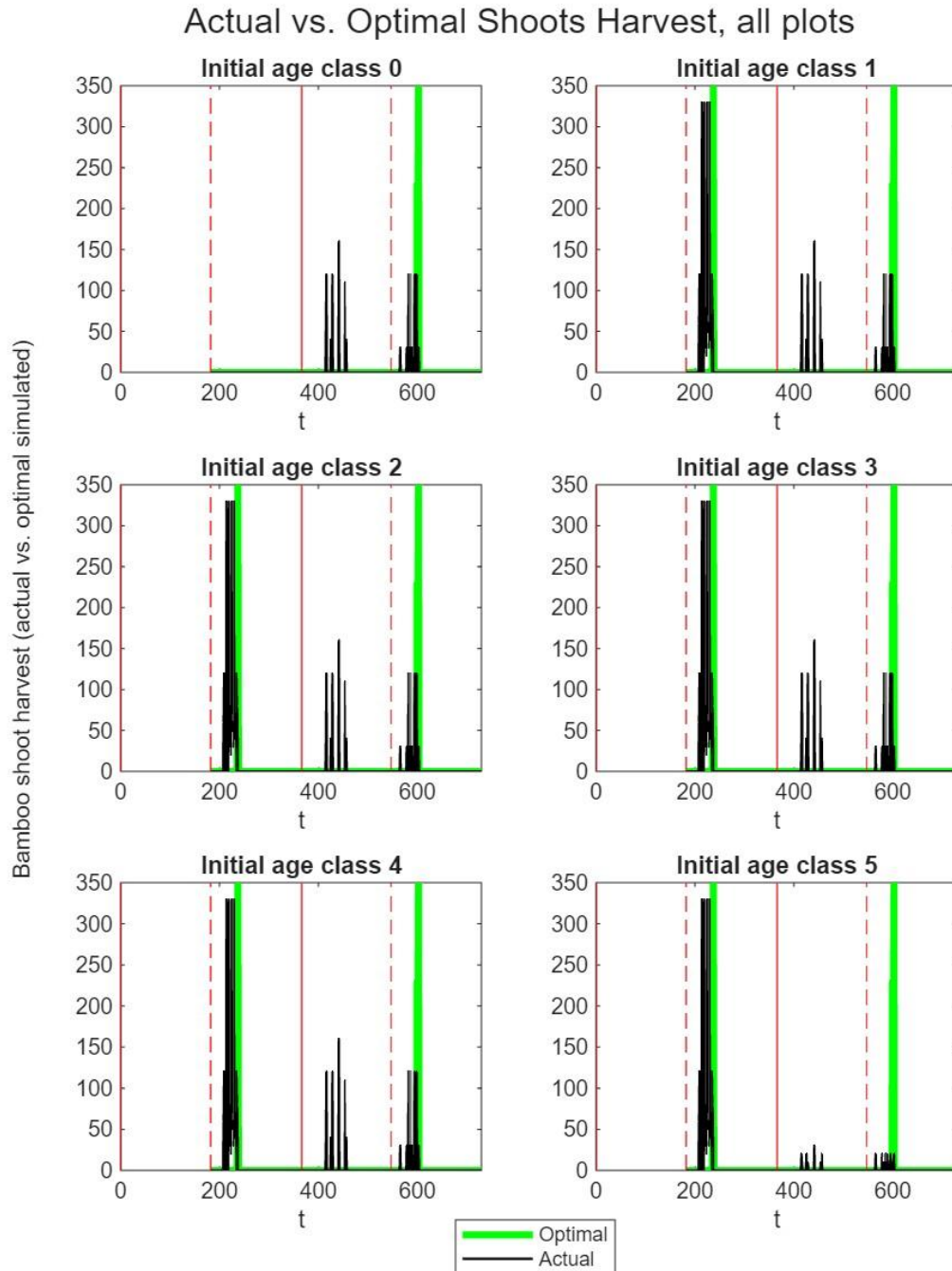
NPV during days with data	Mean (Yuan)
Optimal	2,907
Actual	678
Optimal minus Actual	2,229

(b)

Expected NPV over 11-year horizon	Mean (Yuan)
Optimal	6,832
Actual	5,255
Optimal minus Actual	1,577

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 estimates for the shoot harvest cost of $c_{sw} = 16.43$ and $c_{ss} = 1.69$ from our dynamic structural model in Table 2b. There are 35 bamboo plots in the data set, each with 6 initial age classes; table reports means over all bamboo plot – initial age classes. 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 shoot 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 D.4. Optimal vs. Actual Shoot Harvest: Perceived Winter Shoot 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 shoot decline probability of 0 from Table 2c. Solid 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 D.3. Actual vs. Optimal NPV: Perceived Winter Shoot Decline Probability

(a)

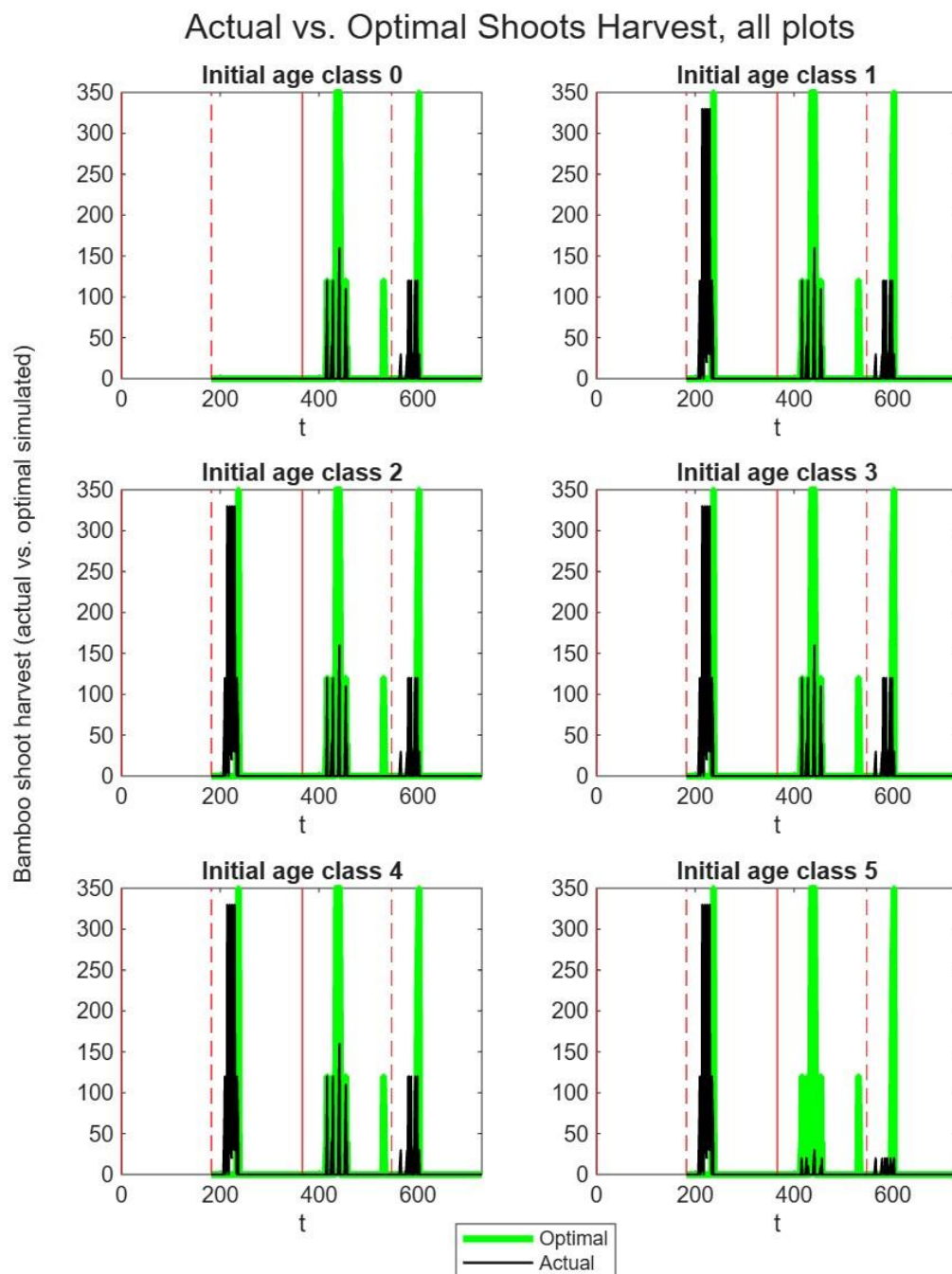
NPV during days with data	Mean (Yuan)
Optimal	2,995
Actual	827
Optimal minus Actual	2,167

(b)

Expected NPV over 11-year horizon	Mean (Yuan)
Optimal	16,109
Actual	12,306
Optimal minus Actual	3,803

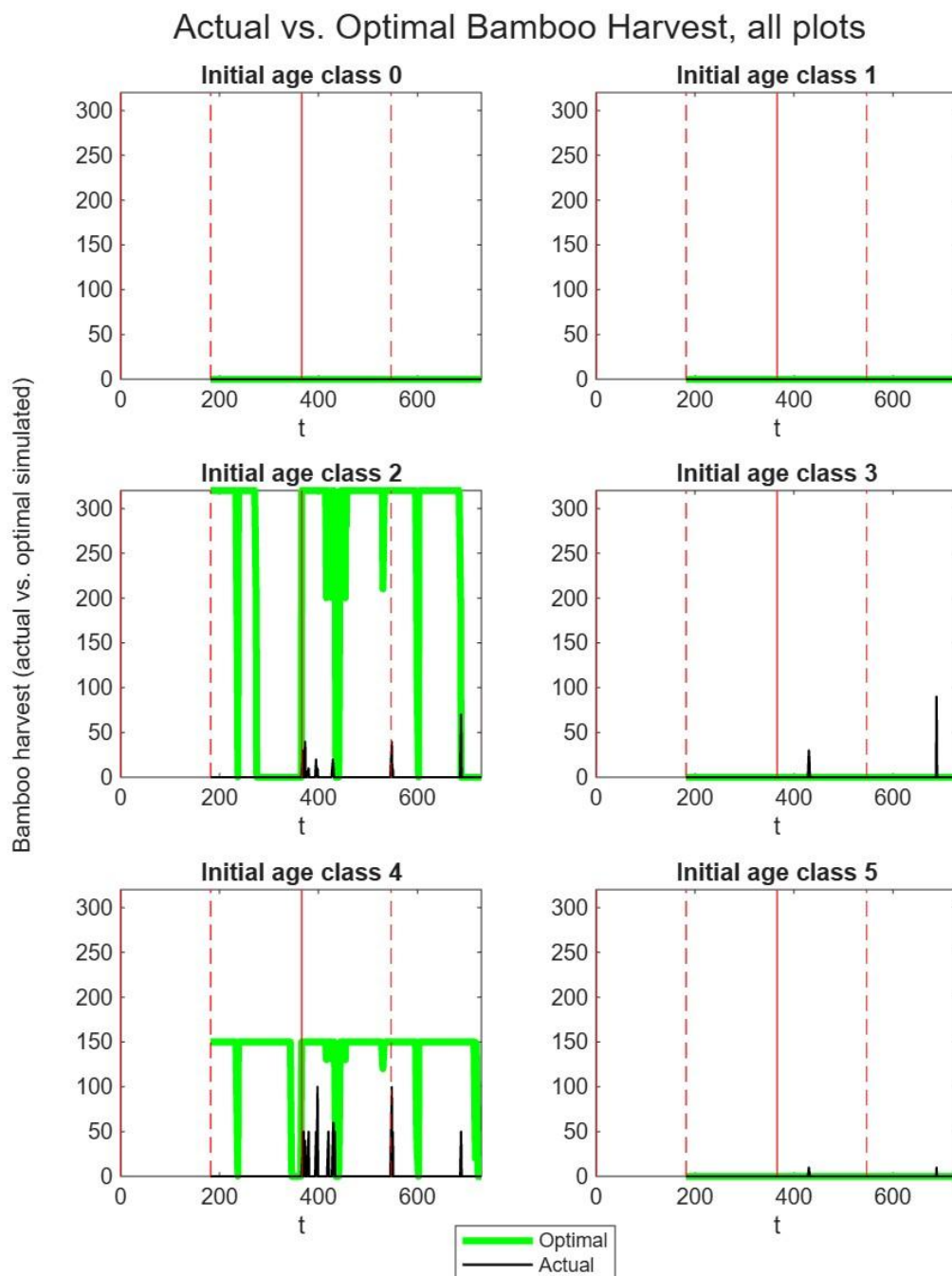
Notes: Table compares actual and optimal net present value (NPV), where net present value (NPV) is defined as the present discounted value (PDV) of the entire stream of daily profits, using the structural parameter estimate for winter shoot decline probability of 0 from Table 2c. There are 35 bamboo plots in the data set, each with 6 initial age classes; table reports means over all bamboo plot – initial age classes. 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 shoot 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 D.5. Optimal vs. Actual Shoot Harvest: 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 η of 0.84 from Table 2d. Solid 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 D.6. Optimal vs. Actual Bamboo Stem Harvest: Risk Aversion



Notes: Time series plots of the optimal and actual number of bamboo stems harvested by initial age class, using the structural parameter estimate for the coefficient of constant relative risk aversion η of 0.84 from Table 2d. Solid 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 D.4. Actual vs. Optimal Welfare: Risk Aversion**(a)**

Welfare (PDV payoffs) during days with data	Mean (Yuan)
Optimal	1,298
Actual	111
Optimal minus Actual	1,187

(b)

NPV (PDV profits) during days with data	Mean (Yuan)
Optimal	8,467
Actual	827
Optimal minus Actual	7,640

Notes: Table compares (a) actual and optimal welfare, where welfare is defined as the present discounted value (PDV) of the entire stream of daily payoffs (or utility), and (b) 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 coefficient of constant relative risk aversion η of 0.84 from Table 2d. NPV is in units of Yuan. There are 35 bamboo plots in the data set, each with 6 initial age classes; table reports means over all bamboo plot – initial age classes. 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 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.

Appendix E. Heterogeneity by Township

Figure E.1 presents time series plots of the optimal vs. actual number of bamboo stems harvested by initial age class on each bamboo plot by township. For both Sian Township and Shanchuan Township, 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.¹⁴

Figure E.2 presents time series plots of the optimal vs. actual number of bamboo shoots harvested on each bamboo plot by township. For both townships, actual shoot harvests also tend to be close to what our model deems to be optimal: bamboo shoot harvest take place when shoot prices are high; and if the number of shoots is very low and there is a possibility of winter shoot death, winter shoots are harvested earlier when the shoot price is high. Nevertheless, bamboo farmers in Sian Township may be harvesting more winter shoots than is optimal; and bamboo farmers in Shanchuan Township are forgoing profits by not harvesting any spring shoots in the second year of data even when it is optimal to do so.

Table E.1 compares actual and optimal NPV by township. For each township, 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.

Our structural model uses separate empirical distributions for shoot prices and for precipitation for each township, and thus allows shoot price uncertainty and precipitation uncertainty to vary by township. Table E.2 presents the results from estimating various specifications of our dynamic structural model by township, thereby allowing perceptions about the winter shoots growth rate, shoot death uncertainty, and risk aversion, respectively, to vary by township as well.

When the structural parameter θ we estimate is the growth rate α_{s_w} for winter shoots (Table E.2a), the structural parameter estimate for the winter shoot growth rate α_{s_w} of 0.012 for Sian Township is lower than the winter shoot growth rate α_{s_w} of 0.016 we calibrated based on biological research and information on winter shoots, while the structural parameter estimate for

¹⁴ Bamboo stems in initial age class 2 turn age 3 at the beginning of the second year of data (as delineated by the solid red vertical line in Figure E.1) and are therefore in their fourth bamboo growth year during the latter half of the time series in our data set.

the winter shoot growth rate α_{sw} of 0.028 for Shanchuan Township is higher than the calibrated value. Figure E.3 plots the bamboo farmers' perceived Chapman-Richards growth function for winter shooting and spring shooting based on our respective structural parameter estimates for the winter shoot growth rate for each township. We rerun our numerical nested stochastic dynamic bioeconomic model using the respective structural parameter estimates for winter shoot growth rate α_{sw} of 0.012 for Sian Township and 0.028 for Shanchuan Township. For Sian Township, actual winter shoot harvests are still higher than the optimal strategy under its structural parameter estimate for winter shoot growth rate α_{sw} of 0.012 (Figure E.4a). For Shanchuan Township, the optimal strategy under its structural parameter estimate for winter shoot growth rate α_{sw} of 0.028 still involves spring shoot harvests in the second year of data even though bamboo farmers in Shanchuan Township do not harvest shoots in the second year of data (Figure E.4b). For both townships, actual harvests still yield a lower NPV than the optimal strategy (Table E.3). Thus, while results suggest that winter shoot growth may differ by township, this heterogeneity in winter shoot growth may only partially explain the discrepancy between actual and optimal strategies.

Table E.2b presents the results by township of the specification of the dynamic structural model in which the structural parameter θ we estimate is the daily shoot decline probability during winter shooting. Our structural parameter estimate for the daily shoot decline probability during winter shooting is statistically insignificant and zero for Sian Township and a statistically insignificant 0.000026 for Shanchuan Township, both of which are lower than the daily winter shoot decline probability of 0.0164 we calibrated based on biological research and information on winter shoots. When we rerun our numerical nested stochastic dynamic bioeconomic model for Sian Township using a daily winter shoot decline probability of zero, the optimal strategy when there is no possibility of shoot death no longer involves any winter shoot harvest (Figure E.5a), and the calibrated parameter better explains the actual winter shoot harvest (Figure E.2a). When we rerun our numerical nested stochastic dynamic bioeconomic model for Shanchuan Township using a daily winter shoot decline probability of 0.000026, the optimal strategy still involves spring shoot harvests in the second year of data (Figure E.5b). In addition, for both townships, the difference between optimal expected NPV and actual NPV over the entire 11-year horizon is higher under the structural parameter point estimate (Table E.4) than under the calibrated parameter (Table E.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., 2026a). For these reasons, while there may be heterogeneity in shoot death by township, it is unlikely that the discrepancy between actual and optimal decisions is due to bamboo farmers misperceiving the daily winter shoot decline probability to be so low or zero.

Table E.2c presents the results by township 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 Sian Township can be rationalized by a coefficient of constant relative risk aversion of $\eta = 0.81$. 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 for Sian Township using a coefficient of constant relative risk aversion of $\eta = 0.81$. When Sian Township farmers are risk averse (with $\eta = 0.81$), the optimal shoot harvest strategy involves relatively more winter shoot harvests, which may better match the actual winter shoot harvests, but also involves harvesting some winter shoots at the end of winter shooting (as seen in the second year of data before the second dashed red vertical line), which does not take place in the actual data (Figure E.6b). The optimal bamboo stem harvest strategy for Sian Township under risk aversion (with $\eta = 0.81$) also involves harvesting some bamboo stems in their third bamboo growth year (as seen in the first half of the graph for initial age class 2 during the first year of data before the solid red vertical line),¹⁵ which also does not take place in the actual data (Figure E.6a). Table E.5 compares resulting optimal welfare with actual welfare for Sian Township, where welfare is defined as the present discounted value (PDV) of the entire stream of daily payoffs. Even if farmers in Sian Township are risk averse, their actual harvests still yield lower welfare as well as lower NPV on average than does the optimal strategy under risk aversion.

The differences in risk aversion between bamboo farmers in the two townships may reflect differences in economic priorities between the two townships. Shanchuan Township, which our structural results found to have bamboo farmers who are risk neutral, is a township in Anji County, and has a strong tourism, homestay, and recreation economy. The bamboo-fighting scene in Ang Lee's movie *Crouching Tiger, Hidden Dragon* was filmed in the China Bamboo Sea in Anji County (China Culture Daily, 2013). Shanchuan Township is recognized as a provincial forest-

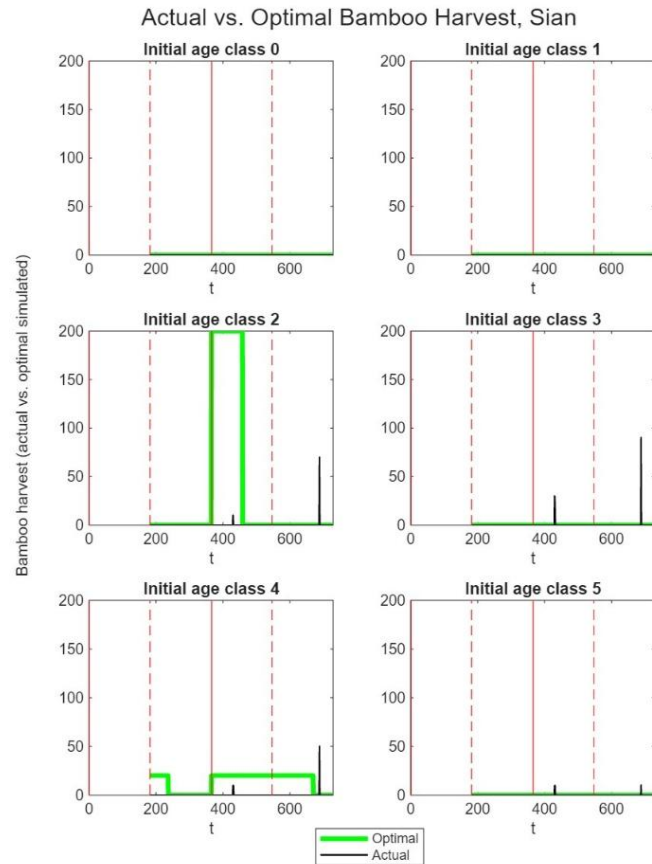
¹⁵ Bamboo stems in initial age class 2 are of age 2 during the first year of data (prior to the solid red vertical line in Figure E.6a) and are therefore in their third bamboo growth year during the first half of the time series in our data set.

health and wellness town, and local government sources describe it as a full-town scenic area (Anji County Committee of the Chinese People, 2019; Zhejiang Provincial Forestry Bureau, 2020). Tourism employment, homestay income, and other local business activities may provide Shanchuan Township households with income sources outside bamboo production. Such diversification may increase their capacity to absorb bamboo-income shocks, and make Shanchuan Township households less risk averse. Having income sources outside of bamboo production may also explain why bamboo farmers in Shanchuan Township forewent bamboo shoot harvest profits in the second year of data if though it would have been optimal to harvest spring shoots that year. In contrast, Sian Township, which our structural results found to have bamboo farmers who are risk averse, has historically been known for its flower and nursery industry (Changxing County Gazetteer Compilation Committee, 2020). Due to the difference in development priorities and industries, households in the two townships may differ in wealth, liquidity, debt, credit access, and dependence on bamboo income. Households with greater savings, more stable wage income, better access to credit, or more diversified assets may be better able to smooth consumption when the profits from bamboo stem and shoot harvests are low, which can make them appear less risk averse in their bamboo-management decisions.¹⁶

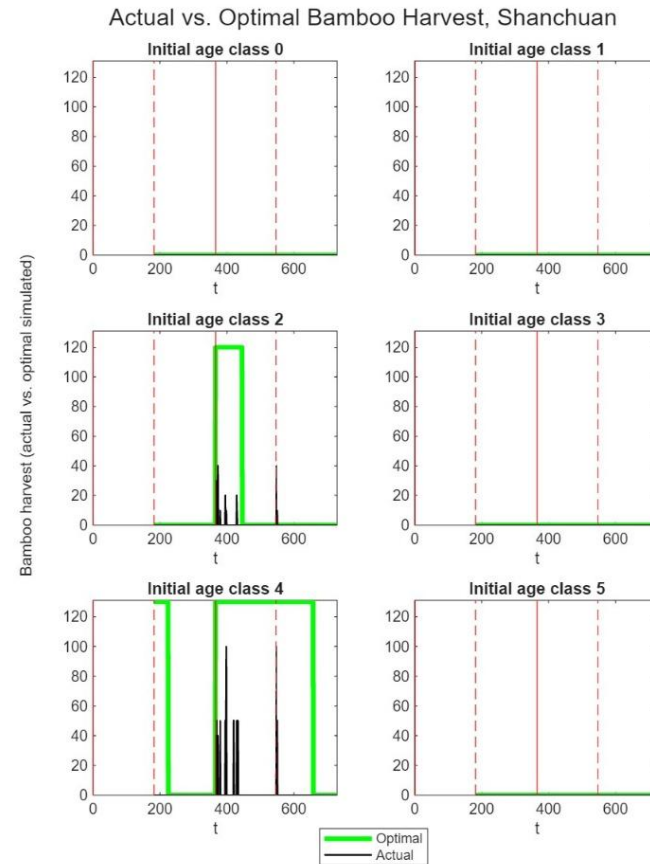
¹⁶ Wealth should not be used as a direct proxy for risk aversion, however, because wealth, liquidity constraints, and preferences have theoretically distinct effects on observed behavior (Bellemare and Brown, 2010).

Figure E.1. Optimal vs. Actual Bamboo Stem Harvest by Township

(a) Sian Township



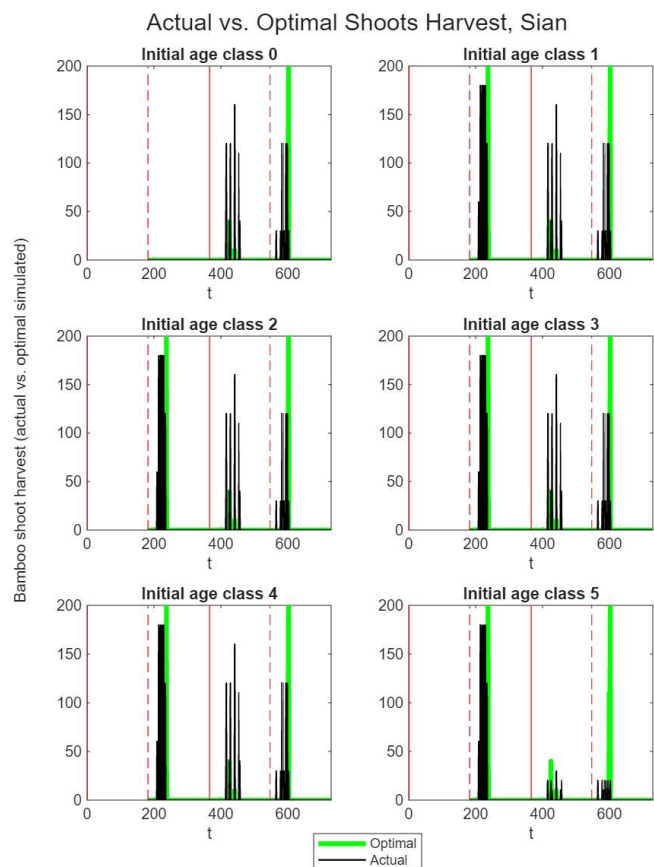
(b) Shanchuan Township



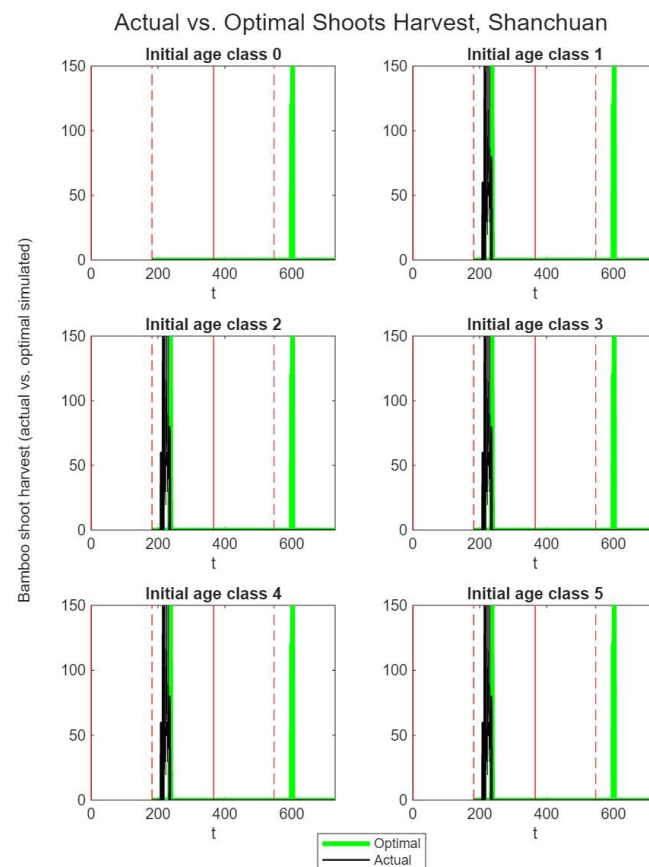
Notes: Time series plots of the optimal and actual number of bamboo stems harvested by initial age class, for each township. Solid vertical lines in red that go from the top to the bottom of the graph denote September 1 (first day of winter shooting) of each year. Dashed vertical lines in red that go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

Figure E.2. Optimal vs. Actual Shoot Harvest by Township

(a) Sian Township



(b) Shanchuan Township



Notes: Time series plots of the optimal vs. actual number of bamboo shoots harvested on each bamboo plot by township. Solid 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 E.1. Actual vs. Optimal Net Present Value (NPV) by Township**(a)**

NPV during days with data	All	Sian	Shanchuan
Optimal	3,013	1,939	4,445
Actual	827	774	899
Optimal minus Actual	2,185	1,165	3,546

(b)

Expected NPV over 11-year horizon	All	Sian	Shanchuan
Optimal	6,943	7,386	6,353
Actual	5,479	6,197	4,523
Optimal minus Actual	1,464	1,189	1,831

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. NPV is in units of Yuan. Table reports means over bamboo plot – initial age classes in the respective sample of data. 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 shoot 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.

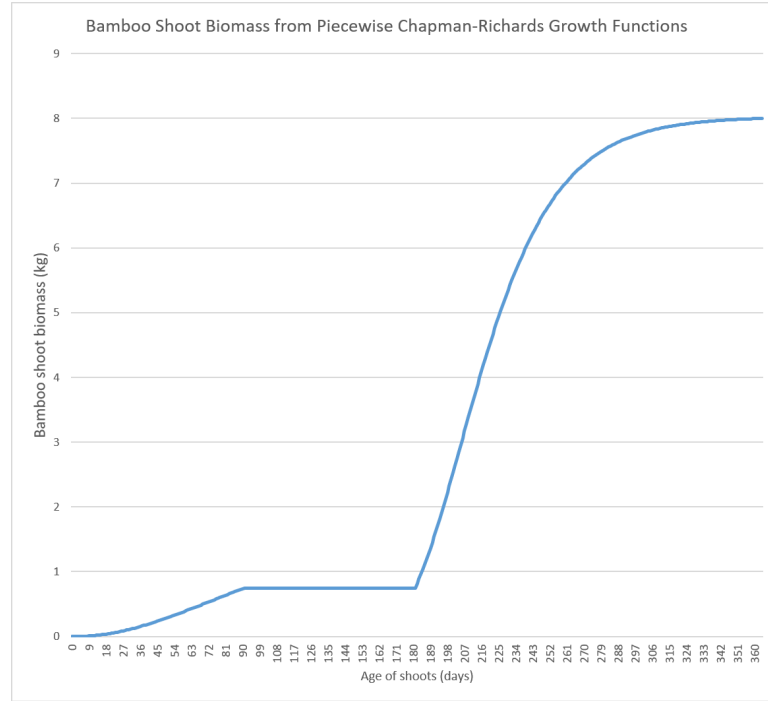
Table E.2. Dynamic Structural Model Results by Township

Structural Parameter	Actual (Assumed Value)	All (1)	Sian (2)	Shanchuan (3)
<i>(a) Winter shoot growth only</i>				
Winter shoot growth rate α_{sw}	0.016	0.012 ** (0.004)	0.012 * (0.005)	0.028 ** (0.010)
# Observations		115,290	65,880	49,410
# Bamboo plots		35	20	15
<i>(b) Shoot decline probability parameter only</i>				
Daily winter shoot decline probability d_w	0.0164	0.000000 (0.000011)	0.000000 (0.000010)	0.000026 (0.003486)
# Observations		115,290	65,880	49,410
# Bamboo plots		35	20	15
<i>(c) Coefficient of relative risk aversion only</i>				
Coefficient of constant relative risk aversion η	0 (risk neutral)	0.837 * (0.342)	0.812 *** (0.007)	0.151 (0.184)
# Observations		115,290	65,880	49,410
# Bamboo plots		35	20	15

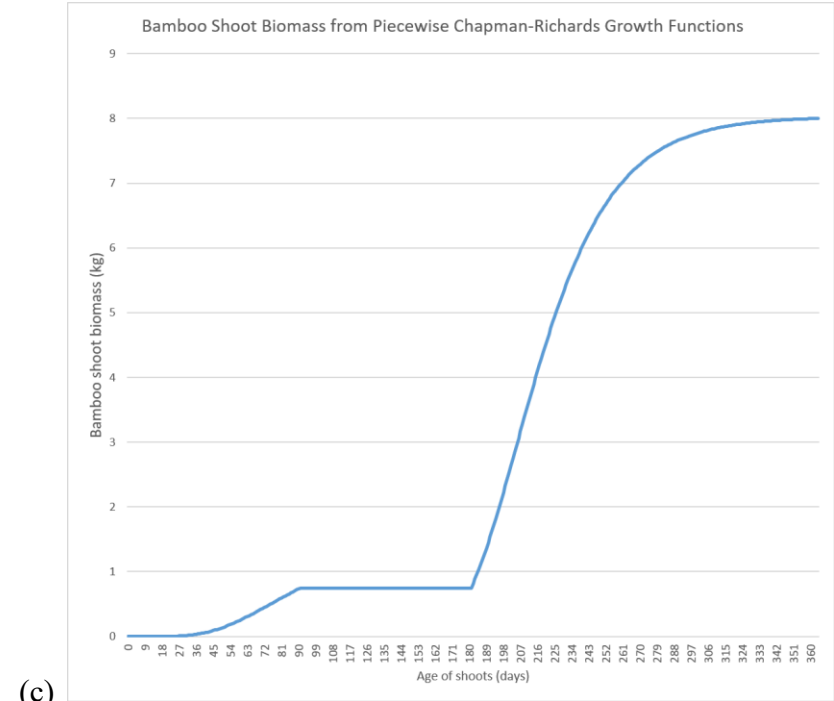
Notes: The structural parameter estimates are the parameter estimates from separate specifications of the structural model estimating (a) the winter shoot growth parameter only, (b) the shoot decline probability only, and (c) the coefficient of relative risk aversion only, respectively, each for (1) the entire sample (“All”), (2) Sian Township only (“Sian”), and (3) 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 are in parentheses. All specifications using the entire sample (a-1, b-1, and c-1), and all subsamples of specification (c) estimating the coefficient of relative risk aversion (c-1, c-2, and c-3) use 100 bootstrap samples each. Owing to computational time constraints for the estimation by township, specification (a) uses 80 bootstrap samples each for Sian (a-2) and Shanchuan (a-3); and specification (b) uses 50 bootstrap samples each for Sian (b-2) and Shanchuan (b-3). Significance codes: *** p<0.001, ** p<0.01, * p<0.05

Figure E.3. Perceived Chapman-Richards Growth Function for Bamboo Shoots by Township

(a) Sian Township: $\alpha_{sw} = 0.012$



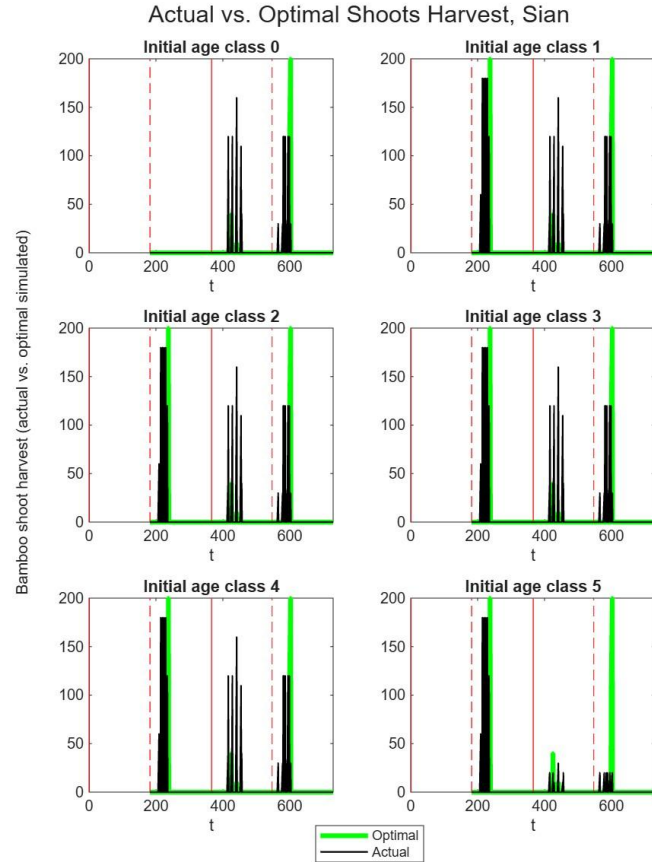
(b) Shanchuan Township: $\alpha_{sw} = 0.028$



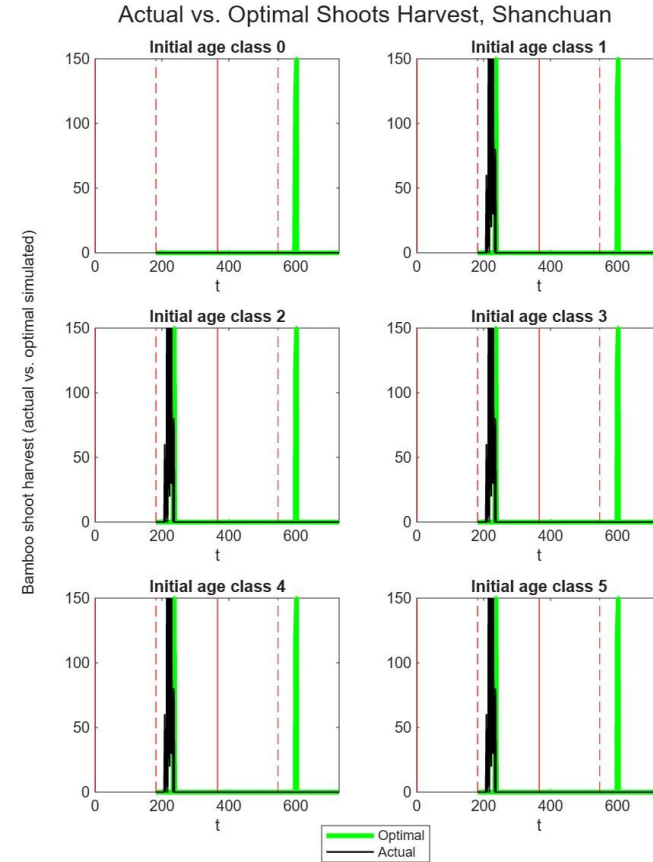
Notes: Figure plots bamboo farmers' perceived Chapman-Richards growth function for winter shooting and spring shooting based on the structural parameter estimate for winter shoot growth rate α_{sw} of (a) 0.012 for the entire sample ("All") and for Sian Township only ("Sian"), and (b) 0.028 for Shanchuan Township only ("Shanchuan") from our dynamic structural model in Table E.2a. 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 E.4. Optimal vs. Actual Shoot Harvest by Township: Perceived Winter Shoot Growth Rate

(a) Sian Township: $\alpha_{sw} = 0.012$



(b) Shanchuan Township: $\alpha_{sw} = 0.028$



Notes: Time series plots of the perceived optimal vs. actual number of bamboo shoots harvested on each bamboo plot by township, using the structural parameter estimate for winter shoot growth rate α_{sw} of (a) 0.012 for the entire sample (“All”) and for Sian Township only (“Sian”), and (b) 0.028 for Shanchuan Township only (“Shanchuan”) from our dynamic structural model in Table E.2a. Solid 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 E.3. Actual vs. Optimal NPV by Township: Perceived Winter Shoot Growth Rate

(a)

NPV during days with data	All $\alpha_{sw} = 0.012$	Sian $\alpha_{sw} = 0.012$	Shanchuan $\alpha_{sw} = 0.028$
Optimal	3,013	1,939	4,445
Actual	827	774	899
Optimal minus Actual	2,185	1,165	3,546

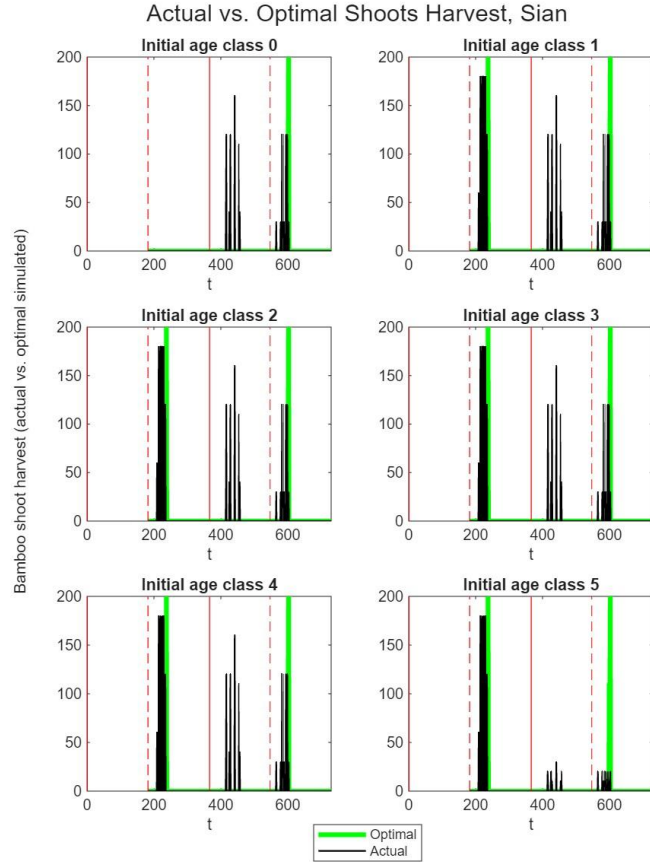
(b)

Expected NPV over 11-year horizon	All $\alpha_{sw} = 0.012$	Sian $\alpha_{sw} = 0.012$	Shanchuan $\alpha_{sw} = 0.028$
Optimal	6,943	7,386	6,353
Actual	5,479	6,197	4,523
Optimal minus Actual	1,464	1,189	1,831

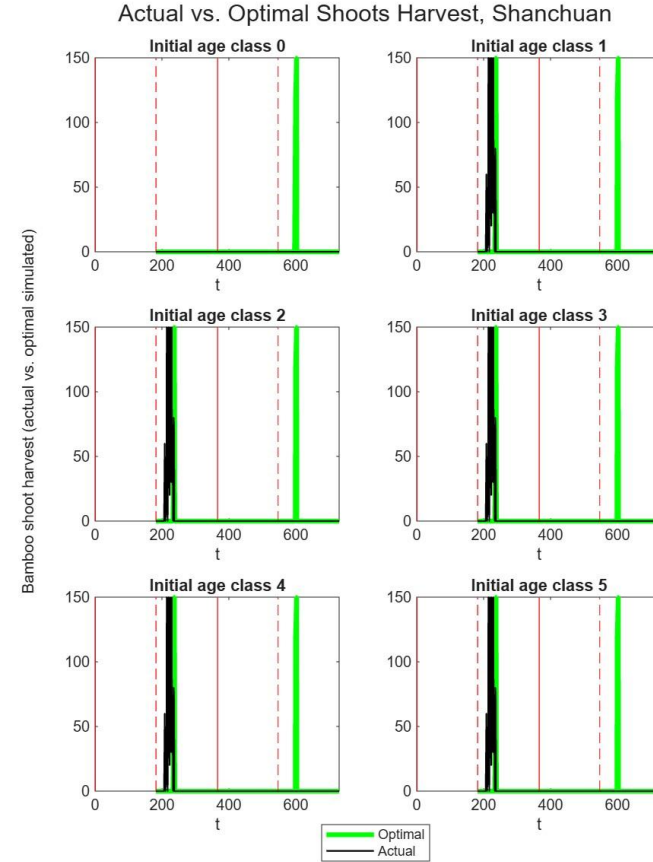
Notes: Table compares actual and optimal net present value (NPV), where net present value (NPV) is defined as the present discounted value (PDV) of the entire stream of daily profits, using the structural parameter estimates for winter shoot growth rate α_{sw} of (a) 0.012 for the entire sample (“All”) and for Sian Township only (“Sian”), and (b) 0.028 for Shanchuan Township only (“Shanchuan”) from our dynamic structural model in Table E.2a. NPV is in units of Yuan. Table reports means over bamboo plot – initial age classes in the respective sample of data. 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 shoot 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 E.5. Optimal vs. Actual Shoot Harvest by Township: Perceived Winter Shoot Decline Probability

(a) Sian Township: $d_w = 0$



(b) Shanchuan Township: $d_w = 0.000026$



Notes: Time series plots of the perceived optimal vs. actual number of bamboo shoots harvested on each bamboo plot by township, using the structural parameter estimates for winter shoot decline probability d_w of (a) 0 for the entire sample (“All”) and for Sian Township only (“Sian”), and (b) 0.000026 for Shanchuan Township only (“Shanchuan”) from our dynamic structural model in [Table E.2b](#). Solid 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 E.4. Actual vs. Optimal NPV by Township: Perceived Winter Shoot Decline Probability

(a)

NPV during days with data	All $d_w = 0$	Sian $d_w = 0$	Shanchuan $d_w = 0.000026$
Optimal	2,995	1,886	4,473
Actual	827	774	899
Optimal minus Actual	2,167	1,112	3,574

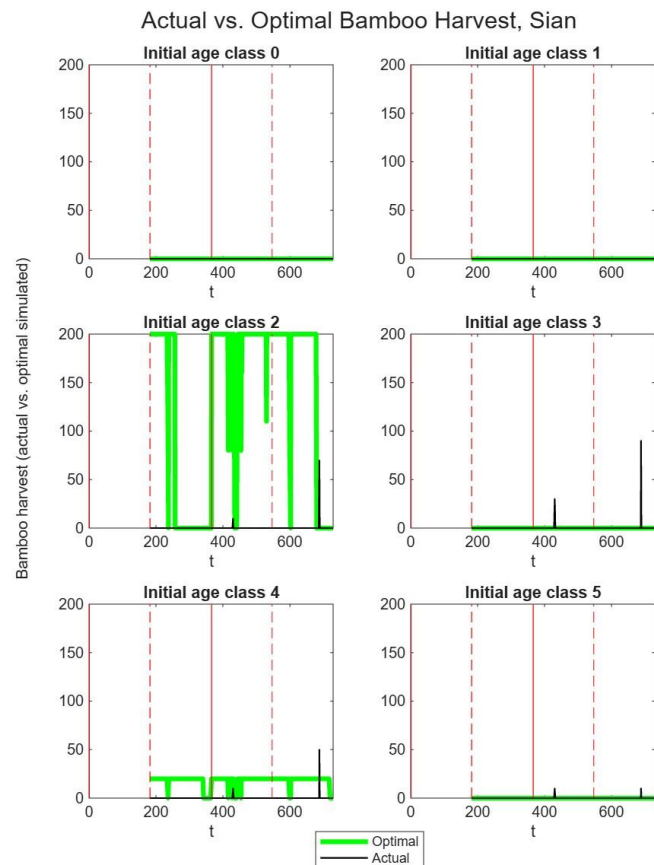
(b)

Expected NPV over 11-year horizon	All $d_w = 0$	Sian $d_w = 0$	Shanchuan $d_w = 0.000026$
Optimal	16,109	18,482	12,933
Actual	12,306	14,779	9,000
Optimal minus Actual	3,803	3,703	3,933

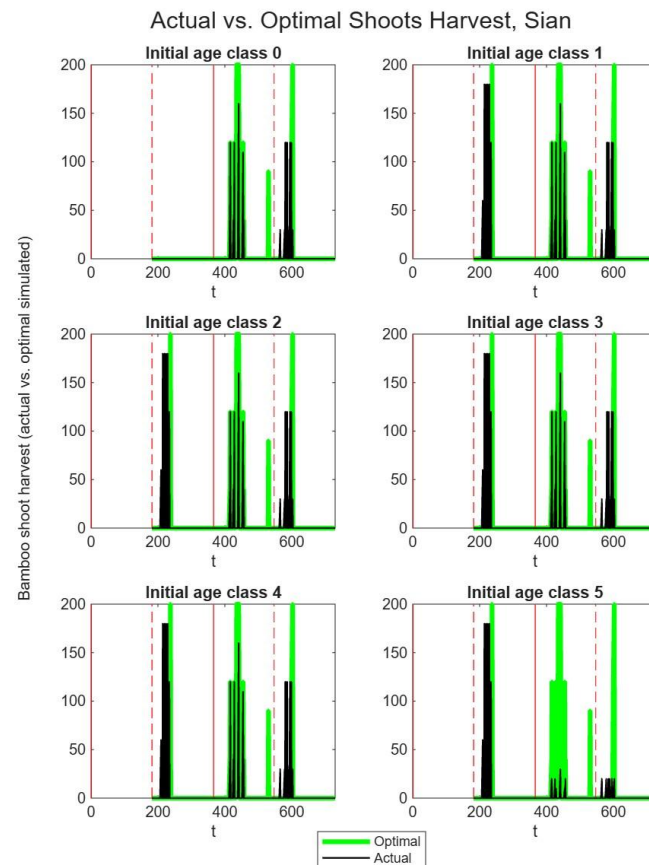
Notes: Table compares actual and optimal net present value (NPV), where net present value (NPV) is defined as the present discounted value (PDV) of the entire stream of daily profits, using the structural parameter estimates for winter shoot decline probability d_w of (a) 0 for the entire sample (“All”) and for Sian Township only (“Sian”), and (b) 0.000026 for Shanchuan Township only (“Shanchuan”) from our dynamic structural model in [Table E.2b](#). NPV is in units of Yuan. Table reports means over bamboo plot – initial age classes in the respective sample of data. 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 shoot 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 E.6. Optimal vs. Actual Bamboo Stem and Shoot Harvests in Sian Township: Risk Aversion

(a) Bamboo stem harvest



(b) Shoot harvest



Notes: Time series plots of the perceived optimal vs. actual (a) number of bamboo stems harvested by initial age class, and (b) number of bamboo shoots harvested on each bamboo plot in Sian Township, using the structural parameter estimate for the coefficient of constant relative risk aversion η of 0.81 for Sian Township only (“Sian”) from [Table E.2c](#). Solid 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 E.5. Actual vs. Optimal Welfare in Sian Township: Risk Aversion

(a)

Welfare (PDV payoffs) during days with data	All $\eta = 0.84$	Sian $\eta = 0.81$
Optimal	1,298	960
Actual	111	111
Optimal minus Actual	1,187	850

(b)

NPV (PDV profits) during days with data	All $\eta = 0.84$	Sian $\eta = 0.81$
Optimal	8,467	6,743
Actual	827	774
Optimal minus Actual	7,640	5,969

Notes: Table compares (a) actual and optimal welfare, where welfare is defined as the present discounted value (PDV) of the entire stream of daily payoffs (or utility), and (b) 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 the coefficient of constant relative risk aversion η of (a) 0.84 for the entire sample (“All”) and (b) 0.81 for Sian Township only (“Sian”) from Table E.2c. NPV is in units of Yuan. Table reports means over bamboo plot – initial age classes in the respective sample of data. 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 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.