THE REAL OPTIONS PUZZLE FOR MICHIGAN TART CHERRY PRODUCERS

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Abstract

Capital budgeting decisions faced by tart cherry producers often challenge our traditional valuation techniques. Real Options Valuation (ROV) methods may be useful but assumptions of existing ROV approaches are restrictive and, in some cases, unrealistic. In this paper we assert that use of existing option pricing methods can not be justified. Instead, dynamic programming approach is more appropriate. We develop a multi-period model and use it to obtain an optimal orchard replacement policy. The model is applied to an example farm from Northwestern Michigan and the results provide the following messages. First, flexibility options can be estimated for individual tart cherry producers using the DP approach albeit, indirectly. Second, a farmer who uses the DP approach to develop contingency optimal replacement rules will be better off than one who uses an ad hoc standard replacement rule. Third, if the SW climate scenario shifts to NW Michigan, tart cherry orchard values may fall substantially with implications on the future of tart cherry production in that region, unless compensating price increases follow.

Introduction

Michigan tart cherry producers face complex capital budgeting decisions that challenge our traditional approaches of evaluating investment. When making a decision to invest in planting a block of trees, farmers are typically making a decision with high costs of reversal that will determine their earnings for the next 20 to 35 years. This decision is very difficult for several reasons. First, farmers face annual variation in yields due to weather. Furthermore, there is evidence that the probability distribution of key weather events, hence yield, has been changing over the last 25 years and this trend is expected to continue(MacCracken *et al.*, 2003; Winkler, 2004). Second, because tart cherries are perennials, farmers face a multi-year risk exposure that the productivity of their capital stock (trees) can be reduced or even lost due to weather or disease. In the latter case, the farmer can re-plant the affected block or a portion thereof but will have to incur additional costs in site preparation, purchase of planting material, and lost earnings until the new block gets into production. Third, as an existing block ages its productivity begins to fall and the farmer has to make a replacement decision. Finally, tart cherry prices have pronounced cycles and farmers have to deal with risk exposure of multiple years with below "normal" prices.

The capital budgeting challenges for Michigan tart cherry growers are as follows. First, most of the trees that were planted in the late 1960s and early 1970s need to be replaced. Farmers with such blocks have to decide whether to replant or not. Second, due to planting that occurred in the late 1970s and early 1980s, when profits were exceptionally high, farmers have had to bear the consequences of oversupply for several years. Changes in weather patterns that have resulted in a string of lower than normal yields portend an even more challenging financial environment. Finally, some farms that have sold the land used for cherry production to real estate developpers, are considering re-investment but in less productive sites. As producers puzzle with their planting (replanting) decisions some farmers have begun considering the idea of abandoning cherry production and switching to other enterprises, such as wine grapes or other crops. Their main challenge lies in finding a practical decision support tool to use in the face of such multi-year yield and price uncertainties.

Traditional capital budgeting techniques such as accounting rate of return, pay-back-period, profitability index, internal rate of return, and the net present value (NPV) have been found to be inadequate for these kinds of investment decisions. The main shortcoming of the traditional techniques is that, they assume that only a one time investment decision is to be made. Hence, they fail to take into account management's flexibility to alter the course of a project in response to changing market and other project conditions (see for example Trigeorgis, 1993, 1995; Trigeorgis and Mason, 2001).

In recent years, substantial literature in finance and management science has been devoted to developing the theory and valuation techniques for real options which, take into account the ability of management to respond appropriately as new information emerges or as uncertainty gets resolved (e.g Dixit and Pindyck, 1994; Trigeorgis, 1995, 1996; Amram and Kulatilaka, 1999). Simply put, real options theory (ROT) extends the thinking behind financial options to opportunities in real markets that offer, for a fixed cost, the right to earn future payoffs in return for additional fixed investments, but without imposing the obligation to invest.

Because of its origin in financial options theory, application of ROT to value real project options requires complete markets and, the existence of a 'twin security' (replicating portfolio of assets) that is traded and has the same risk characteristics (i.e. perfectly or highly correlated) with the project under consideration, so that standard no-arbitrage arguments hold. Furthermore, it is commonly assumed that asset prices follow a Brownian motion, making it possible to apply most common financial formulas such as the Black-Scholes option pricing model (e.g. Brennan and Schwartz, 2001; Trigeorgis and Mason, 2001).

For most investments with real options, however, the assumption of a replicating portfolio does not hold. In particular, it is not clear what can be considered as a replicating portfolio for tart cherry investment projects. There is little guidance in existing literature on how to proceed with real option valuation methods in the absence of a replicating portfolio. Dixit and Pindyck (1994) suggest the use of Dynamic Programming (DP) although they also caution that it makes it difficult to relate the exogenously chosen discount rate to the risk-free interest rate and the market price of risk using CAPM (p.185). Perhaps, in recognition of this difficulty, Childs and Triantis (1999) who use the DP technique to value an R&D program, simply make the assumption that "an equilibrium model such as … CAPM holds and that the development of projects does not alter the equilibrium pricing kernel" (p.1362). Childs *et al.* (1998) also make similar assumptions with little guidance on the appropriateness of these assumptions.

The latest real options valuation approach to be developed is the Integrated Valuation Procedure, which has its roots in management science (see Smith and Nau, 1995; and Smith and McCardle, 1998). This approach recognizes that most investments are characterized by two types of risks: public or market risk and private or project specific risk. The basic idea of this approach is to use option pricing methods to value market risks and to use decision analysis methods to value private risks. This approach would only be appropriate if, say, a futures exchange market for tart cherries existed. If that were the case, then the futures price would serve as the 'twin security' for market price risk. Unfortunately, no futures market for tart cherries exists and, hence, no appropriate 'twin security' for the cherry prices exists. Consequently, the assumptions under which this approach is applicable cannot be met.

Our view is that existing real options valuation techniques may not be appropriate for valuing tart cherry investments. Instead, dynamic programming is a better approach for valuing such investments. In this case, however, the value of the option computed does not represent its (market) equilibrium value. This is because, the chosen discount rate is related to the risk profile of the individual producer's cash flows and, therefore, it does not represent the equilibrium price of the investment's risk. That weakness notwithstanding, the DP approach is still a useful investment tool from an individual producer's perspective. It provides a more accurate valuation of the embedded options in his/her investment than would traditional real options valuation techniques when the assumption of a replicating portfolio does not hold.

The objective of this paper is to explore optimal tart cherry orchard replacement policy and estimate the value of the flexibility option embedded in the decision making process. The objective is accomplished using a stochastic dynamic asset replacement model solved for two plausible climate scenarios. Numerical solution methods are used to determine optimal orchard replacement strategies for an individual farmer. The approach is applied to an example farm using Michigan data.

The results will be of interest to farmers and policy makers concerned with the investment challenges facing tart cherry producers. The results will also lend insights to the emerging debate on the appropriateness and (in)applicability of existing real options valuation methods to capital budgeting problems facing perennial crops' producers.

Conceptual Dynamic Model

A producer's orhcard replacement decision can be studied with a simple dynamic model as an asset replacement problem. We examine a farm with an infinite planning horizon and maximizes expected profit assuming a standard, discounted, sum of profits specification:[1]

$$(1) \qquad \max E_0 \sum_{t=0}^{\infty} \beta^t (\pi_t)$$

where E_t is expectation conditional on information available at the beginning of period t; β is a discount factor representing the farmer's rate of time preference; and π_t is period t profits.

At the beginning of each year, the farmer makes a decision, a, to replace ($a=1$) an existing orchard or not ($a=0$), conditional on available information at that time. An orchard that is x years old produces an output of $y(x)$ lbs each year up to X years, when production is assumed to fall to uneconomic levels and the orchard must be replaced. To replace an orchard, the farmer incurs a one time replacement cost of $c(0)$ dollars per acre. The farmer also incurs an annual cost of $c(x)$ dollars for routine operations in the orchard. Each year, the farmer faces a random price of

1 The assumption of infinite planning horizon is made for convenience only. Virtually identical results can be obtained if a finite planning horizon is assumed.

p_t, which, as of the beginning of the year is a random variable with a cumulative distribution function $F(\xi)=Prob[\, p_t \leq \xi \,]$ defined over the support $[l, u]$ so that $F(l)=0$ and $F(u)=1$. In addition, yield is also uncertain with a cumulative distribution function $G(\zeta)=Prob[\, y(x) \leq \zeta \,]$ defined over the support $[b, d]$ so that $G(b)=0$ and $G(d)=1$. With these assumptions, the farmer's profit function is:

(2) $$\pi_t = p_t y_t(x) - c(x) \qquad \text{if } a=0\text{; and}$$
$$\pi_t = p_t y_t(0) - c(0) \qquad \text{if } a=1.$$

The farmer's problem is to choose a set of contingency plans for orchard replacement that satisfy the Bellman's functional equation:

(3) $$v(p_t, x) = \max_{a=0,1} \begin{Bmatrix} (1-a)[\, p_t y_t(x) - c(x) + \beta E_t v(p_{t+1}, x+1\,], \\ a[\, p_t y_t(0) - c(0) + \beta E_t v(p_{t+1}, 1\,] \end{Bmatrix}$$

as well as the transition functions

(4) $$A(x,a) = \begin{cases} x+1, & a=0 \\ 1, & a=1 \end{cases},$$

$\tilde{p}_{t+1} \sim f(p_{t+1} | p_t, \eta_{t+1})$, and

$\tilde{y}_{t+1} \sim g(y_{t+1} | x+1, \varepsilon_{t+1})$;

the transversality condition,

(5) $\lim_{t \to \infty} \beta^t \pi_t = 0$; and a maximum age constraint on the orchard trees, $x \leq X$.

In general, solutions to such problems take the form of a set of contingency plans $a = a(p_t, x)$ which, together with an initial vector of price states p_0, the transition functions (4), and a set of realizations for the random yields $\{y_t\}_{t=1}^{\infty}$, and prices $\{p_t\}_{t=1}^{\infty}$, determine the entire future path of orchard replacement.

The Bellman equation implies that if the farmer does not replace an orchard of age x, he receives a net profit of $p_t y_t(x)-c(x)$ in the coming year, and, begins the following year with an orchard that is worth $v(p_{t+1}, x+1)$. If on the other hand he replaces the orchard, his net profit is $p_t y_t(0)-c(0)$ in the coming year, and, he begins the following year with an orchard that is worth $v(p_{t+1}, 1)$. Hence, $v(.)$ represents the current and future net profits of the existing orchard, plus the net profits from all future orchards that replace it (see for example Miranda and Fackler, 2002).

The farmer's optimization problem can be solved using discrete time stochastic dynamic programming (Miranda and Fackler, 2002). To solve the model, we used the Adaptive Stochastic Dynamic Programming (ASDP) software developed by Lubow (1994,1995,1997,1999). The ASDP algorithm is coded in the C++ programming language and is fully compatible with the Microsoft visual C++ compiler which we used. Even though the ASDP algorithm was primarily developed for solving wildlife and fisheries management problems, it provides a generalized, flexible, and efficient user-friendly means to define and solve a wide range of stochastic dynamic programming problems.

Data and Model Calibration

We apply the model to the optimal orchard replacement problem faced by a representative tart cherry farmer in Northwestern Michigan under two climate scenarios as described below. In order to estimate the model, however, data on production costs, prices, and yields, as well as a number of assumptions are required. We discuss these below.

Climate Scenarios

Approximately 75% of U.S. tart cherry production is concentrated in the counties of the western lower peninsula of Michigan bordering Lake Michigan. The proximity of the lake moderates temperatures in these counties, reducing the number of damaging low temperature events and, delays early development of tart cherry blossoms in most years until the danger of a spring freeze passes. In recent decades, cherry producers in northwestern Michigan have observed a decrease in the amount of ice cover on Lake Michigan as well as an earlier onset of the seasonal warm-up in spring. This has resulted in earlier development of tart cherry floral and vegetative buds, exposing producers to a relatively greater risk of cold injury and a reduction in yield potential.

Annual mean air temperatures in the area have also increased during the last 20 years, although they still remain within observed historical ranges. This trend is consistent with estimates from general climate circulation models (GCMs), which suggest regional annual mean air temperature increases of 1-5 ˚C over the century. A 1-5 ˚C regional increase in mean air temperatures would affect tart cherry production through several mechanisms. The longer, warmer growing season could, *ceteris paribus*, result in higher potential yields. However, if the risk of low temperature events continues in historic patterns, earlier spring warm-up would also result in greater production losses from cold injury.

As a first order of approximation, in this paper we assume NW Michigan tart cherry producers face two scenarios: (1) a climate representative of the events that have taken place in NW Michigan over the last 30 years; and (2) a climate representative of the events that have taken place in SW Michigan over the last 30 years because the climate in SW Michigan is warmer than the climate in NW Michigan. As a result of the warmer climate, cherry trees in the SW region reach peak production earlier and experience earlier post-peak downward trending yields than those in the NW region. Production is also more variable and has lower kurtosis. We consider the SW climate as an alternative to the NW climate because there is evidence based on preliminary downscaled GCM climate model results, that the NW climate will switch to the SW climate scenario in the near future (Winkler, 2004).

Yield distribution

Unpublished yield estimates for the 1982-2002 period were available for research for three Western Michigan regions (Northwest, West Central, and Southwest) from the Michigan Department of Agriculture which, with tart cherry industry support, conducts more extensive sampling than is conducted by NASS. A shorter unpublished proprietary series (primarily 1989 – 2003) of production for individual blocks of cherries, under constant management, from NW

Michigan was also available. We use information from the longer yield series to weight an extreme value in the shorter one. As would be expected, even though systemic risk is substantial, yield variation falls as one aggregates data from block to farm to region levels. The tracking of yields of the block, farm, and region data suggested that the yield probability density functions (pdfs) have similar shapes at different aggregations.

The methods considered for the estimation of the yield pdfs were the IHST transform adapted by Moss and Shonkweiler (1993), the non-parametric estimators proposed by Kerr and Goodwin (2000), and "standard" kernel density estimators (Silverman, 1986; Wand and Jones, 1994). The IHST transform is a very flexible function form but is best suited to larger samples since the model is estimated using maximum likelihood methods. The Kerr and Goodwin approach, also a kernel density approach, has attractive features but the standard kernel density approach, which has been extensively studied for different sample sizes and pdf shapes, was viewed as an appropriate approach. Order statistics (Anderson *et al*., 1977; David and Nagaraja, 2003) were also plotted for cumulative distributions to provide more insights and double checking.

The yield pdfs used in the analysis were estimated in a four step nonparametric procedure. Beginning with the regional yield time series, first, the trend was removed from the regional data. Second, relative yields were calculated by dividing yield in year *t* by the estimate of expected yield in that year. Third, the pdf of these relative yields was estimated by standard kernel density methods supplemented by reviewing sample order statistics. Fourth, a discrete distribution was developed by dividing the continuous pdf into 18 bins. Last, the regional pdf estimates were re-scaled (transformed) to approximate the relationship between block and region.

Because yields are a function of the age of the orchard trees, a complete characterization of the yield distribution would require a different pdf for each age or cohort of ages. Due to computing limitations, however, we were restricted to only two age cohorts. These were classified as the 'non-peak' and the 'peak' production age cohorts. Assuming maximum productive ages of 30 and 35 years for orchards in NW and SW, respectively, the peak production age cohorts were taken to consist of ages 10-26 and 11-29 years, respectively. Figure 1 shows the estimated yield distributions that were used to calibrate the model and Figure 2 shows the expected yields that these distributions approximate.

The state spaces for yield were specified as 18, equally spaced, possible yield states ranging from 0 to 4.4044 tons/acre and 0 to 4.6786 tons/acre for NW and SW regions, respectively, representing the "non-peak" age cohorts. Similarly, the specified yield state spaces for the "peak" production age cohorts ranged from 0 to 10.0776 tons/acre and 0 to 10.2546 tons/acre, for NW and SW regions, respectively. Each yield state is taken to be the mid-point of the corresponding continuous yield interval with a corresponding discrete probability of being realized. This completes the yield state space specification.

Production costs

Costs of establishing a tart cherry orchard and subsequent production costs were obtained from Nugent *et al.* (2003)'s cost estimates. These estimates were developed via focus group discussions with cherry growers from Antrim, Leelanau and Grand Traverse counties in Northern Michigan. The estimates show that when replacing an aging block of tart cherries, a grower incurs a substantial cost in land preparation and in purchasing planting material as well as other inputs. These costs were estimated at $1,829 per acre.[2] In addition, during the first five years of the orchard, the type and intensity of operations such as, pruning, control of insect pests, diseases, and weeds differ from those that are typically carried out in later years. These costs were estimated at $291, $321, $311, and $355 per acre for years two through five, respectively. From the sixth year onwards, when the orchard is fully established, the major pre-harvest costs (e.g. spraying, pruning, cultivating, etc.) do not vary greatly with yield. Following Nugent *et al.*, we estimated the pre-harvest costs at $581 per acre, for an orchard that is six or more years old.

Once the orchard is in production, the farmer has to incur additional costs for harvesting and marketing operations (e.g. shaking and handling, hauling, promotion assessment, etc.) which vary with yield. Thus, these costs are a function of harvested and marketed yield. Again, using data from Nugent *et al.* on cost of harvesting and marketing for various yield levels, we estimated a harvesting cost function which we found to fit the data well. We specified this funtion as:

$$h = 0.1799 - 1.85*10^{-5}y + 6.88*10^{-10}y^2 \qquad (6)$$

where h is harvesting cost ($/lb) and y is yield in pounds. Further examination of this funtion showed that, within the relevant yield range, harvesting costs decrease with yields. This suggests the existence of economies of scale in harvesting and marketing of tart cherries which is consistent with *a priori expectations*.

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2 Our cost estimates exclude an allocated cost of management's time, in contrast to Nugent *et al.*'s estimates, because we regard the grower as the residual claimant in our calculations. Furthermore, this estimate does not include a cost of trickle irrigation whose initial investment cost ranges between $500 to $700 per acre.

Price distribution

Data on tart cherry prices were available for the state of Michigan for the period 1925 to 2001.[3] Because these data were in nominal values, we converted them to their 2002 dollar equivalents using Producer Price Index (PPI) deflators for Commodities, Farm products, from the Bureau of Labor Statistics, U.S. Department of Labor. To deflate prices of a given year, we divided that price by the PPI deflator of that year. Summary statistics of the deflated prices showed that between 1925 to 2001, Michigan tart cherry prices varied widely ranging from 4.98 cents/lb to 50.12 cents/lb, with a mean of 21.49 cents/lb and standard deviation of 10.16 cents/lb. Finally, to be consistent with the cost data, we converted the price data from cents/lb to dollars/ton before proceeding with identification procedures.

We began identification procedures by first examining a graph of the price data to investigate possible trends and patterns. No trend or systematic patterns were suggested by the graph. We formally tested for evidence of a trend in the series and found the coefficient on the trend term to be statistically insignificant (t-statistic=0.1212, p-value=0.9038). Therefore, no de-trending of the price data was necessary. Further, we examined the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the price series looking for evidence of autocorrelation. The ACF showed a geometric decay while the PACF cut off after the first lag. This suggests a low order AR process. Using a formal test with the Ljung-Box Q-statistic we found evidence of first-order serial autocorrelation with an autocorrelation coefficient of 0.349 and p-value of 0.002. Based on these results, we specified the data generating process (DGP) for

[3] We are grateful to the Michigan Agricultural Statistics Service (MASS) for providing us with these data.

tart cherry prices in Michigan as an AR(1) process with a constant. Table 1 shows the results for this specification. These results show that both the constant term and the AR(1) coefficient are statistically significant. An examination of the correllogram of the residuals from the above regression showed that the ACF and PACF cut off immediately. This suggests that the residuals are now essentially white noise. Furthermore, a formal test for autocorrelation showed no evidence of first order serial autocorrelation in the residuals with an autocorrelation coefficient of -0.059 and a p-value of 0.602.

Therefore, we specified the transition equation for next period's price as

$$P_{t+1} = 430.4311 + 0.3498P_t + \hat{\eta}_{t+1} \quad (7)$$

where $\hat{\eta}_{t+1}$ are iid random shocks with mean zero, standard deviation of 191.64, median value of -28.68, minimum value of -314.07, and maximum value of 574.63.[4]

We tested for normality of the residuals using the Jarque Bera test and rejected the null hypothesis that the residuals are normally distributed (JB=17.84, p-value=0.000). Consequently, we estimated the probability density function for the random shocks using the non-parametric procedures that were used to estimate the yield pdfs as outlined above.

Following these results, the discrete state space for $\hat{\eta}_{t+1}$ was specified as a vector of 18, equally spaced, possible random shock states ranging from - \$307/ton to \$492/ton. Each random shock state is taken to be a mid-point of the corresponding continuous random shock interval, with a corresponding discrete probability of occurring. Finally, to complete the specification of the price state space, a vector of the initial values of prices, P_0, is required. This was specified as a vector of 19, equally spaced, possible price states ranging from \$50/ton to \$950/ton. Similarly,

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4 These figures are the descriptive statistics of the residuals from the regression model in Table 1.

each price state is taken to be a mid-point of the corresponding continuous price interval. The upper bound state of $950/ton represents the price interval of $925/ton or above and the lower bound state of $50/ton represents the price interval of $75/ton or below. This completes the specification of the discrete price state together with its corresponding stochastic environment.

Finally, we assume that the farmer's measure of time preference is constant and is given by $\beta = 1/(1+k)$ where k is the discount rate. Here, the discount rate reflects the risk free rate of return, plus a risk premium required by the farmer based on the risk of the stream of cash flows from the orchard. We use a discount rate of 11.43% based on an annual risk free rate of return of 5.43% on a 30-year T-bill (Federal Reserve Board, 2004) and, a risk premium of 6% based on Hanson (1999)'s estimate of the historical risk premium for Michigan farmland. The assumption of a constant rate is made as a practical necessity in order to simplify computations. This is a common assumption that is made in most empirical work.

Preliminary Results

We solved the model for two scenarios: (1) a farmer who faces a climate representative of the events that have taken place in NW Michigan over the last 30 years; and (2) a farmer who faces a warmer climate representative of the events that have taken place in SW Michigan over the last 30 years. In addition, we compare the results of the first scenario with the case of a farmer who uses the traditional NPV aproach to evaluate his orchard replacement decision. We investigate each of these cases in turn.

Table 2 shows the optimal orchard replacement policy for a famer facing the NW climate.

The results show that if the orchard is between 1-27 years old, the optimal decision is to delay replacement. If on the other hand, the orchard is 28 years old or older and the current price is $50/ton or $100/ton, the optimal decision is to replace it. Otherwise, if the price is $150/ton or higher, the orchard should not be replaced. In general, the optimal decision to replace an orchard depends the current price and the age of the orchard. For example, if the current price is $350/ton, the optimal policy asserts that the orchard should be replaced if its age is 30 years or above. The other results are to be interpreted similarly.

Table 3 shows the optimal replacement policy for a farmer in NW Michigan who faces the SW climate. Hence, the farmer now faces a different yield distribution than he did when he faced the NW climate. As would be expected, the optimal replacement policy changes as well. For example, if the current price is $350/ton, the optimal policy is to replace the orchard if its age is 27 years or above. These results, albeit pertaining to the orchard replacement problem only, suggest that the anticipated climate change may have a significant impact on the optimal capital budgeting decisions by tart cherry farmers in Northwestern Michigan.

Figure 3 shows the value of one acre of tart cherries at the beginning of the year as a function of the orchard's age, assuming a current price of $350/ton. These results show that the value of the orchard is substantially higher under the NW climate scenario than under the SW climate scenario. This suggests that if the anticipated climate change takes place, tart cherry orchards may have significantly lower value than they currently do. This may lead to more farmers opting to shift from tart cherry production and may have implications on overall tart cherry production if a substantial number of growers exit. This inference is, however, based on the assumption that prices do not change. If prices change, the impact of a climate change on the value of the orchard is ambiguous. The problem would need to be studied in a more general equilibrium context.

Finally, we illustrate the estimation of the real option value of the optimal orchard replacement decision, using a one year old orchard of a farmer facing the NW climate. Using the DP approach, the value of this orchard was estimated at $7569/acre, which represents its value at the beginning of the period plus all net earnings from its future replacements, assuming the optimal replacement policy is followed. For a farmer using the traditional NPV approach to value this orchard, the flexibility of following the optimal replacement policy is usually not taken into account. This is because, the farmer would typically compute the NPV based on a 'standard' replacement rule that may not be optimal. Hence, the value computed via the DP approach represents the "expanded NPV" of the orchard, which comprises of the "traditional NPV" plus an option value for the flexibility of following the optimal replacement policy.

Assuming a standard replacement age of 35 years for an orchard in NW Michigan, we computed the traditional NPV based on the costs used in the DP model, expected yields, and expected prices, assuming a current price of $350/ton. We found this value to be $6140/acre. To compare this value with the value from the DP model, we first divided this figure by the present value interest factor of an annuity at 11.43% for 35 years and then divided the result by 11.43%. We obtained a value of $6283/acre, which represents the value of the orchard assuming that it is replicated indefinitely. This value can now be compared with the value from the DP model. Therefore, the value of the flexibility option embedded in following the optimal strategy is $1286. This implies that a farmer who follows the optimal replacement policy is better off by $1286 than one who does not and, who only replaces the orchard when it attains age 35.

Conclusions

This paper investigates a very specific issue concerning extant decision support tools which tart cherry farmers could use in the face of multi-year yield and price uncertainties. Based on a review of the Real Options literature, the authors conclude that existing option pricing methods are inappropriate because the assumption of a replicating portfolio can not be justified in the case of tart cherry investments. Instead, the authors assert that the dynamic programming approach is more appropriate and, develop a model which is used to explore optimal tart cherry orchard replacement policy. The results of the model are then used in conjunction with the traditional NPV approach to estimate the value of the flexibility option embedded in the decision making process. The model pertains to a farmer who faces two plausible climate scenarios and seeks replacement contingency plans in the face of stochastic prices and yields. A discrete time, discrete state and control space dynamic programming approach is applied to an example farm from Northwestern Michigan to determine optimal replacement decisions. The model is solved numerically in a standard, discounted, sum of profit maximization framework with results that provide the following key messages.

First, flexibility options in tart cherry investments can be estimated for individual producers using the dynamic programming approach albeit, indirectly. Second, a farmer who uses the DP approach to develop contingency optimal replacement rules and, therefore, makes optimal replacements, will be better off than if he made replacements based only on a standard replacement rule that may not be optimal. Third, and more important, if the SW climate scenario shifts to NW Michigan, the value of tart cherry orchards may fall substantially with implications on the future of tart cherry production in that region if a compensating price increase does not occur.

Generalization of the results of this paper is limited for the following reasons. First, the yield distributions used in the model pertain only to two age cohorts. This has the consequence of forcing the pre-peak and post-peak production yield distributions to be similar. A model that differentiates these distributions would provide a more accurate characterization of the expected yields and will modify the results. Second, the results pertain only to two scenarios: either the NW or the SW climate scenarios. A model that assigns a probability ($p<1$) for the climate change in the NW region to the SW climate or a hybrid thereof, can lend more insights. Third, while the econometric results did not suggest any systematic patterns in the price series, further investigation is necessary in order to account for price cycles that have been observed in the past. A natural extension of this work is, therefore, to estimate a model that addresses the preceding limitations.

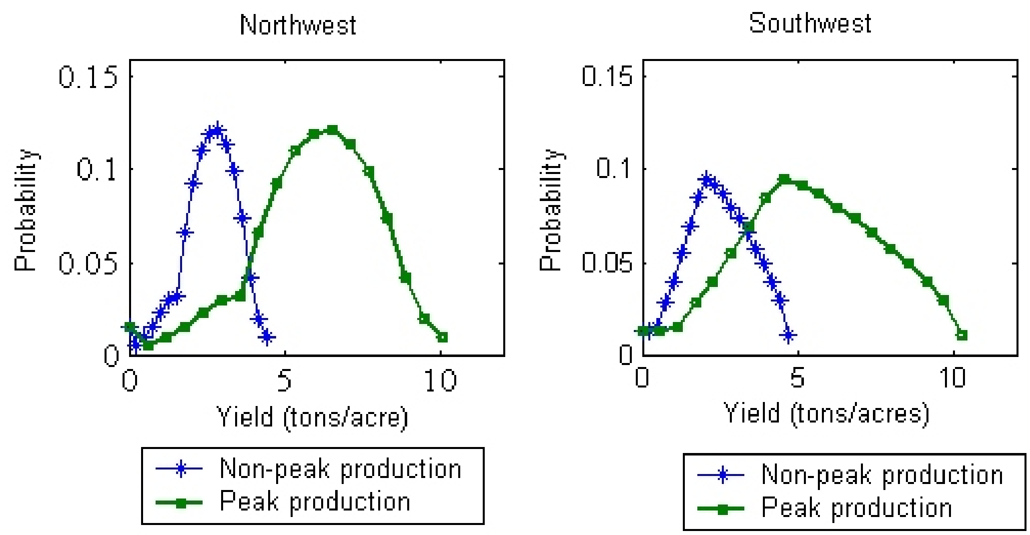

Figure 1. Tart Cherry Yield Distributions for Northwestern and Southwestern Michigan (tons/acre) by tree age Cohorts.

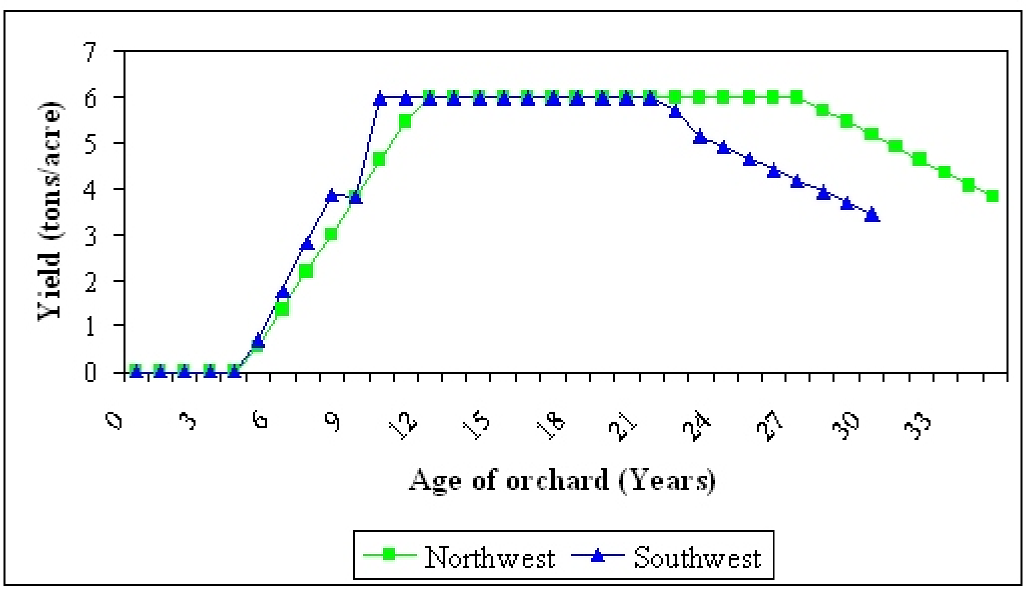

Figure 2. Expected Yield for Tart Cherry Orchards in Northwestern and Southwestern Michigan by age.

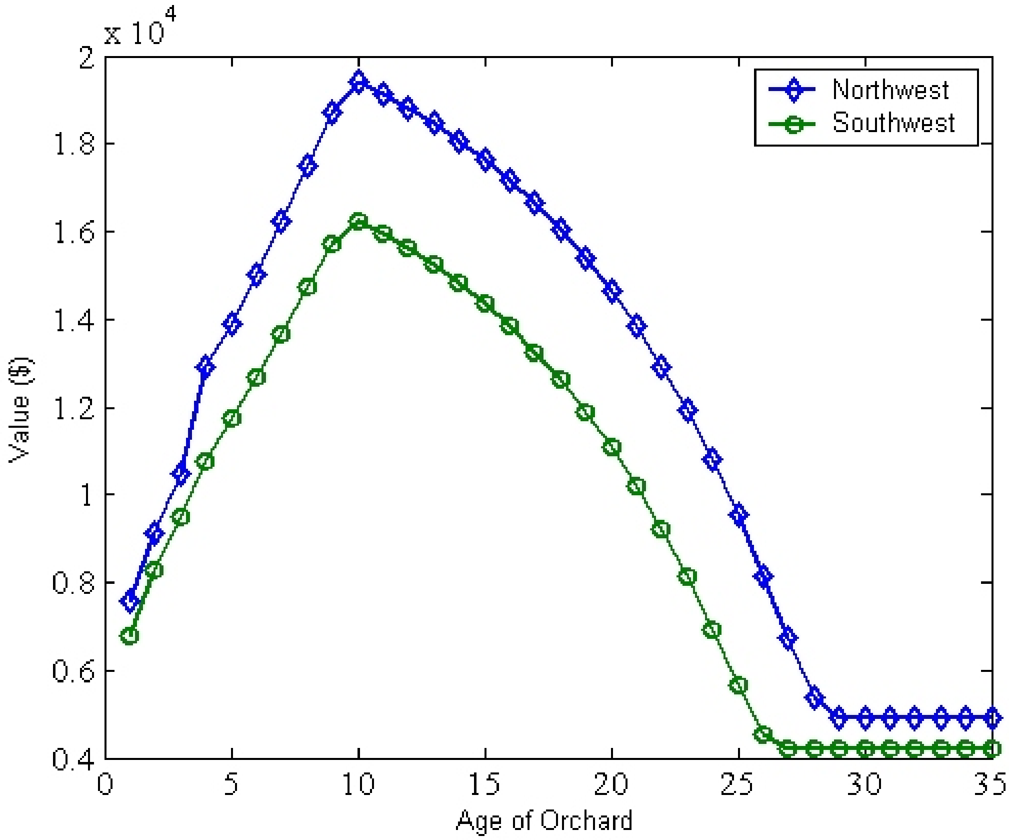

Figure 3. Optimal Value Function for One Acre of Tart Cherries under two Climate Scenarios in Northwestern Michigan

Table 1. Regression results of Michigan tart cherry prices for the years 1925 - 2001.

No. of obs	dependent variable	constant	parameter on P_{t-1}	R^2	F	Prob>F
76	P_t	430.4311	0.3498	0.1221	10.30	0.002
		(34.0354)*	(0.1090)			
		0.000	0.002			

* Figures in parenthesis are standard errors and below them are t-test p-values

Table 2. Optimal Orchard Replacement Policy for a Farmer facing the Northwestern Michigan Climate (0 = do not replace, 1 = replace).

Price ($/ton)	Age: 1-27	28	29	30	31	32	33	34	35	36
50	0	1	1	1	1	1	1	1	1	1
100	0	1	1	1	1	1	1	1	1	1
150	0	0	1	1	1	1	1	1	1	1
200	0	0	1	1	1	1	1	1	1	1
250	0	0	1	1	1	1	1	1	1	1
300	0	0	0	1	1	1	1	1	1	1
350	0	0	0	1	1	1	1	1	1	1
400	0	0	0	1	1	1	1	1	1	1
450	0	0	0	1	1	1	1	1	1	1
500	0	0	0	1	1	1	1	1	1	1
550	0	0	0	0	0	0	1	1	1	1
600	0	0	0	0	0	0	0	0	1	1
650	0	0	0	0	0	0	0	0	0	1
700	0	0	0	0	0	0	0	0	0	1
750	0	0	0	0	0	0	0	0	0	1
800	0	0	0	0	0	0	0	0	0	1
850	0	0	0	0	0	0	0	0	0	1
900	0	0	0	0	0	0	0	0	0	1
950	0	0	0	0	0	0	0	0	0	1

Table 3. **Optimal Orchard Replacement Policy for a Farmer facing the Southwestern Michigan Climate (0 = do not replace, 1 = replace).**

Price ($/ton)	Age 1-24	25	26	27	28	29	30	31
50	0	1	1	1	1	1	1	1
100	0	1	1	1	1	1	1	1
150	0	0	1	1	1	1	1	1
200	0	0	1	1	1	1	1	1
250	0	0	1	1	1	1	1	1
300	0	0	0	1	1	1	1	1
350	0	0	0	1	1	1	1	1
400	0	0	0	1	1	1	1	1
450	0	0	0	1	1	1	1	1
500	0	0	0	1	1	1	1	1
550	0	0	0	0	0	1	1	1
600	0	0	0	0	0	0	1	1
650	0	0	0	0	0	0	0	1
700	0	0	0	0	0	0	0	1
750	0	0	0	0	0	0	0	1
800	0	0	0	0	0	0	0	1
850	0	0	0	0	0	0	0	1
900	0	0	0	0	0	0	0	1
950	0	0	0	0	0	0	0	1

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